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Psychology of Financial Decisions, Using Large Transaction Datasets

by

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A thesis submitted in fulfillment of the requirements for the degree of
Doctor of Philosophy in Psychology

University of Warwick, Department of Psychology

October 2017

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Acknowledgement

I would like to thank Neil Stewart for his supportive supervision of all studies presented in this thesis. His advice was necessary for me to conduct the research. I am also very grateful to John Gathergood and Lukasz Walasek who collaborated on some of the studies presented here and provided useful advice and comments.

I also would like to thank my family for always being there and supporting me.

I was financially supported by the Economic and Social Research Council and this research was supported by the ESRC Network for Integrated Behavioural Sciences ES/K002201/1.

Declarations

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

The studies presented here were carried out by the author with collaborations outlined below: Chapter 2 was written in collaboration with Neil Stewart and John Gathergood; Chapter 3 was written in collaboration with John Gathergood, Neil Stewart, and Joerg Weber; Chapter 4 was written in collaboration with Neil Stewart and John Gathergood; Chapter 5 was written in collaboration with Neil Stewart and Samuel Mohun Himmelweit; Chapter 6 was written in collaboration with Neil Stewart and Lukasz Walasek.

List of submitted papers:

Chapter 2

Sakaguchi, H., Stewart, N., & Gathergood, J. (submitted). Automatic minimum credit card repayments: ‘Nudging’ consumers in the wrong direction.

Chapter 4

Gathergood, J., Sakaguchi, H., Stewart, N., & Weber, J. (submitted). Learning, liquidity and credit card fees.

Chapter 6

Sakaguchi, H., Stewart, N., & Walasek, L. (submitted). Selling winners or losers: Two-stage decision making and the disposition effect in stock trading.

Abstract

Behavioral studies show that people tend to use various decision heuristics which discard part of the available information, simplify the decision problem, and find a good-enough answer. In addition, people's decision and behavior may change because they learn from experience. This thesis investigates people's heuristic decision making and learning from experience in two frequent real-world financial decision contexts—credit card repayments and stock trading.

Chapter 1 reviews the literature about decision heuristics and nudges. Literature about learning from experience is also reviewed. Chapter 2 shows that automatic minimum credit card repayment as a default nudge has the adverse effect of reducing repayments by allowing card holders to neglect their monthly bill. Chapter 3 examines whether people learn from the negative feedback provided by credit card fees. We show that cardholders tend to adapt to late payment fees, which are typically due to forgetting a repayment, by setting up an automatic repayment. On the other hand, cash advance and over-limit fees are due to card holders' liquidity needs rather than their mistakes, and thus, they do not learn from experiencing those fees. Our findings are contrast to those in a previous study in the US suggesting that people learn from all three types of fees. Chapter 4 shows evidence of people's heuristic processing of numerical information in the context of credit card repayments. We find a strong tendency of card holders repaying at several prominent numbers. We also find people's preference for round numbers. Conducting an online experiment, Chapter 5 confirms the anchoring effect of numerical information in a credit card bill, as in previous studies, and finds a false consensus bias where people who usually repay only the minimum greatly overestimate the commonness of minimum repayments among others. However, a social nudge phrase in a mock bill fails to correct the false belief, and thus, dose not reduce the likelihood of people repaying only the minimum. Chapter 6 presents a two-stage model of the choice of a stock to sell. Typically investors show a disposition effect, being more likely to sell a stock in gain than loss, other things equal. In our model, investors first decide whether to sell a stock in the domain of gains or losses, and only then, evaluate stocks within the chosen domain. As evidence for the model, our analysis shows that the likelihood of an individual stock being sold is inversely proportional to the number of stocks in the same domain in the portfolio but is not sensitive to the number of stocks in the other domain. Our findings indicate that existing estimation methods of the disposition effect result in substantial biases because those estimations assume that all stocks in a portfolio are simultaneously evaluated across domains of gains and losses.

Chapter 7 summarizes the findings and implications of Chapters 2-6. Plans and suggestions for future research are also discussed.

Chapter 1 Introduction

1.1 Psychology in The Field

Psychological studies have been contributing to explaining anomalies for classical economic theories. For example, loss aversion in prospect theory explains the equity premium (i.e., high excess returns of equities relative to bonds even after considering their difference in volatility) which risk aversion in expected utility theory cannot solely account for (Camerer, 1998). While economics aims to explain phenomena in real word, traditional psychological studies were conducted in labs. Having said that, psychology now has an alternative methodology using field data. In particular, increasingly available large-sized field data and recent high computation capacity enable researchers to investigate people's behavior in real life in order to test and develop psychological theories on the field data.

In this thesis, we mostly concentrate upon this alternative approach, using large real-world data sets provided by financial institutions. Chapters 2, 3, and 4 use the same credit card repayment records provided by five UK card companies. The data consist of two-years card usage and repayment records of 1.8 million card holders in the UK. The credit card market is one of the largest unsecured lending markets in the UK and about 30 million consumers in the UK have at least one card (Financial Conduct Authority, 2015). Therefore, investigating behavioral patterns in the credit card market is important for policy makers and benefits people. In Chapter 6, we use six years of stock transaction records of retail investors in the US. The data have been available for researchers for more than 10 years and many financial studies were conducted based on the data (e.g., Barber & Odean, 2000, 2001, 2002; Hartzmark, 2015). While the data are not so new, it is good for us to re-analyze the well-known existing data because we aim to show potential biases of existent research by introducing an alternative psychological decision model.

In sum, throughout this thesis, we investigate psychology in people's financial decisions, taking advantage of large-sized field data. (Note that Chapter 5 is based on an online experiment using mock credit card bills rather than field data because the research question suits to a randomized trial.) The presented studies show people's heuristic financial decision making and their behavioral patterns which previous studies did not find. Possible theoretical interpretations and policy implications are also discussed. The rest of this chapter reviews literature in psychology and finance which are relevant to our studies. Overviews of the presented studies and a plan of this thesis are presented at the end of this chapter.

1.2 Heuristics in Decision Making

1.2.1 Overview

Classical normative economic theories consider people as rational agents who optimize their utility or subjective value resulting from their decision by using all available information without time constrains and cognitive limitations. The optimization requires a stable preference which is not affected by environment or decision context (Edwards, 1954). However, people's decisions often deviate from predictions of classical normative theories (Kahneman, Knetsch, & Thaler, 1991; Kahneman & Tversky, 1979; Loewenstein & Thaler, 1989). On the other hand, psychological studies think of people as intuitive thinkers who reduce the complexity of decision problems according to environment (Kahneman, 2011; Kahneman & Tversky, 1984; Tversky & Kahneman, 1974), discard a part of available information (Gigerenzer & Brighton, 2009; Gigerenzer & Gaissmaier, 2011), and find a good-enough (satisficing) answer rather than an optimal one (Simon, 1955).

Kahneman (2011) considers that human decision making is based on an interaction of two distinct but connected systems of human thinking. The first system is fast, unconscious, intuitive, and automatic (System 1) while the second one is slow, conscious, reflective, and rational (System 2). This concept of two systems (or dual processing) is well established in psychological accounts of cognition while properties and cognitive processes attached to two systems slightly differ among theories (Evans, 2008; Stanovich, West, & Toplak, 2011).

Kahneman (2011) argues that The Systems 1 and 2 are not independent of each other. In particular, the System 2 can operate only after information is retrieved by System 1. Thus System 2 tends to be influenced by biases and errors in System 1. This suggests that System 2 may correct biases and errors of System 1 but the perfect correction is not guaranteed.

The sources of biases in System 1 are the heuristics the system uses, including representativeness, availability, and anchoring and adjustment (Ross, 1977; Tversky & Kahneman, 1974). The representativeness heuristic is based on people's tendency to judge the likelihood of an event by the extent to which it is representative of salient features of the population. That is, people are replacing the hard question about the frequency of the event with the cognitively easier question of how well the event description represents their knowledge of the population. With this heuristic, people tend to neglect elements of formal statistical theories including the baseline probability of the relevant events (Kahneman & Tversky, 1972; Ross, 1977). The representative heuristic may lead to the conjunctive fallacy such as the Linda problem (Tversky & Kahneman, 1983). The availability heuristic reflects people's tendency to evaluate the likelihood of events by the ease of retrieving them (Ross, 1977). For example, more recent or more salient events are easier to retrieve, and thus, are judged as more probable. Thus, in using the availability heuristic, people may erroneously believe that their own behavior is common among peers when behaviors of others are rarely observed (the false consensus bias; Discussed in details in Section 1.3.3. The anchoring and adjustment heuristic is a strategy where people adjust their estimate of an uncertain quantity starting from an initial anchor. However, the adjustment is often insufficient, leading to the anchoring effect (Kahneman, 2011). We see the anchoring effect in details in Section 1.2.3.

The decision heuristics tend to result in biased decisions even for trivial problems (Shleifer, 2012). That is, heuristics reduce cognitive effort for making a decision but also reduce accuracy of the decision (the trade-off between accuracy and effort). In this view, the heuristics are used for finding an approximation of an optimal answer to a decision problem when cognitive effort and/or time are constrained. Thus, from the perspective of the accuracy-effort trade-off, the use of heuristics is justified only when those constraints exist (Gigerenzer & Brighton, 2009).

In contrast to the view of the accuracy-effort trade-off, later work showed that the heuristics may be more accurate than formal statistical methods in particular environments (Brandstätter, Gigerenzer, & Hertwig, 2006; Gigerenzer & Brighton, 2009; Gigerenzer & Gaissmaier, 2011; Kurz-Milcke & Gigerenzer, 2007). For example, using datasets from 20 different domains including psychology, sociology, and economics, Czerlinski, Gigerenzer, and Goldstein (1999) showed that the Take-The-Best heuristic outperforms a multiple regression in cross-validations (i.e., predictions) even though the heuristic discards a large part of available information. That is, the Take-The-Best strategy is not only faster and more frugal but also more accurate than optimal statistic models (called the less-is-more effect). Similarly, Mote-Carlo simulations where the number of elementary information processes in decision making represent cognitive effort showed that heuristics with a smaller cognitive effort often lead to more accurate choices than those led by formal statistic models (Payne, Bettman, & Johnson, 1988; Payne, Johnson, Bettman, & Coupey, 1990). Moreover, Brandstätter et al. (2006) argue that the lexicographic heuristic may be more ecological and also more accurate than the complex and compensatory decision rules.

When do the heuristics work better than statistical strategies? In machine-learning literature, it is well-known that a complex model fits each data sample well but tends to be too flexible (i.e., over-fitting the sample), leading to a high variance of predictions for a given data point when models are estimated from different samples. On the other hand, a simple model poorly fits each data sample but the variance of predictions tend to be small (Geman, Bienenstock, & Doursat, 1992). That is, the more complexity and flexibility of the model the lower bias and the higher variance for the model prediction (the bias-variance dilemma). Thus, Gigerenzer and Brighton (2009) argue that the heuristics as a simple model can outperform the complex statistical model by having a small variance. Because the trade-offs between bias and variance depend on the environment and the number of observations, whether the heuristics outperform statistical strategies also depends on environments and contexts. In this sense, heuristics may be ecologically rational (Gigerenzer & Brighton, 2009; Gigerenzer & Gaissmaier, 2011; Kurz-Milcke & Gigerenzer, 2007).

In Sections 1.2.2, 1.2.3, 1.2.4, and 1.2.5, we review four heuristics which are relevant to our studies shown in the subsequent chapters of this thesis.

1.2.2 Status quo bias

Evaluating alternatives relative to a status quo is considered as one of main principles for System 1 (Kahneman, 2011) and people tend to prefer a status quo to other alternatives (Thaler & Sunstein, 2008). The status quo bias is defined as people’s tendency of ‘doing nothing or maintaining one’s current or previous decision’ (Samuelson & Zeckhauser, 1988, p.8). People often stick the status quo option even in the absence of transition costs and uncertainty about alternatives (Samuelson & Zeckhauser, 1988).

Several explanations for the status quo bias have been presented. One major explanation is based on loss aversion. Loss aversion predicts that losses looms larger than gains with the same magnitude (Kahneman et al., 1991). Assuming that people perceive the status quo as the reference point, a loss-averse decision maker tends to prefer not switching from the status quo to alternatives unless an expected gain of switching, relative to an expected loss of giving up the status quo, is large enough to overcome the effect of loss aversion. Alternatively, the norm theory (Kahneman & Miller, 1986) may explain the status quo bias. The theory suggests that negative outcomes are more regrettable when they are caused by actions than when they are caused by inactions, because the regret is based on the counterfactual thinking and it is easier for people to imagine counterfactuals for actions (i.e., outcomes of inactions) than those for inactions (i.e., outcomes of actions) (Feldman & Albarracín, 2017; Ritov & Baron, 1992). This leads people to take no action to avoid a larger anticipated regret resulting from taking the action. This norm-theory account of the status quo bias was supported by neuroimaging findings that neural activities reflecting emotional regret is higher for erroneously rejecting a status quo than erroneously accepting a status quo (Nicolle, Fleming, Bach, Driver, & Dolan, 2011). In addition, Gal (2006) suggests that people tend to stay at status quo when they are indifferent among options because they have no psychological motive to act (i.e., switch from the status quo). Gal (2006) argues that this account is plausible given that people may have *fuzzy* preferences leading to a fuzzy (and possibly broad) range of indifferences.

The definition of the status quo bias by Samuelson and Zeckhauser (1988) (see above) includes two elements—people’s tendency of doing nothing (the omission bias) and their tendency of maintaining one's current or previous decision (the narrowly defined status quo bias opposed to the broadly defined status quo bias in Samuelson and Zeckhauser (1988)). Ritov and Baron (1992) discriminated these two elements and showed that the omission bias plays a large role in broadly defined status quo bias. For example, in their experiment (Experiment 2 in Ritov and Baron (1992)), participants preferred doing nothing, irrespectively of whether the inaction resulted in maintaining or switching from the status quo. This is not the narrowly defined status quo bias but the omission bias.

In addition, psychological theories predict that attribute conflict increases people's preference for deferring a choice or making no choice (e.g., Tversky & Shafir, 1992). Consider that one option is better in one attribute but is worse in another attribute than the other alternatives. According to classical economic theories, this conflict between attributes should have no impact on people's decision because the theories assume that a decision maker can integrate multiple attribute values to identify the best option which maximizes their subjective value. Instead, the psychological theory of choice under conflict (Tversky & Shafir, 1992) predicts that, in facing attribute conflicts, people tend to prefer deferring a decision or making no choice because they are not good at integrating attribute values. That is, in facing the uncertainty, people tend to avoid a commitment to one option (Dhar, 1997). The theory predicts that the more difficult decision problem the more likelihood of people doing nothing or keeping a status quo.

The connection between the status quo bias and the default nudge is discussed in Section 1.3.2.

1.2.3 Anchoring effect

In the anchoring effect, people's judgements tend to be influenced by task irrelevant starting points, even if they are arbitrary or irrelevant (Chapman & Johnson, 1994; Tversky & Kahneman, 1974). In the original study of the anchoring effect, Tversky and Kahneman (1974) asked participants whether the percentage of United Nations representatives from African countries are greater or smaller than a number drawn from a wheel roulette (the comparative judgement task), and then, asked their best estimation of the percentage (the absolute judgement task). The research showed that participants' estimations in the absolute judgement task were influenced by the number drawn from the roulette in the comparative judgement task. Specifically, the larger the number drawn from the roulette in the comparative task the larger the estimation in the absolute judgement task. Tversky and Kahneman (1974) suggested that the number drawn from the roulette worked as a psychological anchor. They propose that, in the presence of a psychological anchor, people tend to start from an initial anchoring number and gradually adjust their estimation of an uncertain quantity to reach their final judgement (anchoring and adjustment heuristic).

However, the adjustment is often insufficient, leading to biased estimations (Kahneman, 2011).

On the other hand, Mussweiler and Strack (1999) suggest the selective accessibility model which explains the mechanism of the anchoring effect quite differently. The model assumes that, in a comparative judgement task where people are asked whether an unknown target value is greater or smaller than a provided anchor value, they test the hypothesis that a target value equals to the anchor value. In doing so, people selectively generate evidence which is consistent with the hypothesis, and thus, increase accessibility of this anchor-consistent evidence in the subsequent judgment phase. According to the model, in the subsequent absolute judgement task, people tend to use the easily accessible knowledge built in the comparative judgment task, leading to their absolute estimations about the target value being influenced by the initial anchor value. For example, when judging whether the temperature on a given (sunny) day is more or less than -20 degrees C, people generate mental images of snow and ice, and then, when judging the actual temperature, some of these congitions remain and bias the mental image towards being cold.

In addition, the anchoring effect indicates that people do not have true stable preferences which classical economics assumes. For example, experiments by Ariely, Loewenstein, and Prelec (2003) showed that people’s willingness to accept (WTA) hearing a painful noise is influenced by an arbitrary anchor value while their WTA coherently increases as the duration of the noise increases. That is, people’s absolute preferences are not stable while only their relative preferences are stable.

Chapter 5 examines the anchoring effect in the context of credit card repayment in an online experiment.

1.2.4 Consideration set heuristic

Classical additive decision models assume that people add up subjective values of attributes within an alternative to have an overall value of the alternative, and then, compare all alternatives using their overall values to choose one alternative. Because the overall value of an alternative is used for the comparison among alternatives, the decision rule is compensatory: being low on one attribute can be compensated by being high on others. However, people tend to use non-compensatory decision rules to reduce the complexity of a decision problem and find a satisficing choice (Simon, 1955). For example, in the conjunctive strategy, only alternatives which satisfy the minimum requirement on all attributes are considered (Hauser, 2014; Payne, 1976). Further, in some decision heuristics, evaluations are not only non-compensatory but also sequential. For example, in the lexicographic strategy, people first order the attributes by importance. All alternatives are then evaluated on the most important attribute and an alternative with the highest value on the attribute is chosen. If two or more alternatives are tie in the first attribute value, those alternatives are evaluated on the second most important attribute. This process continues until one alternative remains in the choice set. Similarly, the elimination-by-aspects model (Tversky, 1972) suggests that people choose one option out of multiple alternatives by sequentially eliminating alternatives which do not satisfy the minimum requirement in a selected aspect at each stage. That is, people proceed through a list of desirable attributes discarding the alternatives that do not possess the attributes at each stage. Consider a consumer choosing a new bike for purchase out of many bikes sold in a shop, he may first exclude all bikes whose price is higher than his budget. In this case, the aspect evaluated at the first stage is price. Then, at the second stage, all bikes with the size of tires smaller than 26 inches are excluded. Such elimination processes continue until one bike remains in his choice set. Because, in the theory, people's decision making consists of multiple stages where at each stage the choice set is reduced by a criterion on one selected aspect, the comparison is within attribute.

Chapter 6 proposes a two-stage stock selling decision model where, in choosing a stock for sale, investors first decide whether to sell a stock from those in gains or sell a stock from those in losses. Then, once a domain—either gains or losses—is selected, people evaluate the stocks within only that domain to select one for sale. (Section 1.4 reviews the literature on the positivity-negativity asymmetry.) We test the model in the empirical US stock trading data.

1.2.5 Heuristic processing of numerical information

When people mentally process numerical information (e.g., prices of consumer goods), they frequently use heuristic ways to save cognitive effort (Albers, 1997; Brenner & Brenner, 1982; Todd & Gigerenzer, 2000). Brenner and Brenner (1982) argue that, because the capacity of human memory is limited, people tend to store and process the most valuable part of numerical information—the first digit (e.g., store £1xx.xx in the memory in seeing £123.33). This heuristic leads people to compare two numbers from the leftmost to the rightmost digit (the left-digit bias). As a consequence, people tend to perceive incorrectly that £2.00 is *much* more expensive than £1.99 (Brenner & Brenner, 1982; Sonnemans, 2006). The left-digit bias influences market prices. For example, Lacetera, Pope, and Sydnor (2012) found that prices of used cars in the US discontinuously drops at 1,000- and 10,000-mile odometer thresholds, suggesting that the left-digit bias leads people to perceive a millage of 20,000 miles as much larger than 19,999 miles but very similar to 20,001 miles.

In addition, the theory of prominence in the decimal system (Albers, 1997) defines prominent numbers as $a10^i$ where $a = 1$, 2, or 5 and i is an integer (e.g., 1, 2, 5, 10, 20, 50, 100…), and suggests that, when faced with a numerical question, people find a reasonable answer by combining a set of prominent numbers with coefficients of +1, 0, or -1. For example, 148 is a combination of prominent numbers, 100, 50, and 2, with the coefficients of +1, +1, and -1, respectively. (Coefficients for other prominent numbers in between are 0.) That is, in the mental process, people start from a high enough prominent number for the numerical question and move down in the sequence of prominent numbers to first find a crude tentative answer at a prominent number which they perceive is more adequate as an answer than 0. (That is, the coefficients of prominent numbers above this tentative answer are 0). Then, from the crude tentative answer, they sequentially decide whether to add, subtract, or not use the next smaller prominent number in order to improve the tentative answer. The theory predicts that the large the number of the mental operations the greater the cognitive effort required. It therefore predicts that, in order to minimize cognitive effort, people prefer responding to a numerical question with prominent numbers. It was evident that people's willingness to pay in the contingent valuation tasks cluster at prominent numbers (Whynes, Frew, Philips, Covey, & Smith, 2007; Whynes, Philips, & Frew, 2005). Also, the previous studies in finance suggest that people's preference for prominent and round numbers results in the price clustering at those numbers in many asset markets (e.g., Ball, Torous, & Tschoegl, 1985; Christie & Schultz, 1994; Harris, 1991; Kandel, Sarig, & Wohl, 2001; Sonnemans, 2006).

Chapter 4 examines people's preference for prominent and round numbers in the context of credit card repayments with the empirical data.

1.3 Nudge

1.3.1. Overview

The choice architecture is a design of the context or the environment where people make a decision. In classical normative models treating people as rational agents, people's decisions are independent of the irrelevant features of the environment where they make a decision. However, in using heuristics, people tend to contextualize available information to simplify decision problems and to reduce cognitive effort for making a decision, leading to the context-dependence of people's decisions (Croskerry, 2009). Thus the choice architecture matters to people's decision making (Thaler & Sunstein, 2008).

It was evident that how alternatives are framed influences people's preference and decision (Kahneman & Tversky, 1984; Tversky & Kahneman, 1981, 1986). Thaler and Sunstein (2008), in their famous book 'Nudge', argue that, through operations of the System 1, choice architecture is likely to affect people's decision making, and thus, a nudge may be useful to improve or guide people's behavior. For example, etching a small fly near to a drainage of urinals in male toilet greatly reduces the spillage because users tend to aim at the fly (Thaler & Sunstein, 2008). The order of a restaurant menu changes people's choices of food (Thaler, Sunstein, & Balz, 2014). Similarly, a small change in accessibility to food items in a salad bar affects people’s consumption of the food items (Rozin et al., 2011). Foods were less consumed when they were located in the middle of a table than at the edge of the table.

Because choice architecture may affect decisions, it is important for policy makers to well design the choice architecture. Thaler and Sunstein (2008) defines a nudge as ‘any aspect of the choice architecture that alters people’s behavior in a predictable way without forbidding any options or significantly changing their economic incentives’ (p. 6). That is, the nudge is a policy tool to improve peoples' behavior by changing the choice architecture but preserving individual freedom of choice (i.e., people are allowed to choose options which they favor to the nudged option).

Sunstein (2014a) listed several advantages of nudges over mandates. First, by preserving individual freedom of choice the nudge can decrease costs caused by imposing a single solution to everybody. That is, the nudge can respond to individual heterogeneity. For example, mandatory 'optimal' saving in pension plan may be harmful for people who are still repaying other debt or those with low income while the nudge can avoid this cost. Second, because people are allowed to freely discard nudged choices, the nudge can significantly reduce the cost caused by policy makers' mistakes. Such mistakes may come from a lack of policy makers' knowledge or biased opinions from influential private organizations. In addition, preserving the freedom of choice, the nudge is considered much more respecting of dignity. In sum, Sunstein (2014a) argues that nudges are, in general, less risky policy tools than mandates.

On the other hand, there is a critique that the nudges are less transparent than the mandate and people may be in danger of being unconsciously influenced by the nudge (Sunstein, 2014a). The nudges are also questioned from a perspective of their basis of justification. Gigerenzer (2015) argues that, while the libertarian paternalists justify the nudge based on their belief that people’s decisions are systematically biased and deviate from the rationality, scientific evidence for the belief is sparse if the rationality is measured by the ecological one rather than the logical and statistical one (see the ecological rationality discussed in Section 1.2.1). He suggests that people can learn and, in many circumstances, should be educated rather than be nudged. This leads to the *boost* approach which intends to boost people’s competences of processing information by, for example, providing them with fundamental knowledge or changing presentation of information to easily-understandable format (Grüne-Yanoff & Hertwig, 2016).

Table 1.1 shows ten important nudges listed by Sunstein (2014b). Among them, we see the default nudge and the social nudge in details in Sections 1.3.2 and 1.3.3, respectively.

Table 1.1. A List of Important Nudges in Sunstein (2014b)

Type of Nudge	Description	Example
Default	Setting a default option which is chosen if people do not make an active choice.	Opt-out policy for organ donation
Simplification	Reducing unnecessary complexity of a program.	Simplification of application forms
Social norm	Informing people about a behavior which most other people follow.	Inform people "Most people plan to vote"
Increase in ease and convenience	Reducing the barriers to choose a certain option.	Making healthy foods visible in cafeteria
Disclosure	Providing comprehensive, accessible, and simple disclosure with people.	Disclosure of the full cost associating with credit card use
Warning, graphic or otherwise	Showing a salient warning.	Health warning on a cigarette box
Precommitment strategy	Asking people to commit a certain future goal.	Precommitment to stop drinking
Reminders	Sending a timely reminder.	A text message to remind repaying a credit card
Eliciting implementation intentions	Asking people about their intention for their future behavior.	Asking people "Do you plan to vote tomorrow?"
Informing people of the nature and consequences of their past choices	Informing people of the nature and consequences of their past choices.	Letting people know their past energy bills

1.3.2 Default nudges

The default nudge is one of most well-established policy tools. The strength of the default effect has been evident in a variety of important settings including pension saving (Cronqvist & Thaler, 2004), insurance coverage (Johnson, Hershey, Meszaros, & Kunreuther, 1993), web marketing (Johnson, Bellman, & Lohse, 2002), taxi tipping (Haggag & Paci, 2013), and energy markets (Momsen & Stoerk, 2014). For example, setting double-sided printing as a default in printers can save paper cost (Simon, 2008). In countries having a opt-out policy (i.e., presumed-consent policy) the organ donation rate is typically about 90% while in countries with a opt-in policy (i.e., explicit-consent policy) the rate is 5-30% (Johnson & Goldstein, 2003). Automatic enrolment (i.e., opt-out policy) remarkably increases the participation rate in saving plan (Thaler & Benartzi, 2004). Interestingly, Loewenstein, Bryce, Hagmann, and Rajpal (2014) showed that the effect of a default option is largely preserved even when people are aware that they are nudged toward the default.

Several causes of the default effect have been presented. First, people may think that a default is an implied recommendation (Smith, Goldstein, & Johnson, 2013; Thaler & Sunstein, 2008). Second, due to cognitive laziness, people tend to choose an option requiring the smallest effort (Johnson & Goldstein, 2003; Thaler et al., 2014). Third, the default option may work as a psychological anchor or a subject of the comparisons among options, resulting in a large probability to be chosen (Johnson et al., 2002). Finally, the default option is thought as a status quo and, because of the loss aversion, people tend to stick to the status quo (Tversky & Kahneman, 1991; see Section 1.2.2 for details).

While the default nudges are often used as a policy tool, the oppositions claim that the default nudge invades people's right to choice and violates their autonomy (Smith et al., 2013). On the other hand, Sunstein (2015) warns that policy makers recommending active choices may form choice-requiring paternalism. Sunstein (2015) argues that choosing a default option is beneficial depending on the context. For example, when a decision maker is busy or has little knowledge or information about the decision, the decision is costly for them and an erroneous choice is likely. In such a circumstance, people prefer a default option to an active choice, and the default option can reduce both the decision cost and the error cost.

Using a large dataset provided by five credit card companies in the UK, Chapter 2 shows that the automatic credit card repayment as a default nudge may backfire by leading people to greatly reduce the frequency of making manual repayments.

1.3.3 Social nudges

Psychological studies have been observing that people tend to conform to the majority. For example, in a famous lab experiment by Asch (1951), a group of participants were asked to judge lengths of vertical lines in 12 trials. The experimenter asked participants to state their answer in turn. Among participants in a group, only one was a real participant while all the other participants were confederates cooperating with the experimenter. In a part of trials, confederates uniformly stated an incorrect answer even though the correct answer was obvious. The experiment found that the real participant frequently conformed to the clearly incorrect majority. Bernheim (1994) suggests that people prefer conforming to the majority because they think that a deviation from a social consensus may hurt their status.

However, people's belief about the consensus among their peers tend to be biased (Mullen, 1983; Prentice & Miller, 1996; Ross, Greene, & House, 1977). The false consensus bias represents people's tendency to believe that their own behaviors, attributes, or opinions are more common than it is believed by people with a different position (Mullen, 1983; Ross et al., 1977). For example, students who prefer a group research to an individual research for their assignment estimated that 67% of students preferred the group research while those preferring the individual research estimated that only 33% of students prefer the group research (Ross et al., 1977). The false consensus bias is observed both in experimental hypothetical situations and in real-life situations (Mullen, 1983; Ross et al., 1977). Several possible mechanism underlying the false consensus bias have been presented (Marks & Miller, 1987). One possible mechanism of the false consensus bias is based on the availability heuristic—people's tendency to estimate the likelihood of events by the ease of retrieving them (Tversky & Kahneman, 1973). According to this account, when observations of others' behaviors are limited, the information available in memory is unlikely to be a representative sample of the population but instead is likely to be information about one's own behavior and the behaviors of others close to oneself. If similar others around oneself are more likely to share one's own behavior, the availability heuristic tends to lead people to falsely believe that their own behavior is more common than it really is. From this perspective, the false consensus bias is caused by people's biased cognitive process. Another possible mechanism is driven by people's motivation to justify themselves. The theory of social comparison (Festinger, 1954) suggests that, in the absence of objective and non-social means, people tend to make self-evaluations by means of comparison with others. According to the theory, people's evaluation of the correctness of their own behavior depends on the degree of its commonness among others. Thus, the theory predicts that people are motivated to justify themselves by overestimating the commonness of their own behavior, leading to the false consensus bias (Marks & Miller, 1987). In addition, Mullen (1983) found that the false consensus bias appeared even with a large monetary incentive offered for an accurate estimation, suggesting that the mechanism behind the bias is likely to be unintentional perceptual distortions rather intentional strategies to justify oneself.

As reviewed above, people incline to conform to the common behavior while they tend to falsely overestimate the commonness of their own behavior. The social nudge is a policy tool guiding people toward a better behavior by informing them about the norm which most other people follow (Sunstein, 2014b). In other words, the social nudge helps people to improve their behavior by correcting their false belief about the consensus. Perkins and Berkowitz (1986) found that most college students overestimate the proclivity for alcohol consumption among peers and the overestimation predicts the amount of individual alcohol consumption. Based on these findings, they suggested that a social norm intervention (i.e., a social nudge) correcting a misperception about peers' proclivity for alcohol consumption with accurate information may reduce alcohol consumption among students with a high consumption level. The effects of social nudges were evident in a variety of fields (e.g., Bartke, Friedl, Gelhaar, & Reh, 2017; Cialdini, 2003; Gerber & Rogers, 2009; Goldstein, Cialdini, & Griskevicius, 2008; Haines & Spear, 1996). For example, a social norm message describing the average energy consumption among neighbors leads households with a high level of energy consumption to reduce consumption (Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007).

The experiment shown in Chapter 5 examines the existence of the false consensus bias and the effect of a social nudge in the context of credit card repayments.

1.4 Positivity-Negativity Asymmetry

Psychological theories argue that the positive and the negative tend to be separately processed by people (Kanouse & Hanson Jr, 1987; Lewicka, Czapinski, & Peeters, 1992; Peeters, 1971). Peeters and Czapinski (1990) postulate that stimuli with a negative valence lead to more complex cognitive representations than those with a positive valence. Similarly, Rozin and Royzman (2001) suggest that, in reality, positive things are frequent and simple while negative things are rare and complex. In the linguistics literature, Garcia, Garas, and Schweitzer (2012) found that words with a positive valence are more frequently used than those with a negative valence and, due to their rareness, negative words tend to be more informative than positive words, leading to different cognitive processes for positive and negative words. Prospect theory (Kahneman & Tversky, 1979) is based on an assumption of the gain-loss separability, where alternatives are perceived as positive (gain) or negative (loss) relative to a reference point with loss aversion making a loss loom larger than the equivalent gain. McGraw, Larsen, Kahneman, and Schkade (2010) showed that loss aversion appears only when an experimental design requires people to conduct cross-valence comparisons on a common scale. If people were allowed to use two distinct scales for gains and losses, the loss aversion disappears. They suggested that, in the absence of a mandatory common scale across gains and losses in experiments, people tend to compare gains with other gains but not with losses and compare losses with other losses but not with gains (i.e., within-domain comparisons), leading to the disappearance of the loss aversion. Kassam, Morewedge, Gilbert, and Wilson (2011) also showed different cognitive processing for the positivity and the negativity, and, in particular, deeper processing of the negativity. Kassam et al. (2011) found that when people win a lottery by receiving the larger of two possible gains they are just happy to have won, irrespective of the size of the gain they received, but when they lost the lottery by receiving the smaller of two possible gains, their happiness ratings depended on the size of the smaller gain they received. Kassam et al. (2011) argued that, when people win, the comparison between the large gain they received and the small gain they could have had makes them happy and processing stops. But when they lose, the comparison between the small gain they received and the larger gain they could had had, if only they had won, makes them unhappy. They argue that because they are unhappy they engage in further cognitive processing, comparing the gain they have received against other amounts, and it is this further processing that makes them sensitive to the magnitude. Further, an experimental study by Scholten, Read, Canic, and Stewart (2015) observed the mutable-zero effect where a zero outcome is perceived as more positive when the outcome is framed as ‘pay 0’ than when the outcome is framed as ‘receive 0’. They argued that the origin of the mutable-zero effect is people’s tendency to conduct within-payment and within-receipt comparisons, supporting an existence of distinct evaluation processes for the positive- and negative- valenced stimulus.

Chapter 6 proposes that, because comparing across the domains of gains and losses is cognitively effortful, when stock investors choose a stock for sale, they tend to first decide one of the domains of gains or losses, and then, conduct a within-domain comparison among stocks in the chosen domain. We examine this with empirical data from retail investors in the US.

1.5 Learning and Forgetting

Psychological studies consider two major factors influencing the likelihood of people recalling a past event—how long it passed since experiencing the event (recency) and how many times the event was experienced (frequency) (see, e.g., Anderson & Milson, 1989; Anderson & Schooler, 1991). Indeed the identification of these factors goes back to Ebbinghaus (1885/1964) and is some of the earliest work in the scientific study of psychology. These two factors can be reduced to three functions—retention, practice, and spacing functions (Anderson & Schooler, 1991). The retention function measures the likelihood of people recalling an event as a function of time elapsed since the event was experienced (i.e., the delay between the event and a test of recalling it; the test delay). The practice function measures the likelihood of people recalling an event as a function of the number of the events being experienced (or practiced). The spacing function measures the likelihood of people recalling an event as a function of time intervals among two or more experiences of the event (the experience lag). Both the retention and the practice functions decay over time with a negative acceleration (e.g., in the exponential form or in the power form) (Anderson & Schooler, 1991). For example, in the retention function, a drop in the recall likelihood from one-day delay to two-days delay is large while the difference in the likelihood is small between 100- and 101-days delays. Similarly, in the practice function, a difference in the recall likelihood is large between experiencing the event once and twice while the difference is small between experiencing it 100 and 101 times. On the other hand, a functional shape of the spacing function is more complex with an interaction between the test delay and the experience lag (Glenberg, 1976). That is, when the test delay is short, the shorter the experience lag the larger the recall likelihood. However, when the test delay is long, the longer the experience lag the larger the recall likelihood. Anderson and Schooler (1991) postulate that the recall likelihood, given the number and timing of past events, is determined by a net effect of these three functions.

Now consider a person who missed repaying his credit card bill and incurred a late payment fee. In the next month, he was more aware of making a repayment, and thus, his fee likelihood was lower. That is, he has learned from the negative experience of having the fee. However, after three months, he was less likely to recall the negative experience and forgot a repayment again. This is consistent with the declining shape of the retention function. Then, in the next month, again, he was more aware of making a repayment and avoided having a fee. Moreover, just after the second fee, he was more likely to remind making a repayment than just after the first fee. This is predicted by the practice function. In addition, the spacing function may also involve the likelihood of forgetting a repayment. In this way, the fee likelihood is a function of forgetting. If the net effect of three functions on forgetting is negative, we expect that the fee likelihood decreases over time.

In Chapter 3, we see the declining pattern in the average likelihood of having a late payment fee in the UK credit card data. However, we find that the smooth ‘learning’ curve is not due to the forgetting mechanism described above, but instead, is the aggregation of a series of differently offset step functions caused by people switching to an automatic repayment method at different times.

1.6 Learning from Experience

Before the study by Hertwig, Barron, Weber, and Erev (2004), most experimental studies concerned decision making where clear descriptions of decision problems were provided with participants (decisions from description). However, in real life, people often use their experiences in memory for making a decision (decisions from experience). Many studies observed how people treat rare events in gamble choice differs depending on whether a lab experiment requires them to make a decision based on described probabilities and outcomes or based on their estimations about probabilities and outcomes obtained through sampling outcomes (Hertwig et al., 2004; Rakow & Newell, 2010). Specifically, in a decision from description, people tend to overweight the probability of rare events, showing risk-seeking for gains and risk-aversion for losses with a small probability. On the other hand, in a decision from experience, people tend to underweight the probability of rare events, showing risk-aversion for gains and risk-seeking for losses with a small probability.

In decisions from experience, people update their belief by combining new samples with previous ones (Hertwig et al., 2004). Such an experience-based decision making resembles adaptive learning models in which options are sequentially sampled and the probability of an option being sampled is a function of experienced outcomes on the option (Denrell & March, 2001). For example, March (1996) showed that, in choices between a risky binary gamble and a certain alternative, stochastic adaptive learning models, where the probability of an option being chosen (thus being sampled and observed) is an increasing function of experienced returns on that option, predict a larger risk-aversion in the gain domain than in the loss domain when the probability of winning the risky gamble is small. This is consistent with the pattern of risk-taking behavior observed in the lab experiments described above. The mechanism behind the learning model's predictions is as follows. Because winning a risky lottery is a rare event, the certain alternative tends to be more attractive than the risky option in most trials. If the probability of people sampling an option positively associates with experienced outcomes, the risky gamble is getting less likely to be sampled. While the risky gamble may infrequently provide a large outcome, people tend not to experience the large outcome because they are likely to sample the certain alternative whose experienced outcomes seem to be better than those of the risky gamble (Denrell, 2007). Such learning models explain people's risk preference by experiencing-and-learning process without any assumptions about people's traits-based risk preference or a shape of utility function (March, 1996).

Interestingly, when information about an alternative is obtained only from experiences, this sampling process may result in biased decision making. That is, information about an alternative with favorable experience tends to be further gathered through additional experiences even if their belief about the option is better than the reality. On the other hand, additional information about an alternative with unfavorable experience tends not to be accumulated, and thus an erroneous belief about the option is unlikely to be corrected even if the belief is worse than the reality. This asymmetry predicts that negative belief about an alternative which initially unfavorably experienced tends to be persistent, leading to a smaller probability of the alternative being chosen in subsequent decisions than it should be (Denrell & March, 2001).

The Rescorla-Wagner model (Rescorla & Wagner, 1972), a key model in the comparative psychology literature, was developed in order to predict behavior in classical Pavlovian conditioning paradigms. The model predicts how the associative strength of the conditioned stimuli (CS) as a signal to the unconditioned stimuli (US) as a reward changes over repeated pairings of the CS and the US. Specifically, for given intensity of the CS and the US, a change in associative strength (i.e., the amount of learning) is determined by to what extent the occurrence of the US is surprising comparing with an expectation (Rescorla, 2008). The larger the degree of surprise the larger the degree of associative learning. In other words, learning happens when observations violate expectations, and the degree of the learning depends on the size of the discrepancy between expectations and observations (i.e., prediction errors). While the Rescorla-Wagner model has been influential in the literature, the model has several limitations. For example, the model cannot predict learning in second-order conditioning. In second-order conditioning, one CS, A, paired with a US is further conditioned by another CS, B. Although these conditioning pattern empirically leads to an association between B and US (Sutton & Barto, 1990), the Rescorla-Wagner model predicts no or negative association between them because the US is offset during the B-A conditioning, and thus, the model predicts zero or negative prediction errors in the B-A conditioning period.

The temporal difference (TD) model (Sutton, 1988) is one of the most well-known and successful machine learning algorithms that builds on the earlier Rescorla-Wagner model. In the TD model, agents learn from a difference between successive predictions of all future rewards (i.e., a change in the discounted sum of all (expected) future rewards between adjacent time steps), while, in its predecessors including the Rescorla-Wagner model, agents learn from prediction errors between expected and actual outcomes only when the actual outcome is revealed. When applied to the Pavlovian conditioning, the TD model resolves some shortfalls of the Rescorla-Wagner model including the second-order conditioning problem (Sutton & Barto, 1990).

In addition, machine learning models allow agents' actions to change a sequence of signals and rewards. Thus predictions are a function of both actions and signals. Agents improve their predictions by learning from reward history resulting from previous actions and signals, and dynamically change their actions. The process resembles people learning from experience in real life.

Several studies found that people learn from experiences in economic decisions. For example, US senior citizens who initially chose a suboptimal Medicare plan in 2006 tended to switch the plans to reduce the overspending in 2007 (Ketcham, Lucarelli, Miravete, & Roebuck, 2012). Interestingly, the larger the overspending in insurance in 2006 the larger the likelihood of switching from the initial plan, leading to a larger reduction in cost in 2007. Agarwal, Rosen, and Yao (2012) showed that, while refinancing a mortgage, US mortgage borrowers tend to make mistakes by choosing an incorrect refinancing rate or missing the right timing of the refinance, the likelihood of mistakes is smaller on the second refinancing than on the first refinancing. That is, people learn from the first refinancing experience to reduce the likelihood of mistakes in the second refinance decision. However, people do not always learn from experience. For example, Della Vigna and Malmendier (2006) found that people who had paid a flat monthly fee for a sports gym did not attend the gym frequently enough for the flat fee to be better value than pay-as-you-go. Those individuals also tended to delay cancelling the automatic renewal of their monthly membership over a year without switching it to a cheaper annual membership. Della Vigna and Malmendier (2006) suggest that people rolling the monthly membership over a year overestimate both the probability of attending the gym and the probability of cancelling the membership.

Using large-sized empirical data provided by credit companies in the UK, Chapter 3 examines whether and how people learn from experiences and mistakes in the context of credit card usage. Namely, we examine whether experiencing late payment fees, cash advance fees, and over-limit fees influences their subsequent behavior in credit card repayment and usage.

1.7 Disposition Effect

One of the most well-evidenced behavioral biases in finance is the disposition effect—people's tendency to hold losing investments too long and to sell wining investments too early (Odean, 1998; Shefrin & Statman, 1985). The disposition effect has been evident both in empirical stock trading data (Brown, Chappel, da Silva Rosa, & Walter, 2006; Grinblatt & Keloharju, 2000; Odean, 1998) and in laboratory experiments (Weber & Camerer, 1998). While the origin of the disposition effect continues to be debated in the literature (Ben-David & Hirshleifer, 2012; Hens & Vlcek, 2011; Kaustia, 2010), one of the most popular explanations is based on prospect theory. There are two key features of prospect theory at play in the explanation of the disposition effect. First it is assumed that the purchase price acts as a reference point. Empirically there is a nearly symmetrical distribution of expected future returns. The second feature is a kinked S-shaped value function with curvatures indicating that investors are risk-seeking in the loss domain and are risk-averse in the gain domain. This results in holding a risky stock in the loss domain rather than selling for cash, but selling a risky stock in the gain domain in favor of the cash price. However, some studies argue that prospect theory may not sufficiently explain the disposition effect. For example, Hens and Vlcek (2011) found that, with parameter values which conform to the disposition effect, the prospect theory predicts that investors do not make an initial purchase of the stock. Similarly, Kaustia (2010) showed that, assuming that the expected future returns are normally distributed, the prospect theory with realistic parameter values predicts that the subjective value of holding the stock is higher than that of selling the stock for a large range of prior returns across gains and losses, indicating that an exogenous reason for selling the stock is required in order for the prospect theory to explain the disposition effect.

On the other hand, one of alternative explanations is based on investor's belief in mean-reversion of stock prices. That is, people believe that a stock price is negatively autocorrelated and thus the price should revert to a long-term mean (Andreassen, 1987; Kahneman & Tversky, 1973). The belief in mean reversion indicates that stocks which have recently depreciated are likely to appreciate toward the long-term mean, and conversely, stocks which have recently appreciated are likely to depreciate towards the long-term mean. As a result, investors tend to hold stocks in loss and to sell stocks in gain, leading to the disposition effect. Another explanation is based on the theory of regret avoidance (Bell, 1982; Loomes & Sugden, 1982). The theory suggests that investors anticipate that they will feel regret about their past decision of purchasing the stock when they consider realizing a loss on the stock, but anticipate that they will feel pride when they consider realizing a gain on the stock. This asymmetry leads investors to hold stocks in loss and to sell stocks in gain.

In Chapter 6, we show that the degree of the disposition effect is highly sensitive to how many gains and losses are in a portfolio (i.e., the composition of a portfolio). Specifically, the smaller the number of gains relative to the number of losses in a portfolio the larger the degree of the disposition effect. Interestingly, the disposition effect even reverses in a portfolio with many stocks in gain and a singleton stock in loss. We argue that this composition-sensitivity of the disposition effect results from a part of investors conducting a two-stage decision making where they first decide whether to sell one of gains or one of losses, and then, evaluate individual stocks within the chosen domain. The presented two-stage model is contrast to the existing models which assume that all stocks in a portfolio are simultaneously evaluated no matter whether they are gains or losses. While our study is not intended to identify the origin of the disposition effect, implications of the two-stage model for the origin of the effect are discussed.

1.8 Plan of Thesis

In Chapter 2, we show that the automatic credit card repayment as a default nudge helps people to avoid a late payment fee by ensuring the monthly minimum repayment but may backfire by leading them to neglect the card bill and not to make an additional manual repayment. We use the empirical credit card repayment data provided by five credit card providers in the UK. Using the same data, Chapter 3 examines whether and how cardholders learn from experiencing late payment, cash advance, and over-limit fees. As evidence of people’s heuristic processing of numerical information, Chapter 4 shows that people prefer repaying round and prominent amounts, and thus, the repayments highly cluster at those numbers. Using the data from an online survey and a hypothetical credit card repayment experiment, Chapter 5 examines the anchoring effect of numerical information in the credit card bill and the effect of an inclusion of a social nudge phrase in the bill. Chapter 6 proposes a two-stage decision model where, in choosing one stock for sale, investors first choose one of the domains of gains or losses, and then, conduct within-domain comparisons among stocks in the chosen domain to decide a stock for sale. We find evidence of this model in the stock trading data of the US retail investors. The study has an important implication for existing estimation methods in the disposition effect. The theme linking all of these chapters is the use of “big” machine recorded data from thousands or millions of transactions to explore the psychology of economic behavior. Chapter 7 recaps the findings of Chapters 2 to 6 under this theme.

Chapter 2 Automatic Minimum Credit Card Repayments: 'Nudging' Consumers in the Wrong Direction

2.1 Background

Perhaps the most well-known and well-evidenced behavioral science intervention is the default option 'nudge' whereby the status-quo option for a decision is changed by a policymaker (Thaler & Sunstein, 2008). One prominent example is the adoption of an opt-out policy for organ donation instead of an opt-in policy. Opt-out is associated with substantially increased organ donation rates (Johnson & Goldstein, 2003). Setting the default option is a powerful tool which has been used in a variety of important settings including pension saving (Cronqvist & Thaler, 2004), insurance coverage (Johnson et al., 1993), web marketing (Johnson et al., 2002), and energy markets (Momsen & Stoerk, 2014).
Defaults change the status-quo choice, but do not limit the options available to the individual, and thus preserve individual freedom (Sunstein, 2014a). Psychological theories suggest that a default option has a large probability of being chosen because of people's cognitive laziness or status quo bias (Johnson & Goldstein, 2003). However, defaulting consumers into one choice deemed to be 'good' can potentially lead to unintended effects. Given the power of default options to influence individual behavior their design, and use, are important issues (Thaler et al., 2014).

Credit card companies create the near perfect default nudge by changing the status quo option of credit card customers. Traditionally, customers have to settle their bills each month by manual payment. However, payments technology now allows credit card companies to offer automatic payments, including the option to automatically pay the minimum amount due. This seems like a great idea—no longer will people forget to pay their bills, and be charged late fees, because the minimum to keep the account good is paid automatically. At the same time, the consumer is free to pay more if he or she wishes. The automatic minimum payment nudge is near perfect, because it protects the consumer without limiting their freedom (Thaler & Sunstein, 2008). The nudge almost entirely eliminates the late fees, as intended, without apparently making it harder in any way to pay down more debt.

Here we use data on 1.8 million credit card holders across five credit card companies in the UK to show how this well-intended nudge in practice works out to be bad for consumers. This is because, in practice, consumers who set up an automatic minimum payment are breaking the psychological link between spending and repayment. They neglect to make extra manual payments. As a result, consumers take longer to repay their credit card debt and incur twice as much interest as manual repayers. This extra interest is 10 times more than the fees they avoid. And we estimate that this extra interest is more than 10% of all of the interest paid on credit cards—an economically large effect.

2.2 Data

The data were provided by five UK credit card issuers. Cardholders and issuers were not identified. The data were extracted and provided by Argus Information & Advisory Services in collaboration with the UK Cards Association, without constraint on the research agenda. Under the terms of the agreement with Argus, we are not able to share the data directly. Meta data and complete R source code are available for all steps from importing the data export from Argus to the statistics, tables, and figures in this chapter. We are retaining the data for 10 years. The data are a 10% sample of all UK consumers who held a credit card during January 2013 to December 2014 within Argus's database, which covers nearly 100% of UK card holders. We received data for cards from five providers, who together cover 40% of all UK credit card consumers. (Note that Chapters 3 and 4 use the same data though data-restriction criteria differ across the chapters.)

The data include card numbers (anonymized), balances, required minimum amounts, purchase amounts, purchase types, repayment amounts, and various types of fees and finance charges for 1,790,191 cards during 24 months from January 2013 to December 2014. In the data, repayments appear in the statement for the month after the statement containing the balance. For example, repayments reported in December 2014 statements were made against the bill showing the balance and the required minimum in November 2014. Because no repayment data are available for January 2015, repayments for balances in December 2014 are unknown. Thus, the data provide at maximum 23 balance-repayment observations per card from January 2013 to November 2014.

We extracted only cards which had full 23 balance-repayment observations and excluded cards closed or charged-off during the data period. Cards which never had positive balances and those which had a zero merchant APR for part of the sample period were excluded from the analysis (in the latter case these cards may not require any repayment in some months). In addition, cards with a balance transfer were excluded. (Note that cards were treated as having a balance transfer when an aggregation of the beginning balance and all transaction amounts within a month including purchases, cash advances, fees, finance charges, and repayments differ from the end of the month balance by £10 or more.) All cards which had an unclassified transaction were excluded. After the data restriction described above, 10,122,300 repayment observations of 440,100 cards remain in our sample.

The minimum amount people must pay each month is, in the UK, normally interest and fees accrued within the month plus 1% of the card balance, or a fixed sum such as £5 or

£10, whichever is the greater. Making a repayment of at least the monthly accrued interest ensures that the value of the debt does not grow. Additionally, repaying 1% of the balance implies that over time the debt will be repaid, though the pay-down horizon is typically many years.

An advantage of our data is that manual repayments and automatic repayments are reported separately. Automatic repayments are made by a mechanism known as “Direct Debit”. Direct Debit is an extremely common method for paying bills in the UK. The analogous mechanism in the US has been introduced more recently and is variously known as “AutoPay” or “automatic payment”. We flagged cards where the direct debit repayment matched the required minimum repayment. If the required minimum was the same as the full balance for all observations of a given card (typically for small balances), we cannot know whether the direct debit covers the full balance or required minimum. These cards were not flagged as having a minimum direct debit.

We constructed two subsets of the data. The first subset is a between-cards dataset consisting of cards who never repaid by direct debit throughout the data period (Non-Auto cards) and those whose direct debits were at the required minimum throughout the data period (Min-Auto cards). We investigated the difference in repayment behaviors between these two groups. Because we are interested in repayments, the data were restricted to observations with a positive balance and a positive required minimum. Summary statistics are shown in Table A1.2 in Appendix 1.6. Our data do not provide demographics for individual cardholders. But we do have partial postcodes (ZIP codes) and so we matched the cardholders’ postcodes with geographic variables retrieved from the UK national census 2011 and the small area income estimates 2013 (provided by the Office for National Statistics). We use these matched data to control for possible difference in socioeconomic status between cardholders with Non-Auto cards and those with Min-Auto cards.

The second subset is a within-card dataset consisting of cards that initially made manual repayments every month before setting up a direct debit and making automatic minimum repayments using direct debit afterwards. After setting the direct debit, cardholders may and do often make additional manual repayments. The within-card dataset was restricted to cards with a positive balance in at least one month both before and one month after the first direct debit. Thus we can investigate the effect of setting a minimum direct debit on repayment behaviors within the same cards. The data were restricted to observations with a positive balance and a positive required minimum. Summary statistics are shown in Table A1.3 in Appendix 1.6.

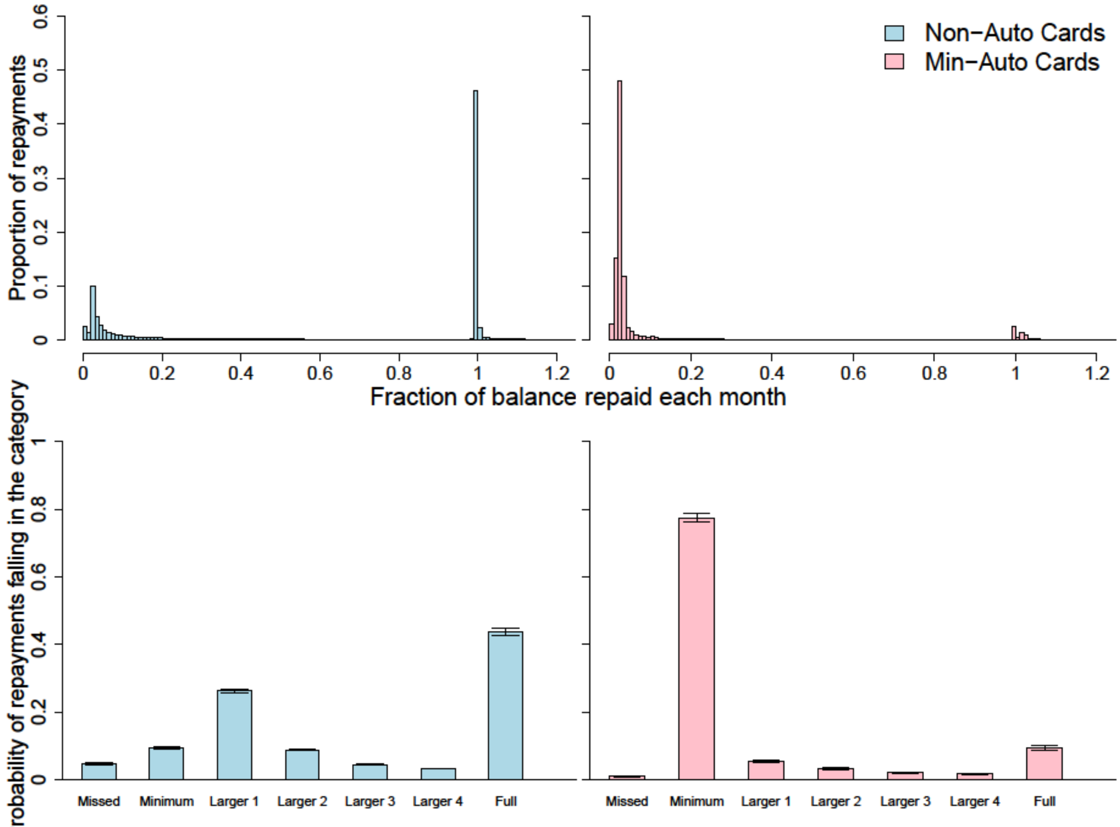


Figure 2.1. The fraction of balance repaid each month. The top panels show histograms of monthly credit card repayments, expressed as fractions of the credit card balances due, for Non-Auto cards and Min-Auto cards. The width of each bar is 0.01. The bottom panels show predicted probabilities from a multinomial logit model of seven different categories of repayment from missed (no payment made) to full (balance cleared in full). Values are predicted at the medians of covariates. The error bars are 95% confidence intervals.

2.3 Results

2.3.1 Between-cards analysis

We first compare differences in repayment behavior between consumers with their card repayment set to pay the minimum automatically (Min-Auto) throughout the sample period and those with no automatic repayment (Non-Auto). Consumers in the Non-Auto group need to make manual repayments each month in order to avoid late fees. Those in the Min-Auto group can make additional manual repayments if they wish. (Note, Min-Auto is different from full autopay where the customer repays the entire balance each month.) The top panels of Figure 2.1 show the distribution of repayments, expressed as a fraction of the card balance. In the Non-Auto group, nearly half of the cards are repaid in full each month, and only a small fraction pay only the minimum (top left). In the Min-Auto group, only a very small fraction of cards are repaid in full each month, and nearly half pay only the minimum (top right).

We fitted a multinomial logit model of repayments to control for individual and card characteristics (Equation 2.1). The results are essentially the same as the simple proportions presented above. The model estimates the probability that repayments fall into each of seven categories: Missed, Minimum, Larger 1, Larger 2, Larger 3, Larger 4, and Full. Missed includes repayments less than the required minimums. Minimum includes repayments which are equal to or greater than the required minimum and less than the required minimum plus £10. This £10 allowance is for including repayments slightly larger than the minimum, which were possibly caused by rounding up of the required minimum, in Minimum category. Larger 1 includes repayments which are not included in Missed and Minimum, and are less than 25% of the balance. Larger 2 includes repayments equal to or more than 25% of the balance and less than 50% of the balance. Larger 3 includes repayments equal to or more than 50% of the balance and less than 75% of the balance. Larger 4 includes repayments equal to or more than 75% of the balance and less than the full balance. Full includes repayments equal to or more than the full balance. If a repayment was equal to the required minimum which was also equal to the full balance, the repayment was included in Full. We included $Balance$, $Credit\ Limit$, $Utilization$ (how much of the credit limit is utilized), and $Charge\text{-}off\ Rate$ (a monotonic transform of credit score). To control for the possibility that individuals in Min-Auto group differ from those in Non-Auto group, we included postcode-level socioeconomic status control variables. $Average\ Weekly\ Income$ represents the average weekly income for a postcode. $Proportion\ with\ Higher\ Education$ represents the proportion of people having a post-high school educational qualification within a postcode. The independent variable of interest is $Min\text{-}Auto\ Card$ which is a dichotomous variable having a value of 1 if a card was a Min-Auto card, otherwise having a value of 0. For ease of computation the analysis was conducted on 100,000 randomly sampled accounts.

$$\begin{aligned}
&\log\left(\frac{P(Repayment\ Category(t)=Category\ k)}{P(Repayment\ Category(t)=Missed)}\right)=\beta_0+\beta_1 Balance(t-1)+\\
&\beta_2 Credit\ Limit(t-1)+\beta_3 Utilization(t-1)+\beta_4 Spending\ Amount(t-1)+\\
&\beta_5 Merchant\ APR(t-1)+\beta_6 Cash\ APR(t-1)+\beta_7 Charge\text{-}off\ Rate(t-1)+\\
&\beta_8 Average\ Weekly\ Income(Postcode\ level)+\\
&\beta_9 Proportion\ with\ Higher\ Education(Postcode\ level)+\beta_{10} Min\text{-}Auto\ Card \qquad (2.1)
\end{aligned}$$

The bottom panels of Figure 2.1 show estimated probabilities of repayments in any month falling into each category from the multinomial logit model. Table A1.4 in Appendix

1.6 reports the coefficients. Min-Auto cards have a very low probability of missing payments (0.9%, 95% CI [0.7%, 1.2%]), which is lower than the probability of missed payment for Non-Auto cards, (4.6%, 95% CI [4.4%, 4.8%]). This is the ‘good’ effect of Min-Auto. Results also show that Min-Auto cards have a 77.5%, 95% CI [76.3%, 78.7%] probability of only paying the minimum, compared with a 9.2%, 95% CI [8.9%, 9.6%] probability of Non-Auto cards paying minimum. This is the ‘bad’ effect of Min-Auto, and it is much larger than ‘good’ effect.

It is unlikely that the effect of Min-Auto repayment is due to consumers self-selecting into Non-Auto and Min-Auto based on their intention to repay. It could have been that those choosing Min-Auto always intended to make lower repayments. Table A1.5 in Appendix 1.6 shows that there are only very small differences in socioeconomic status for consumers in the Non-Auto group and those for cardholders in the Min-Auto group. We might have expected those with lower socioeconomic status to be less likely to choose to repay their bill in full. And the effect of Min-Auto repayment is robust to the inclusion of the socioeconomic controls in Equation 2.1. But the most telling finding is that, in the rare months when those in the Min-Auto group do make an additional manual repayments, they look just like those in the Non-Auto group. Figure A1.1 in Appendix 1.1 and Table A1.6 in Appendix 1.6 show how similar these distributions are. We suggest that this similarity is not consistent with the hypothesis that those in the Min-Auto group cannot afford to repay. In particular, we estimated that, in months with repayments greater than the minimum, the probability of full repayments are virtually identical between Min-Auto cards (63.2% 95% CI [61.4, 65.0]) and Non-Auto cards (63.9%, 95% CI [63.5, 64.2]). It is hard to imagine that consumers wanting to make smaller repayments would do so entirely by making larger repayments in some months and minimum repayments in others, rather than making reduced repayments across all months. In fact, it would be very strange if everyone decided to reduce their repayments by making a series of monthly repayments like: minimum, minimum, minimum, larger, minimum, minimum, minimum, larger,... . Perhaps some people might do this if they periodically have bursts of disposable income, but that everyone would do it seems unlikely. Instead, we see the similarity as evidence that when those in the Min-Auto group do make additional manual repayments in a particular month, it is because they have remembered to pay their bill. In summary, our robustness checks leaving a causal effect of automatic payment on repayments as entirely plausible.

To recap, the between-cards analysis showed that the Min-Auto group repay much less than the Non-Auto group because the Min-Auto group rarely made extra manual repayments over and above their automatic minimum payment. This is the adverse effect of automatic minimum repayments.

2.3.2 Within-card analysis

To control for the possibility that consumers with automatic minimum repayments differ from those with manual repayments (i.e., unobserved heterogeneity), we introduce here a within-card analysis using consumers who switch from Non-Auto to Min-Auto, comparing their repayment profiles before and after.

As seen in the top panels of Figure 2.2, after the switch to a Min-Auto the share of minimum payments increased from 25.6% to 73.1% (shown as the sum of bars about from .01 to .05 on the x-axis within each panel). The share of full payments dropped by an absolute 7.6% from 19.1% to 11.5% (shown as sum of bars equal to or greater than 1 on the x-axis within each panel).

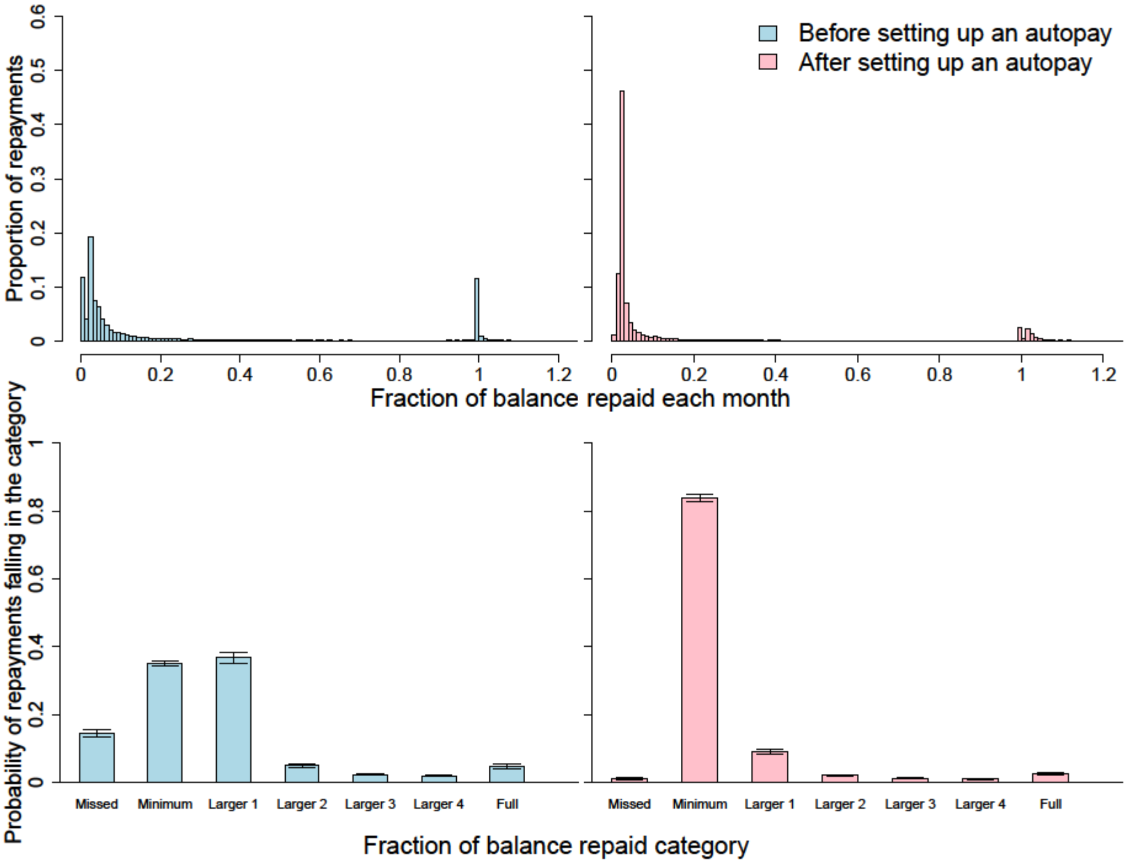


Figure 2.2. The fraction of balance repaid each month before and after cards switch from Non-Auto to Min-Auto. The top panels show histograms of monthly credit card repayments expressed as fractions of the credit card balance due. The width of each bar is 0.01. The bottom panels show predicted probabilities from a multinomial logit model of Before- and After-Min-Auto repayments falling in categories of fraction repaid from missed (no payment made) to full (balance cleared in full). Values are predicted at the medians of covariates. The error bars are 95% confidence intervals.

To confirm the findings in the top panels of Figure 2.2, we fitted a multinomial logit model to estimate the probabilities of repayments falling into each of the same seven repayment categories above (Equation 2.2). The specifications of repayment categories are identical to those in Equation 2.1. The independent variable of interest is $Before\ Min\text{-}Auto$ which is a dichotomous variable having a value of 1 if a card had not started using a Min-Auto, otherwise having a value of 0.

$$\log\left(\frac{P(Repayment\ Category(t)=Category\ k)}{P(Repayment\ Category(t)=Missed)}\right)=\beta_0+\beta_1 Balance+\beta_2 Credit\ Limit+\beta_3 Utilization+\beta_4 Spending\ Amount+\beta_5 Merchant\ APR+\beta_6 Cash\ APR+\beta_7 Charge\text{-}off\ Rate+\beta_8 Before\ Min\text{-}Auto \tag{2.2}$$

The bottom panels of Figure 2.2 shows the results. Table A1.7 in Appendix 1.6 reports the coefficients. Consistent with the finding in the top panels of Figure 2.2, after setting up Min-Auto the likelihood of paying only the minimum within the month increases sharply from 35.1%, 95% CI [34.4%, 35.9%] to 83.9%, 95% CI [83.0%, 84.9%], the likelihood of paying the full balance halves from 4.8%, 95% CI [4.0%, 5.5%] to 2.4%, 95% CI [2.0%, 2.7%], and the likelihood of missing the minimum payment decreases sharply from 14.4%, 95% CI [13.3%, 15.5%] to 1.0%, 95% CI [0.8%, 1.3%].

We also examined the distribution of repayments in months after the switch to Min Auto when people do make an additional manual repayment. The supplemental analyses presented in Figure A1.2 in Appendix 1.2 and Table A1.8 in Appendix 1.6 show that, given an additional manual repayment, the probability of accounts repaying in full does not differ before and after the switch to Min-Auto. As with the additional manual repayments in the between-cards analysis, we suggest that finding the same pattern of repayments when Min-Auto repayers do make an extra manual repayment implicates forgetting or neglect rather than an inability to repay.

The above results suggest that the default option causes consumers to act sub-optimally. If consumers act optimally then their repayment amounts should be adjusted according to changes in circumstance in each month. For example, we might expect consumers to repay more after spending more than usual if they can afford to do so. In order to investigate whether setting a Min-Auto discourages consumers from increasing a repayment after a large spend in the previous month, we calculated the repayment-spending ratio as a repayment at month t divided by a total spending in month $t-1$, for each account month. If an account repaid exactly the same amount as a total spending in the previous month, the ratio has a value of 1. If an account repaid less than the purchase amount, this ratio is less than 1. Conversely, if an account repaid more than the purchase amount, the ratio is greater than 1.

Figure 2.3 plots the distribution of repayment-spending ratios. The data were restricted to card-months with spending greater than minimum. First, before setting a Min-Auto, card holders missed repayments in about 8.5% of observations (the bar at 0 on the x-axis in the left panel). Missed repayments were almost eliminated after they set a Min-Auto (the right panel). This is the positive effect of a Min-Auto we saw before. However, we also see a negative effect. Before setting a Min-Auto, card holders matched their repayments with total spending in the previous month in about 14% of observations (the bar at 1 on the x-axis in the left panel). After setting a Min-Auto (right panel), card holders matched their repayments with total spending in the previous month in about 8% of observations. Consumers are more likely to match their repayment to spending before rather than after setting a Min-Auto. This suggests that, while automatic payments prevent consumers from missing repayments, it reduces the linkage between purchases in one month and repayments in the next. The proportion of the ratios equal to or greater than 1 (i.e., the proportion of cards repaying at least total spending in the previous month) decreased from 40.6% (the left panel) to 29.8% (the right panel) after cards switched to a Min-Auto.

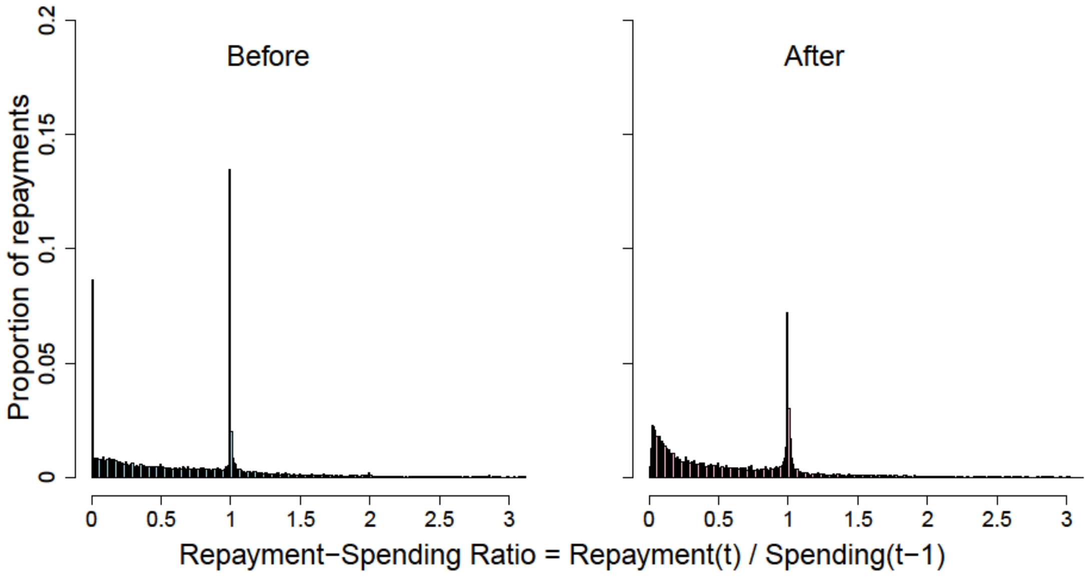


Figure 2.3. The distribution of repayment-spending ratios. The left panel is for observations before cards set a Min-Auto repayment. The right panel is for observations after cards set a Min-Auto repayment. The width of each bar is .01.

Both of the between-cards and the within-card analyses showed the negative effect of Min-Auto on repayments. However, one potential concern with these analyses is that cardholders may endogenously select into Min-Auto due to their intentions to reduce repayments. In order to address this concern, in Appendix 1.3, we present an additional analysis where repayments of cardholders setting up a Min-Auto after a refund of a late payment fee are compared with those of cardholders keeping manual repayments after the refund. The analysis exploits a natural experiment (see the Appendix 1.3 for details). Late payment fees are mostly the results of forgetting rather than economic difficulty, and we select consumers who have contacted their credit card company and received a refund of the late fee and, at the same time, set up a Min-Auto. Thus the forgetting in the previous month acts as an exogenous manipulation of automatic payment status (i.e., as a natural experiment). The results showed that the effect of Min-Auto repayment is not attributed to Min-Auto cardholders' ongoing intention to make small repayments (see Figure A1.3 in Appendix 1.3 and Table A1.9 in Appendix 1.6). In addition, for the robustness check, we repeated the between-cards and the within-card analyses with an alternative and broader definition of Min-Auto cards (see the Appendix 1.4 for details of the definition). The results are nearly identical to those in the main analysis (see Figures A1.4, A1.5, and A1.6 in Appendix 1.4, and Tables A1.10 and A1.11 in Appendix 1.6).

2.3.3 Excess interest cost simulations

We calculated the financial and time costs arising from lower repayments among consumers setting Min-Auto. A typical approach used by regulators is to assume no further purchases and a fixed monthly repayment (e.g., the required minimum repayment), calculating how long it would take to clear the debt and the total cost. However, very few consumers adhere to the above assumptions (i.e., in reality, many consumers make additional purchases and change their repayment behavior over time). We use Monte Carlo simulations, with repayments (and spending) drawn from their actual distributions (see the Appendix 1.5 for details and results). In the Pay-Down-Only Simulation (assuming no further spending), we see Min-Auto more than doubles the time duration and total costs (interest and fees) until clearing the balance compared with the Non-Auto group. In the Spending-and-Repayment Simulation, we see consistently higher balances and about double the total costs in the 20-month period. As a result, for average repayers, the extra interest due to Min-Auto is about 10 times more than the late fees avoided.

We also conducted a simulation estimating what proportion of total interest and fees incurred by all cards across the entire credit card market is due to Min-Auto (see the Appendix 1.5 for details and results). Cards using Min-Auto at least once in the data period could save about 36% of interest and fees if they never used Min-Auto. This is about 15.5% of the all interest and fees paid in the credit card market. Even an effect ten times smaller would be very economically significant.

2.4 Discussion

Using the data from 1.8 million credit cards held by UK consumers, we have shown that, although setting automatic minimum repayments mostly eliminates the likelihood of missed repayments, it also substantially decreases the likelihood of consumers paying over the required minimum and reduces the link between spending and repayments. Consumers neglect bills and only passively manage their credit card debt once they set up an automatic minimum payment, leading to repeated minimum repayments. The results indicate that promoting automatic minimum payment, which we had considered as a near perfect default nudge, has an unintended side effect. Automatic payment is promising in a sense of reducing the likelihood of forgetting repayments but is unfavorable in a sense of suppressing active debt management.

We suggest that this unintended effect of automatic minimum repayment could be partially addressed through interventions which bring the repayment decision back to the top of the consumer’s mind, drawing attention to the repayment decision. More generally, what should policymakers and industry do to avoid introducing nudges with unintended effects? We have two suggestions. The first is to assess the effect of the nudge across as broad a range of outcome behaviors as are available, and to follow up on these assessments. The second is to consider the status quo effects resulting from the nudge itself. The Save More Tomorrow nudge towards retirement saving has both properties (Benartzi & Thaler, 2013). Consumers are automatically enrolled into minimum contributions to a retirement saving scheme to get them started, but contributions automatically escalate, ensuring low saving is not the status quo. Follow-up assessments show the additional pension savings have not come at the cost of savings elsewhere (Benartzi & Thaler, 2013). Smart nudges like this can avoid the pitfalls seen in automatic minimum repayment and ensure choice architecture interventions work in the best interests of consumers.

Chapter 3 Learning, Liquidity, and Credit Card Fees

3.1 Background

In the economics literature there is a theme exploring the extent to which consumers learn in economic scenarios, particularly learning from fees and other economic incentives. Previous studies have examined whether consumers respond to negative feedback and adapt their behavior in various domains (e.g., Della Vigna & Malmendier, 2006; Ketcham et al., 2012; Miravete, 2003). For example, Miravete (2003) found that, in the choice between a flat telephone tariff and a measured alternative, consumers who initially chose a suboptimal option rapidly switched to the optimal one. On the other hand, Della Vigna and Malmendier (2006) showed that people with a rolling monthly sport gym membership did not attend the gym frequently enough for the membership to be worth it, and did not cancel it.

In this chapter, using individual level card data in the UK, we investigate whether and how consumers respond to negative feedback in credit card use. In the credit card market, card holders receive negative feedback when they incur fees for late payment, taking a cash advance, and going over-limit (see Appendix 2.1 for detailed description of these fee types). If the negative feedback is led by card holders' mistakes, they may adapt their behavior in order to avoid having the fee again.

Earlier work by Agarwal, Driscoll, Gabaix, and Laibson (2013) showed that, in the US credit card data, the proportion of cards having late payment, cash advance, and over-limit fees sharply declines over the first few months since the card was opened (i.e., early account tenure). They argue that this declining pattern reflects consumers learning from experience in response to negative feedback of having the fees. Our data show a similar pattern for late payment and cash advance fees. However, the pattern for over-limit fees considerably differs from that in Agarwal et al. (2013). That is, in our sample, the average proportion of cards having an over-limit fee increases to 2% over the first seven months and plateaus afterwards.

We identify quite different mechanisms behind the declining pattern in late payment and cash advance fees. The decline in late payment fees is completely attributed to card holders who switched their repayment method from manual repayments to automatic repayments (autopay) in response to having a late payment fee. Switching to the autopay mostly eliminated the likelihood of subsequent fees. In other words, those card holders learned from their mistakes of forgetting the repayment and adjusted their repayment behavior by setting up the autopay. However, for non-switchers, the likelihood of having a subsequent late payment fee remained just as high. That is, a part of card holders respond to the experience of having a late payment fee and set the autopay to insure themselves against future forgetting, while others do not learn from the experience and tend to have subsequent fees. In addition, we found that card holders who received a refund of the late payment fee were more likely to switch to the autopay, indicating that, in communicating with card companies for the refund, card holders might be prompted to set up the autopay. This provides additional evidence for a late payment fee triggering setting up autopay.

Autopay is a new concept in the academic literature on credit cards and our study is the first one to investigate the role of autopay as an adaptation tool for responding to the negative feedback of having a late payment fee.

On the other hand, the declining pattern in cash advance fees is due to time-varying liquidity needs rather than card holders’ learning from the experience. Our data show that the likelihood of having a cash advance fee is larger for high-risk cards and positively associates with non-cash purchases and utilization rates. These findings indicate that card holders tend to use cash advances when their liquidity is constrained. Because consumers with liquidity needs are likely to take a new card, the proportion of cards with a cash advance fee peaks just after account opening and tends to decline afterwards. Thus the declining pattern in cash advance fees reflects time-varying liquidity needs rather than card holders learning from the experience which Agarwal et al. (2013) suggested. In other words, cash advance fees are not led by card holders’ mistakes but their liquidity needs, and thus, the declining pattern is not attributed to card holders’ learning from the experience.

We do not see a declining pattern in over-limit fees over account tenure. However, we found that, as soon as card holders resolved the over-limit, their purchases sharply drops, indicating that over-limit fees are also led by time-varying liquidity needs. In our sample, while the median tenure at which cards had a first fee is seven months after account opening, the timing of a first over-limit differs among cards. When we divide cards with over-limit fees by account tenures at which the card holder had a first over-limit fee, we see a declining pattern in over-limit fees after the first one for each subset of cards. The declining pattern is quite similar to that seen in cash advance fees. Because the speed of accumulating the balance differs among individual cards, the average (or aggregated) likelihood of having an over-limit fee over tenure shows a different shape.

This chapter contributes to the literature in learning from experience by distinguishing different mechanisms forming patterns in the three types of credit card fees over account tenure. That is, late payment fees are mostly due to card holders’ mistakes (i.e., forgetting a repayment) and thus they tend to respond to the mistakes by setting up autopay. On the other hand, cash advance and over-limit fees are led by card holders’ liquidity needs rather than their mistakes. Thus they do not learn, but the likelihood of having those fees declines as the liquidity constrains ease over time.

3.2 Data

The data used in this chapter are the same as those used in Chapters 2 and 4, though the data-restriction criteria described below are different. The data are provided by five anonymous UK credit card issuers who together comprise 40% of the UK credit card market (by number of cards). We source the data via Argus Information and Advisory Services, who collate and harmonize data from credit card issuers. Argus provided us with account level data for a 10% random sample of consumers who held at least one card among the five credit card issuers in the period between January 2013 and December 2014. Hence, our data is an unbalanced panel in which we observe cards openings and closures. The total data sample comprises 1.4 million customers and approximately 48 million card-months. The data includes transaction level data (e.g., spending, manual repayment, automatic repayment, fees, etc.) alongside card month summary data (e.g., balance, credit limits, charge-off rate, etc.). The data also show the opening date of each account in the sample which allows us to calculate the account tenure. Because this chapter investigates patterns in fee payments early in the life of new cards, we restricted the data to cards which opened within our sample period. After this restriction, we have approximately 2.6 million card-months for about 243,000 cards.

Summary statistics are shown in Table A2.1 in Appendix 2.2. (Note that, because our sample contains only new cards and many of those have an initial discount ‘teaser’ rate deals, the mean merchant annual percentage rate of charge (APR) is low at 9.3%.)

Our sample used in the main analysis below is based on the unbalanced panel. Therefore, the observed pattern could potentially arise due to selective attrition or survivorship bias, if cards which had fees are more likely to close or charge off. From this reason, we repeated a part of the main analyses on the first 15 card-months of cards having at least 15 months (i.e., a balanced panel; see Table A2.2 in Appendix 2.2 for summary statistics).

3.3 Results

3.3.1 Summary of three types of fees

First, Table 3.1 summarizes the value and frequency of three types of fees—late payment, cash advance, and over-limit fees. Fees are quite common within our sample. 34% of cards had a fee at least once within the data period. Late payment fees are most common with 24% of cards having a late payment fee at least once. Cash advance and over-limit fees are less common with about 13% of cards having a cash advance fee and 7% of cards having an over-limit fee. Card holders on average had about £9 in fees over the data period, approximately half of which are for late payment fees.

Table 3.1. Fee Summary Statistics

Fee Types	Proportion of cards having the fee (%)	Ave. fee amounts during the data period (£)
Any fee	33.63	8.99
Late payment fee	24.17	4.33
Cash advance fee	13.05	2.59
Over-limit fee	7.26	2.06

3.3.2 Credit card fees over account tenure

We corroborate in our data the main finding from Agarwal et al. (2013) that all of three types of credit card fees decline over account tenure.

Figure 3.1 shows the proportion of card-months with each of three fee types on account tenure measured in months. (Figure A2.1 in Appendix 2.2 shows the results on the balanced panel.) Note that, because late payment fees appear in the data one month after the card holder paid late, we lagged tenure by one month for late payment fees. Also, because a part of cards did not have a full month in the first billing cycle, we excluded the first tenure of each card from the analysis for cash advance and over-limit fees. Late payment (Figure 3.1a) and cash advance fees (Figure 3.1b) show a sharp decline in the proportion of cards with the fee over the first few months of account tenure. The proportion of cards with a late payment fee declines from 6% in the first month to 2.8% by month 23. The proportion of cards with a cash advance fee declines from 4.8% to 1.8% over the same period. The decline is sharper in the first few months than in subsequent months. On the other hand, for over-limit fees (Figure 3.1c), we observe a different pattern. The proportion of cards with an over-limit fee increases steadily for the first several months, and then, keeps about 2% level afterwards. This pattern is considerably different from that in Agarwal et al. (2013), who found that, in the US data, over-limit fees also concentrate in early tenure and sharply decrease over tenure. In our data, card holders take time after opening to accumulate balances. Among cards with at least one over-limit fee, the first fee is on average at 7.6 months after opening. Few card holders exceed their credit limit just after opening the card (fewer than 0.5% of cards in our sample). This difference may reflect differences in card usage between the UK and US, with possibly a part of US card holders opening accounts with large balance transfers that might lead to over limit soon after opening.

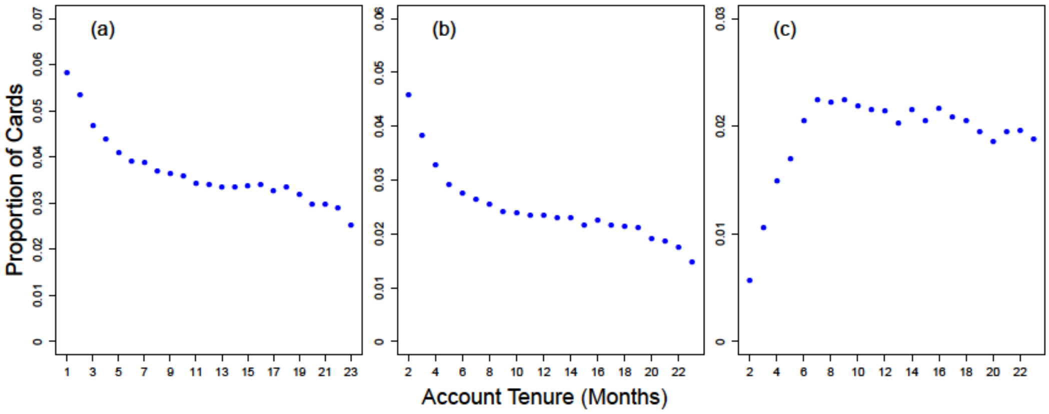


Figure 3.1 The proportion of cards with the fee over account tenure. Panel (a) shows the proportion of cards with a late payment fee. Panel (b) shows the proportion of cards with a cash advance fee. Panel (c) shows the proportion of cards with an over-limit fee. The scale of the y-axis differs among panels. In Panel (a), the x-axis variable was adjusted one month forward.

The declining pattern of fees seen in Figure 3.1 may reflect time-varying card characteristics or calendar time effects. In order to exclude these possibilities, we conducted linear regressions with Equation 3.1 which controls for time-varying card characteristics, the card fixed effect and the calendar month fixed effect. In Equation 3.1, the dependent variable is a dichotomous variable, $P(fee = 1)^{j}_{i,t}$, which have a value of 1 if card *i* had a fee of type *j* at tenure *t*, otherwise 0. $Tenure_{i,t}$ represents the account tenure of card *i*. φ_i is the fixed effect of card *i*. ψ_{month} is the fixed effect of calendar months. X is a vector of time-varying card characteristics including balance, credit limit, utilization, charge-off rate, and total monthly purchase. (All variables in X are in a cubic form.) Standard errors are corrected for clustering by cards. A regression was conducted separately for each of the three types of fees.

$$P(fee = 1)^{j}_{i,t} = \alpha + \varphi_i + \psi_{month} + \Omega_t Tenure_{i,t} + \beta(X)_{i,t} + \epsilon_{i,t} \qquad (3.1)$$

Figure 3.2 shows the model predictions with median values of covariates. (Tables A2.3 and A2.4 in Appendix 2.2 report coefficients.) Figure 3.2 shows very similar patterns to those in Figure 3.1. That is, the likelihood of late payment and cash advance fees sharply declines over the first few months, while the likelihood of over-limit fees increases for the first seven months. (Figure A2.2, and Tables A2.5 and A2.6 in Appendix 2.2 show the results on the balanced panel. Note that, in the estimation, the fixed effect of calendar months was excluded because the calendar months are identical to account tenures in the balanced panel.)

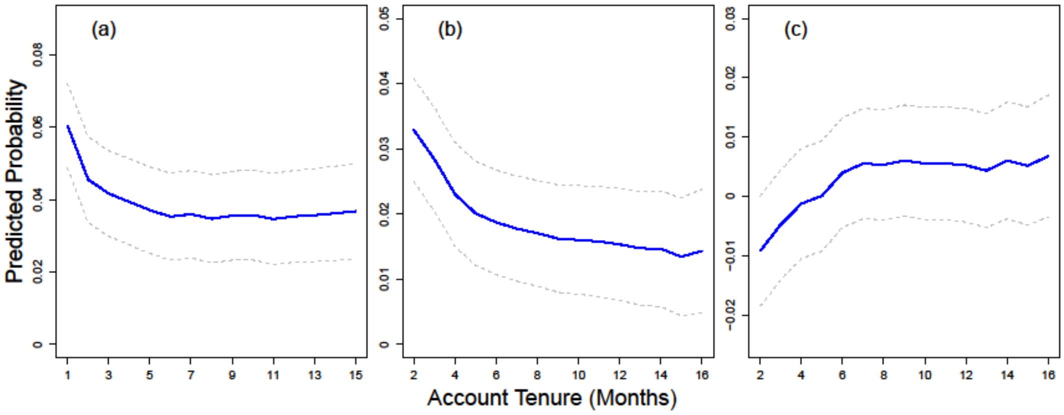


Figure 3.2 The probability of cards having the fee as a function of account tenure. Predictions are from a linear probability model at covariates medians (Equation 3.1). Panel (a) shows the probability of cards having a late payment fee. Panel (b) shows the probability of cards having a cash advance fee. Panel (c) shows the probability of cards having an over-limit fee. The scale of the y-axis differs among panels. In Panel (a), the x-axis variable was adjusted one month forward. The dashed lines are 95% confidence intervals. The standard errors were corrected, for clustering by cards.

To recap, late payment and cash advance fees are front loaded and decline over account tenure while over-limit fees grow in early account tenure. What follows investigates the mechanisms behind these patterns.

3.3.3 Late payment fees and autopay

Here we show that the declining pattern in late payment fees is wholly attributed to card holders switching their repayment method from manual repayments to automatic repayments.

Autopay is a relatively new in the US credit card market, but has existed in the UK credit card market since 1990s. By setting up the autopay, card holders can avoid forgetting the minimum repayment, keeping freedom to make additional manual repayments. (Note that, in the UK, an autopay cannot be set up on behalf of a card holders without their consent, and thus, autopay should be intentionally set up by the card holders. The amount covered by the autopay can be the minimum, the full balance, or any intermediate values between the two depending on the card holder’s preference.)

Figure 3.3 shows the proportion of cards with a late payment fee separately for three types of cards which differ in autopay status—Always-Autopay Cards, Always-Non-

Autopay Cards, and Switched-To-Autopay Cards. Always-Autopay Cards opened with autopay setting and kept being repaid by the autopay throughout the data period (Figure 3.3a). Always-Non-Autopay Cards were manually repaid throughout the data period (Figure 3.3b). Switched-To-Autopay Cards opened without autopay setting but switched to the autopay during the data period (Figure 3.3c). As seen in Figure 3.3a, unsurprisingly, the proportion of Always-Autopay Cards having a late payment fee is close to zero throughout the data period. This is because the autopay prevented card holders from forgetting repayments. On the other hand, as seen in Figure 3.3b, the likelihood of Always-Non-Auto Cards having a late payment fee is constantly about 5-6% throughout the data period without declining over account tenure. Instead, Figure 3.3c shows a steep downward curve for Switched-To-Autopay Cards, which is very similar to the pattern seen in Figure 3.1a, indicating that the declining pattern in late payment fees is wholly attributed to Switched-To-Autopay Cards. (Figure A2.3 in Appendix 2.2 shows the results on the balanced panel.)

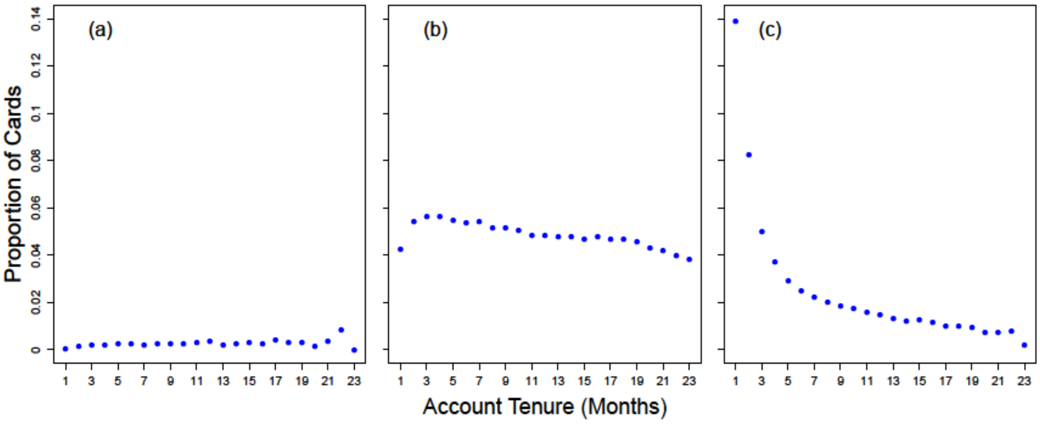


Figure 3.3. The proportion of cards with a late payment fee over account tenure by autopay status. Panel (a) is for Always-Autopay Cards. Panel (b) is for Always-Non-Autopay Cards. Panel (c) is for Switched-To-Autopay Cards. The x-axis variable was adjusted one month forward.

In order to confirm the findings in Figure 3.3 in multivariate setting, we repeated the estimation with Equation 3.1 separately for three types of cards. Figure 3.4 shows the model predictions, confirming the findings of Figure 3.3 that the declining pattern in late payment fees is only seen in Switched-To-Autopay Cards. (Table A2.3 in Appendix 2.2 reports the coefficients. The results on the balanced panel are shown in Figure A2.4 and Table A2.5 in Appendix 2.2.)

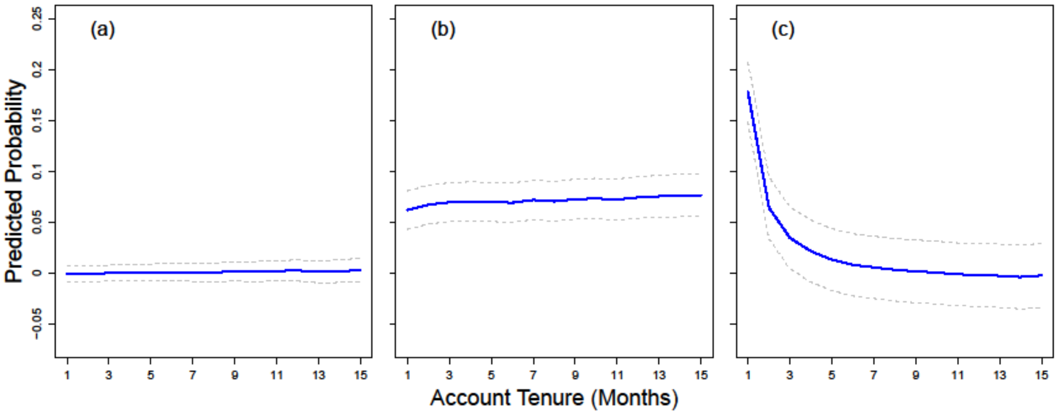


Figure 3.4. The probability of cards having a late payment fee as a function of account tenure by autopay status. Predictions are from a linear probability model at covariates medians (Equation 3.1). Panel (a) is for Always-Autopay Cards. Panel (b) is for Always-Non-Autopay Cards. Panel (c) is for Switched-To-Autopay Cards. The x-axis variable was adjusted one month forward. The dashed lines are 95% confidence intervals. The standard errors were corrected, for clustering by cards.

Next we investigate the effect of switching to autopay on the likelihood of having a late payment fee. To do so, we conducted a liner regression with Equation 3.2. In Equation 3.2, $Distance_{i,t}^{1st\ late}$ represents the number of months since card *i* had a first late payment fee. The definitions of other variables are identical to those in Equation 3.1. A regression was conducted separately for Always-Non-Autopay Cards having at least one late payment fee and Switched-To-Autopay Cards having at least one late payment fee. The regressions were conducted on card-months where $Distance_{i,t}^{1st\ late} \geq 1$.

$$P(fee = 1)_{i,t}^{late} = \alpha + \varphi_i + \psi_{month} + \Omega_t Distance_{i,t}^{1st\ late} + \beta(X)_{i,t} + \epsilon_{i,t} \quad (3.2)$$

Figures 3.5a and 3.5b show the model predictions for Always-Non-Autopay Cards and Switched-To-Autopay Cards, respectively (Table A2.7 in Appendix 2.2 reports coefficients). In the figures, the x-axis represents the number of months elapsed since the first fee and the y-axis represents the probability of cards having a late payment fee. Figure 3.5a shows that the fee likelihood is persistently high for Always-Non-Autopay Cards because they did not respond to the experience of having a fee and continued to rely on manual repayments which may be forgotten. On the other hand, Figure 3.5b shows that, for Switched-To-Autopay Cards, the fee likelihood declined to nearly zero just after the month with a first fee because they set up the autopay in response to the experience of having the fee.

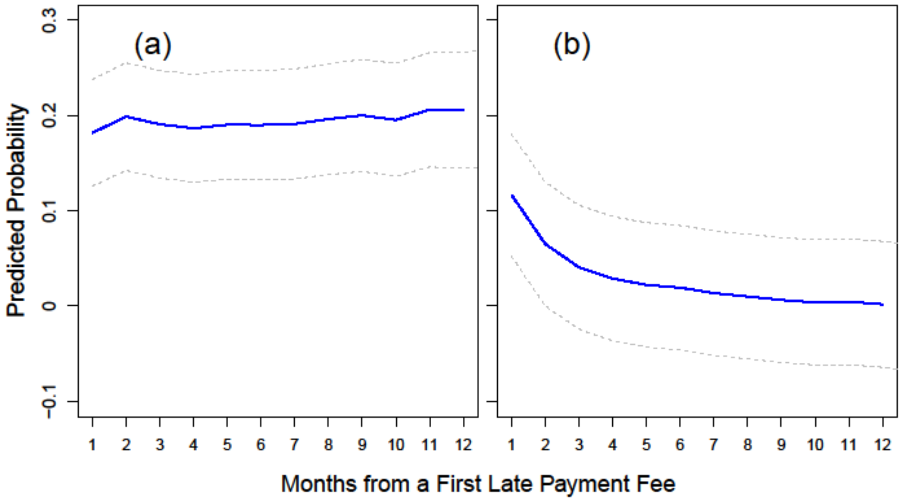


Figure 3.5. The probability of cards having a late payment fee after a first fee by autopay status. Panel (a) is for Always-Non-Autopay Cards. Panel (b) is for Switched-To-Autopay Cards. Predictions are from a linear probability model at covariates medians (Equation 3.2). The dashed lines are 95% confidence intervals. The standard errors were corrected, for clustering by cards.

3.3.4 Late payment fees as a trigger of switching to autopay

In order to show that a late payment fee is a trigger for switching to autopay, we examine how the likelihood of Switched-To-Autopay Cards having a late payment fee changed before and after they switched to autopay. Figure 3.6 shows the proportion of Switched-To-Autopay Cards having a late payment fee as a function of the number of months elapsed since a first autopay. Three or more months before switching to autopay, the fee likelihood among Switched-To-Autopay Cards is about 7-8%. The likelihood spikes at over 15% two months before the switch and is also high at 13% one month before the switch, indicating that some card holders set up the autopay in response to the experience of having the late payment fee. (Note that this one or two months lag between the peak of late repayments and the first autopay is likely to be due to operational time-lag between an application and an activation of autopay.) Unsurprisingly, after switching to autopay the likelihood of a late payment fee reduces to nearly 0%. Overall, Figure 3.6 shows that a late payment fees is likely to be a trigger for switching to autopay.

In addition, we found that card holders who received a refund of late payment fees were more likely to set up the autopay. Figure 3.7 shows the proportion of repayments through autopay as a function of the number of months elapsed since a first late payment fee for cards on which the first late payment fee was refunded (the red dots) and for those without a refund (the blue dots). While the proportion of repayments through autopay increases after a first late payment fee, irrespective of whether the fee was refund, the increase in autopay repayments after the first fee is much sharper for cards with a refund than those without a refund. This may be because card holders were prompted to set up the autopay in communication with card companies regarding the refund. Alternatively, only card holders who upset with a late fee called the card companies to get a refund. That is, card holders with a refund may differently perceived the experience of having a fee from those without a refund. We cannot know which interpretation is correct from the data. Nevertheless, Figure 3.7 provides additional evidence for a late payment fee to trigger setting up the autopay.

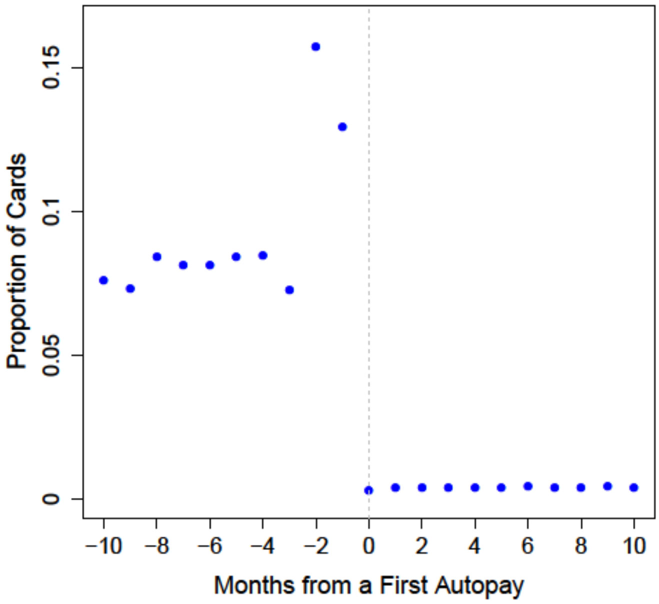


Figure 3.6. The proportion of Switched-To-Autopay Cards having a late payment fee before and after switching to autopay.

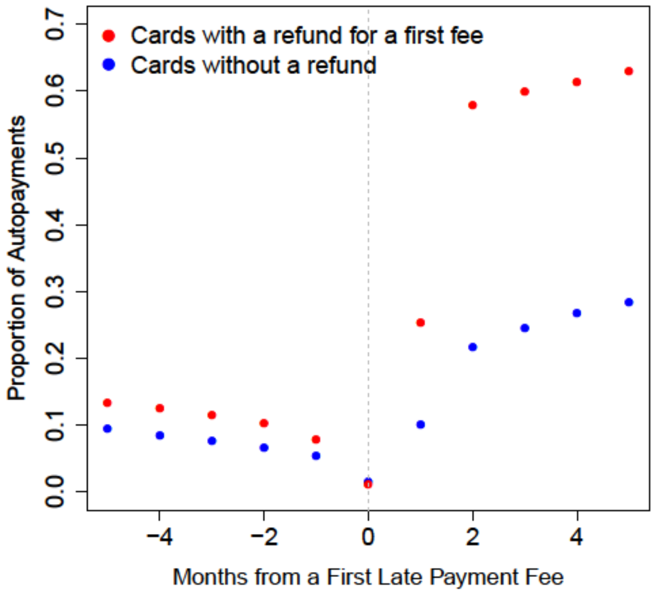


Figure 3.7. The proportion of cards repaid by autopay before and after a first late payment fee for cards with and without a refund of the fee. The red dots are for cards with a refund of a first late payment fee and the blue dots are cards without a refund.

In summary, the declining patterns in late payment fees over account tenure is wholly attributed to card holders changing their repayment method from manual repayments to automatic repayments. Those switchers learned from their mistakes (i.e., forgetting repayments) and insured themselves against future forgetting by setting up the autopay, while non-switchers persistently kept high fee likelihood even after the first fee. In addition, card holders receiving a refund of the first fee are more likely to switch to autopay probably due to a suggestion by the card company.

3.3.5 Cash advances and liquidity needs

Cash advance fees show a declining pattern over account tenure, which is similar to that seen in late payment fees. One explanation for this pattern is that cash advance fees may also decline due to learning dynamics. That is, card holders may be initially unaware that using their credit card for financing cash leads to an additional fee and, after having the fee, they may learn that using cash advance is costly and then adjust their behavior. In this section we show that the decline in cash advance fees over tenure is unlikely to be explained by card holders learning from the experience. Instead, our analysis shows that the decline is due to the time-varying liquidity needs of card holders, which tend to concentrate around the timing of account opening.

We first show that the decline in cash advance fees over tenure is not uniform across all cards, but is concentrated among cards with a high charge-off rate at the time of account opening. (Note that the charge-off rate measures the probability of the card being charged-off within the next six months and can be considered as an inverse of credit score.)

Figure 3.8 shows the proportion of cards with a cash advance fee separately for those with a charge-off rate below the median values (low-risk cards) and for those with a charge-off rate above the median value (high-risk cards). For low-risk cards, the proportion is steady low around 2% throughout the date period (Figure 3.8a), while, for high-risk cards, the proportion declines from over 7% at account opening to about 2% after 20 months (Figure 3.8b).

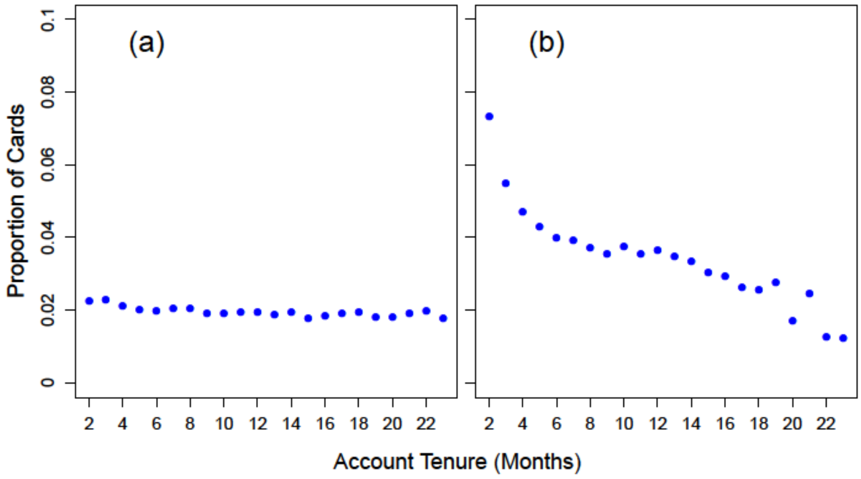


Figure 3.8. The proportion of cards with a cash advance fee over account tenure by charge-off rate. Panel (a) is for cards with a charge-off rate below the median value. Panel (b) is for cards with a charge-off rate above the median value.

In order to confirm the findings of Figure 3.8, we conducted a linear regression with Equation 3.1 separately for low-risk cards and for high-risk cards. Figure 3.9 plots the model predictions. (Table A2.4 in Appendix 2.2 reports the coefficients.) The model predictions are very similar to Figure 3.8, showing that cash advance fees concentrate among high-risk cards and the declining pattern in the fees is only seen for high-risk cards.

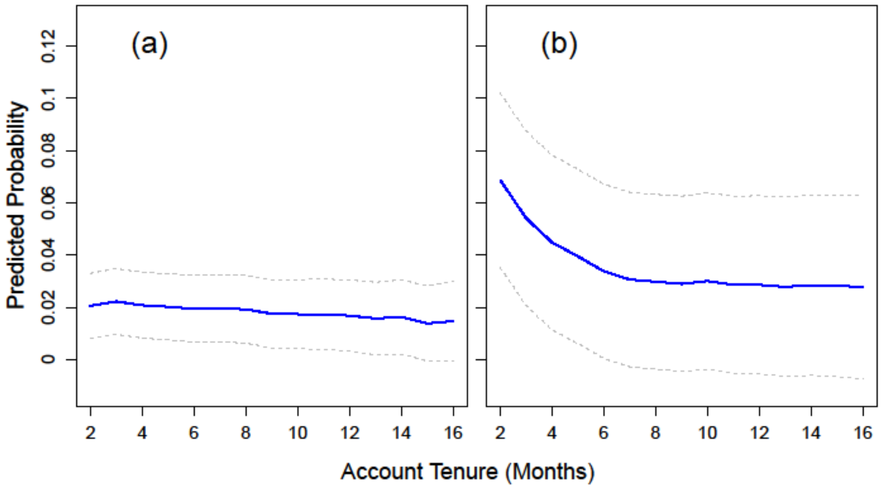


Figure 3.9. The probability of cards having a cash advance fee as a function of account tenure by charge-off rate. Panel (a) is for cards with a charge-off rate below the median value. Panel (b) is for cards with a charge-off rate above the median value. Predictions are from a linear probability model at covariates medians (Equation 3.1). The dashed lines are 95% confidence intervals. The standard errors were corrected, for clustering by cards.

The concentration of cash advance fees among high-risk cards does not rule out the possibility that the high-risk card holders learn from the negative feedback. That is, higher risk card holders may have a larger propensity to make mistakes of using cash advances and learn from the experience, leading to the reduction of the likelihood of subsequent fees. However, we also found that the likelihood of cards having a cash advance fee positively associates with balances and non-cash purchases. These associations are consistent with card holders facing liquidity constraints. Figure 3.10 shows the average balance among cards in the months before, during, and after the card had consecutive cash advance fees. Each card contributes to one of the panels in the figure, depending on the number of consecutive cash advance fees starting from the first fee. In each panel, the shadow area represents the period in which card had the consecutive fees. Figure 3.10 shows that the average balance increased during the period in which the card holders consecutively used cash advances and then plateaued or slightly decreased after they stopped using cash advance. Figure 3.11 confirms that higher balances translate to higher utilization. This pattern may occur mechanically through cash advances adding to balances. However, this is not our case as Figure 3.12 shows that the average monthly purchase sharply increased at the beginning of the period with consecutive cash advance usage and gradually decreased throughout the period. That is, cash advances occurred with large non-cash purchase, indicating that card holders were liquidity constrained in the period of consecutive cash advance usage.

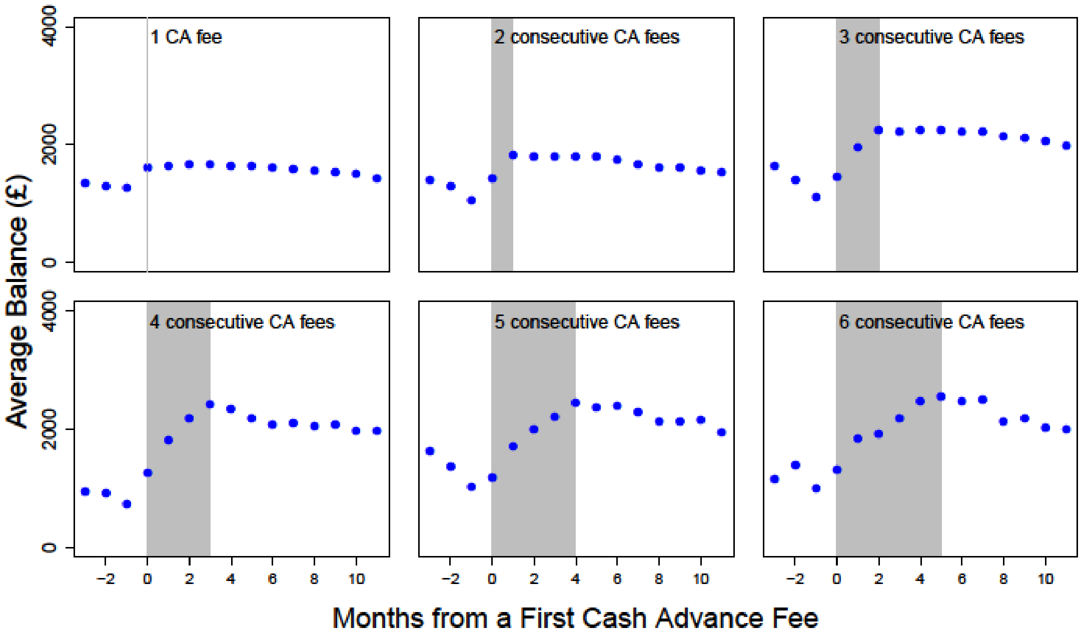


Figure 3.10. Average balance through a period with consecutive cash advance fees. The shadow area represents the period in which cards had consecutive cash advance fees.

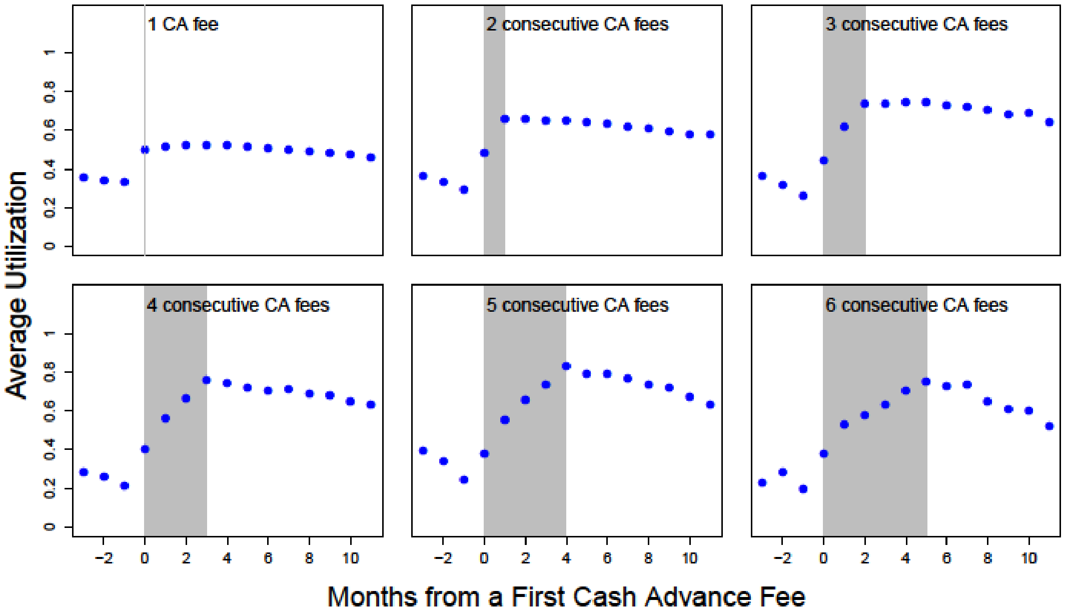


Figure 3.11. Average card utilization through a period with consecutive cash advance fees. The shadow area represents the period in which cards had consecutive cash advance fees.

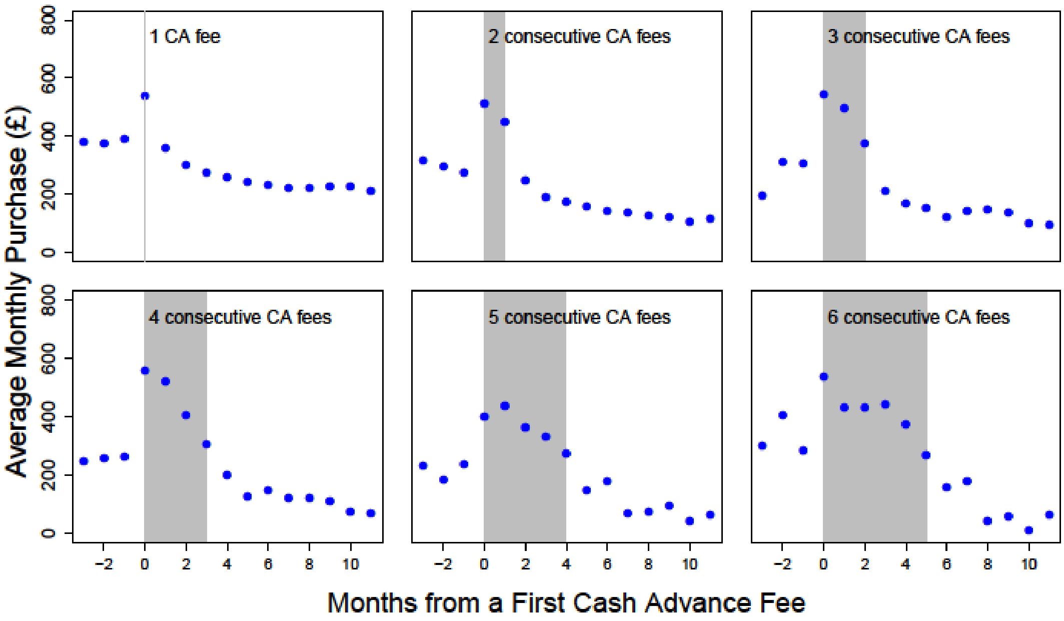


Figure 3.12**.** Average monthly purchase through a period with consecutive cash advance fees. The shadow area represents the period in which cards had consecutive cash advance fees.

To recap, Figures 3.10, 3.11 and 3.12 together showed that cash advances were consecutively used during the period in which purchase and utilization increased. These associations indicate that the card holders are more likely to be liquidity constrained during the period of consecutive cash advance usage. This finding in our sample differs from that in the sample used by Agarwal et al. (2013), who found no clear association between card usage and incursion of any types of fees.

3.3.6 Over-limit fees and liquidity needs

Figures 3.1c and 3.2c showed that the likelihood of over-limit fees increases during the first few months since account opening. This pattern is in contrast with Agarwal et al. (2013), who find that over-limit fees peak at the first month of card opening and decline over account tenure. This difference may be because a part of US card holders opening accounts with large balance transfer, leading to over limit soon after opening.

Here we show that over-limit fees are also driven by card holders' time-varying liquidity needs rather than their mistakes. To do so, we examine how purchases changed before and after the month in which card holders had a last over-limit fee (Note that the card-months with a last over-limit fee include card-months where the card had only one over-limit fee.)

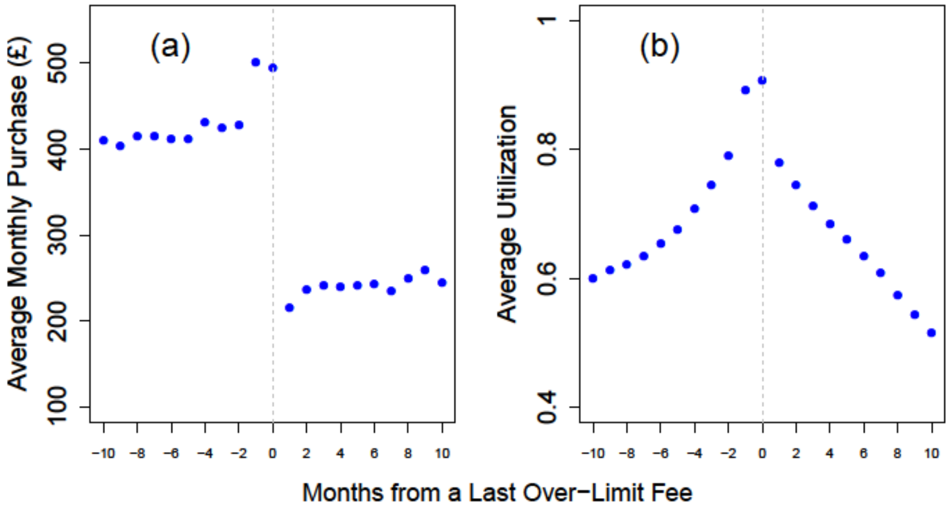


Figure 3.13. Average monthly purchase and average card utilization after a last over-limit fee. Panel (a) shows the average monthly purchase before and after a last over-limit fee. Panel (b) shows the average utilization before and after a last over-limit fee.

Figure 3.13a plots the average monthly purchase as a function of the number of months elapsed since the card holder had a last over-limit fee, showing that purchases sharply dropped just after the month with the last over-limit fee. One explanation for lower purchases is that the card holders still had high utilization even after they resolved the over-limit, and thus, kept purchases low in order to avoid going over-limit again. However this is not our case because Figure 3.13b shows that, after card holders resolved the over-limit, utilization rate constantly decreased, indicating that lower purchases after the last fee were likely to be due to card holders' liquidity needs easing rather than their persistently high utilization.

In order to confirm the finding in Figure 3.13a in multivariate setting, we conducted a linear regression with Equation 3.3. In Equation 3.3, the dependent variable is $Purchase_{i,t}$ representing total monthly purchase on card *i* at tenure *t*. $Distance_{i,t}^{last\ OL}$ represents the number of months elapsed since card *i* had a last over-limit fee. The definitions of other variables are the same to those in Equation 3.1, except that X excludes monthly total purchase and balance and utilization were lagged by a month.

$$Purchase_{i,t} = \alpha + \varphi_i + \psi_{month} + \Omega_t Distance_{i,t}^{last\ OL} + \beta(X)_{i,t} + \epsilon_{i,t} \qquad (3.3)$$

Figure 3.14 plots the model predictions. (Table A2.8 in Appendix 2.2 reports coefficients.) Purchases peak in the month with the last over-limit fee and decreases afterwards, consistent with the finding in Figure 3.13a.

In sum Figures 3.13 and 3.14 together indicate that over-limit fees reflect card holders' liquidity needs.

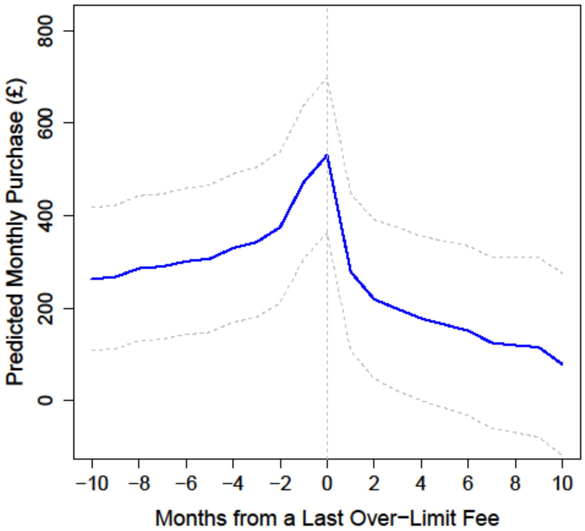


Figure 3.14. Predicted monthly purchase before and after a last over-limit fee at covariates medians (Equation 3.3). The dashed lines are 95% confidence intervals the standard errors were corrected, for clustering by cards.

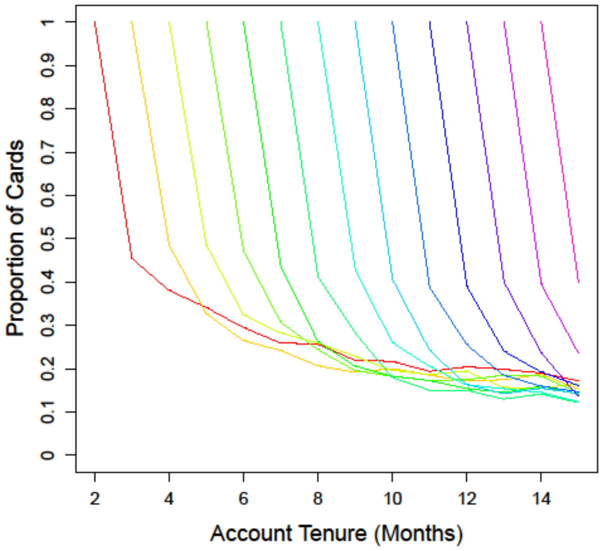


Figure 3.15. The proportion of cards with an over-limit fee over account tenure by subsets of cards which had a first over-limit fee at the same tenure. Each line is for a subset of cards which had a first over-limit fee at the same account tenure.

Based on the above analysis, we argue that both cash advance and over-limit fees are driven by card holders' liquidity needs. However, the declining pattern over tenure appears in cash advance fees but not in over-limit fees (see Figures 3.1b and 3.1c). Here we show that this difference is caused by different mechanisms for having two types of fees. That is, cash advance fees are incurred as soon as the card holder uses a cash advance. Thus cash advance fees reflect card holders' instantaneous liquidity needs. On the other hand, for having an over-limit fees, the balance needs to be accumulated. Thus over-limit fees reflect card holders' cumulative liquidity needs. Accumulating the balance may take time and the time taken for the accumulation may differ among card holders. If so, even if each card holder tends to decrease the likelihood of having an over-limit fee over months after the first fee, an aggregated pattern may not be downward over tenure. In order to illustrate this, we divided cards having at least one over-limit fee by account tenures at which the card had a first over-limit fee.

Figure 3.15 shows the results. In the figure, each line represents the proportion of cards with an over-limit fee for a group of cards which had a first over-limit fee at the same account tenure. It is clear that, for each group of cards, the proportion of cards with an over-limit fee declines over tenure after the first fee. The individual declining pattern in Figure 3.15 is quite similar to that seen in cash advances (see Figure 3.1b). This indicates that the card holders accumulated the balance due to their liquidity needs and had a first over-limit fee, and then, the liquidity needs gradually decreased, while the time taken for accumulating the balance differed among cards.

In sum, over-limit fees are also driven by time-varying liquidity needs. After having a first over-limit fee, the likelihood of subsequent fees declines over account tenure. However, because the timing of the first over-limit fee differs among subsets of cards, the average (or aggregated) likelihood of having an over-limit fee seen in Figure 3.1c does not show the declining pattern.

3.4 Conclusion

This chapter examined patterns over account tenure in credit card fees among newly opened credit cards. We show that the likelihood of having a late payment and cash advance fees peaks in the first month of account life and then sharply declines afterwards. We investigated whether this declining pattern is due to card holders learning from the experience to avoid subsequent fees. We found that all of the decline in late payment fees over account tenure is attributed to card holders who switched from manual repayments to automatic repayments in response to having a late payment fee. Among non-switchers, the likelihood of having subsequent late payment fees remains persistently high. Our results suggest that late payment fees are mostly due to card holders' mistakes (i.e., forgetting repayments) and a part of them adapt to the negative feedback by switching to the autopay. Those card holders learn from experiencing a late payment fee and adjust their behavior.

However, the presented study did not address why only a part of card holders adapt to experiencing a late payment fee by switching to the autopay. The switchers and non-switchers may differ in individual characteristics including socioeconomic status and personality traits, leading to the different reaction to their experience. A limitation of the presented study is that our data do not include card holders' individual characteristics. It may be informative that future studies investigate a possible association between card holders' response to negative experience (e.g., having a fee) and their characteristics.

In contrast to late payment fees, our analysis showed that cash advance and over-limit fees are due to card holders' time-varying liquidity needs. Cash advance fees are more common among cards with higher risk profiles at the time of opening, and positively associate with non-cash purchases and utilization. Over-limit fees correlate with the increase in purchases. These associations indicate that card holders have these fees when they are liquidity constrained. In other words, cash advance and over-limit fees are not due to card holders' mistakes, and thus, the pattern over tenure in those fees are driven by time-varying liquidity needs rather than learning from the experience.

In summary, our results emphasized that not all patterns which resemble 'learning' in fee payments are necessarily the result of card holders' corrective response to their mistakes. Late payment fees are largely due to card holders' mistakes (i.e., forgetting repayments), and thus, a part of card holders adapt to the experience of having the fee by setting up autopay. Without setting up autopay, we saw absolutely no evidence of any other learning to avoid late fees. In contrast, cash advance and over-limit fees reflect time-varying liquidity needs, and thus, card holders do not learn from the experience, but the fee likelihood declines as the liquidity constrains resolve (i.e., their economic circumstances improve).

Chapter 4 Individual Preference for Prominent and Round Numbers: Evidence in Credit Card Repayments

4.1 Background

When faced with the task of choosing a number value, individuals often adopt simple heuristics (Brenner & Brenner, 1982; Todd & Gigerenzer, 2000). The theory of prominence (Albers, 1997) defines prominent numbers as $a10^i$ where $a = 1$, 2, or 5 and i is an integer (e.g., 1, 2, 5, 10, 20, 50, 100…). The theory postulates that, when faced with a numerical question, people find an answer by combining a set of prominent numbers with coefficients of +1, 0, or -1. For example, 108 is a combination of 100, 10, and 2 with coefficients of +1, +1, and -1, respectively (coefficients for other prominent numbers in between are 0). That is, in the mental process, people start from a high enough prominent number for the numerical question and move down in the sequence of prominent numbers to first find a crude tentative answer at a prominent number which they perceive is more adequate as an answer than 0. (That is, the coefficients of prominent numbers above this tentative answer are 0). Then, from the crude tentative answer, they sequentially decide whether to add, subtract, or not use the next smaller prominent number in order to improve the tentative answer. The process continues until the limit of the decision maker's ability to judge (Albers, 2001). The theory measures the precision of a numerical answer as a ratio of the smallest prominent number being added or subtracted to arrive at the answer (i.e., the smallest prominent number with the coefficient of +1 or -1 in the mental process) over the absolute value of the answer number (the relative exactness ratio). The smaller the relative exactness ratio the greater the precision. Continuing the above example, the smallest prominent number used to derive 108 is 2. Thus the relative exactness ratio is 2/108 = 1.85%. On the other hand, by definition, a prominent number itself has the ratio of 100%. The theory predicts that the greater the precision of a numerical answer the larger the number of cognitive operations conducted and thus the greater the cognitive effort required. It therefore predicts that responding to a numerical question with a prominent number requires less cognitive effort than responding to it with non-prominent numbers (Albers, 2001; Dennis, 2012).

In this chapter, we examine individual preference for prominent and round numbers in the context of credit card repayments. The decision of how much to repay on a credit card is a common financial decision. For credit cards, most individuals make an active choice over the repayment amount, requiring them to choose a specific number value. This requirement to choose a specific number stands out from most other financial contexts, such as paying a mortgage, cell phone, or utility bills where the repayment amount is fixed, or decisions over spending where individuals typically choose from a menu of fixed prices. Hence credit card repayments offer an ideal real world setting for examining preferences over prominent and round numbers.

Individuals' tendency to prefer prominent and round numbers (or round fractions) has been evident in both experimental (Whynes et al., 2005) and field data (Ball et al., 1985; Christie & Schultz, 1994; Dennis, 2012; Harris, 1991; Kandel et al., 2001). For example, in an experiment by Whynes et al. (2005), participants were asked their willingness to pay (WTP) for taking health check by selecting one of 29 different round values ranging from £0.00 to £1000.00 with an option to answer over £1000.00 if they wanted. The results showed that participants' WTPs highly concentrated at £20.00, £50.00, and £100.00. In field data, Kandel et al. (2001) found that stock prices cluster at round numbers in Israeli IPO auctions. Similarly, closing prices of the US stocks cluster at round fractions (Harris, 1991). Sonnemans (2006) found that the Dutch stock prices cluster at round numbers and that the round numbers play a role as resistance points which a price is reluctant to cross.

While the price clustering may result from people's heuristic processing of numerical information as Albers (1997) suggested, in many settings where prominent numbers appear to be preferred, other explanations have arisen. One alternative explanation is based on traders' motivation to lower costs in price negotiations by reducing the size of a set of prices (Harris, 1991). Another explanation argues that market makers intentionally use low-resolution prices to preserve wide bid-offer spreads (Christie & Schultz, 1994). However, Dennis (2012) found that trade sizes in the US stock markets also cluster at prominent numbers (e.g., 2000 shares) and at sums of two prominent numbers (e.g., 1000 + 500 = 1500 shares). Because negotiation costs and bid-offer spreads do not involve selections of trade sizes, Dennis (2012) suggested that the clustering is likely to be caused by people's heuristic processing of numeric information.

Section 4.3.1 shows that individuals have strong preferences for repayments at prominent number values, leading to credit card repayments clustering at those prominent numbers. Strikingly, repayments at exact £50.00, £100.00, £150.00, and £200.00 together occupy more than 30% of all partial repayments (i.e., all payments where people are not repaying less than the minimum or paying in full).

Section 4.3.2 finds evidence of people's preference for round numbers: more than 70% of repayments are multiples of £10. We present the results of a natural experiment that allows us empirically to examine people's rounding behavior. Due to a natural experiment in the data, the set of potential numbers that a credit card holder can choose to repay is not bounded at a value of zero but varies as a function of credit card balance. This is due to a feature of credit card bills whereby they require a minimum repayment. The US and UK regulators require card companies to collect at least the required minimum amount in each month in order to prevent cardholders from accumulating debt. In the UK, the required minimum is normally interest and fees accrued within the month plus 1% of the card balance, or a fixed sum such as £5.00, £10.00, or £25.00, whichever is the greater (though some companies round up or down the minimums to a nearest pounds rather than keep them in pounds and pence.) Hence cardholders freely choose a repayment amount equal to or greater than the minimum.

This generates a natural experiment in adding or removing prominent number values from the feasible choice set of repayment amounts, which allow us to quasi-experimentally estimate the preference for prominent and round numbers. For example, an individual with a minimum payment of £29.99 has a lower bound on the choice set of £29.99, just below the round number of £30.00. However, a small increase in balance may raise the minimum to £30.01, in doing so exclude the round number £30.00. This feature allows us to estimate the jump in likelihood of repayment at the next round number (£40.00 in this example) when the last round number falls just out of reach. In Section 4.3.3, we find that due to an interaction of the preference for prominent numbers and that for round numbers, the proportion of repayments at a certain prominent number tends to jump at the point where the distance between the prominent number and the required minimum becomes less than £10.

In Sections 4.3.4, we show that, as predicted by Albers (1997), the likelihood of repayments falling at a certain integer (i.e., exact pounds) decreases as the precision of the repayment number increases (i.e., the relative exactness ratio decreases). In Section 4.3.5, we propose a model of prominence. We estimate the relative prominence of the 10 most frequent prominent numbers in repayments. We are the first to provide such an estimation. The results show that £50.00 and £100.00 are the most prominent numbers.

4.2 Data

The data used in this chapter are the same as those used in Chapters 2 and 3, though the data-restriction criteria described below are different. The data were provided by five UK credit card issuers. Card holders and issuers were not identified. The data were extracted and were provided by Argus Information & Advisory Services in collaboration with the UK Cards Association, without constraint on the research agenda. The data are a 10% sample of all UK consumers who held a credit card during January 2013 to December 2014 within Argus's database, which covers nearly 100% of UK card holders. The five card companies which provided the data cover about 40% of the market. The data include card numbers (anonymized), balances, required minimum amounts, purchase amounts, and repayment amounts. Monetary values including repayments and required minimums are provided in the data in decimal units (i.e., pounds and pence).

We focus on card-months where we observe card holders actively choosing monthly repayment amounts. To do so, card-months were excluded if the card carried no balance (and thus card holders were not required to decide repayment amounts), if the card holders failed to meet the minimum repayment (largely due to forgetting repayments), or if the card balance was repaid in full (largely repaid exactly at the balance). Hence our sample consists of card-months where card holders decide a partial repayment amount equal to or greater than the minimum but less than the full balance. (Note that, in Appendix 3.2, we see a tendency of card holders rounding up the full balance, leading to overpayments.) We also exclude card-months in which card holders repaid through an automatic repayment facility (called Direct Debit in the UK) because the automatic repayment allows card holders not to decide monthly repayment amounts unless they intend to top up the automatic repayments.

After these restrictions, we have a total sample of 5,634,840 card-months in which we observe repayment choices, comprising 526,365 cards. Summary statistics for the sample are shown in Table A3.1 in Appendix 3.1. By construction all card-months in the sample have a positive balance, with the median balances of approximately £1600 with the median repayment of £100. The median minimum required payment is £32. Note that, in our sample, the minimums at exactly £5.00, £10.00, and £25.00 together account for 13% of all minimums.

4.3 Results

4.3.1. Card holders' preference for prominent numbers

Figure 4.1 shows a histogram of card-month repayment amounts for the 5.6 million repayments in our sample. The width of each bar in the figure is the smallest decimal unit of repayment value (i.e., one penny). The mass of repayment amounts is right-skewed, reflecting the right-skewed distribution in card balances. A striking feature of the distribution is that repayments cluster at several prominent numbers (e.g., at £50.00, £100.00, £200.00). In between these values, many bins of single-penny values are completely empty.

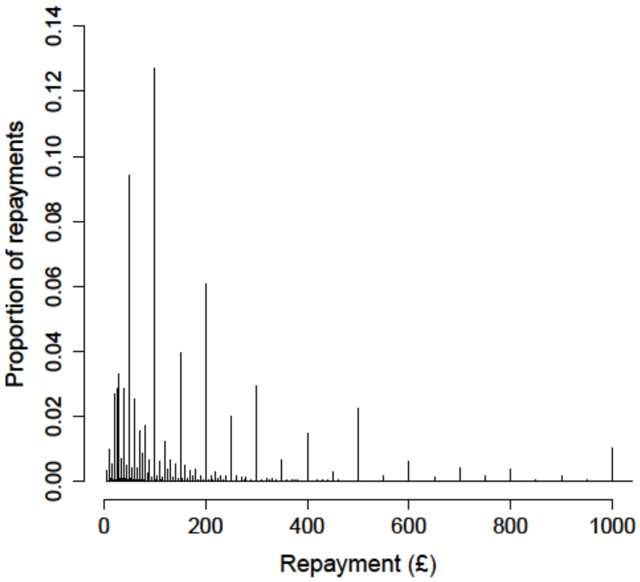


Figure 4.1. Histogram of credit card repayment amounts. The width of each bar is a penny.

Table 4.1 shows the 10 most frequent repayment amounts. The 10 most frequent repayment amounts occupy nearly 50% of all partial repayments. The aggregated proportion of top four repayments (i.e., £100.00, £50.00, £200.00, and £150.00) is over 30%. Hence a set of prominent numbers dominates the distribution of repayments. (Note that, while, according to Albers's (1997) definition, several frequent repayment amounts (e.g., £150.00) are a sum of two prominent numbers rather than a prominent number itself, we call them generally as prominent numbers unless specified.)

Figure 4.1 and Table 4.1 clearly showed that card holders prefer repaying at prominent numbers and that the preference results in the clustering of repayments at those numbers.

A notable feature of the distribution of prominent number repayment amounts is that some larger value prominent numbers dominate smaller value prominent numbers, despite larger repayment amounts being less likely due to the increased financial cost to the individual holding the credit card. (Note that the concentration of balances around small values also tend to make repayments at larger prominent numbers less likely.) For example the proportion of card-months with repayments at £200.00 is larger than the proportion of card-months with repayments at £150.00. Hence there is a non-monotonic relationship between the prominent repayment value and the frequency with which the value is chosen.

Table 4.1. The 10 Most Frequent Repayments

Repayment (£)	Proportion among all partial repayments	Cumulative proportion
100.00	12.7%	12.7%
50.00	9.4%	22.1%
200.00	6.1%	28.2%
150.00	3.9%	32.2%
30.00	3.3%	35.5%
300.00	2.9%	38.4%
40.00	2.9%	41.3%
25.00	2.9%	44.1%
20.00	2.7%	46.8%
60.00	2.5%	49.3%

Note. 60.7% of repayments at exact £25.00 are in months where the minimum was exactly £25.00.

4.3.2 Card holders' preference for round numbers

The prominent numbers in credit card repayments shown above are round numbers. Therefore, next we investigate card holders' preference for round numbers more generally. To do so, we divided repayments into those at exact pounds (without pence; e.g., £11.00) and those in pounds and pence (e.g., £10.99), and counted the frequency of the last digit for repayments at exact pounds.

Figure 4.2 shows the distribution of repayments at exact pounds by the last digit (the white bars) and the proportion of repayments in pounds and pence (the rightmost grey bar). 87% of repayments were made at exact pounds (the sum of white bars) and only 13% of repayments were in pounds and pence (the grey bar). These results are not sensitive to the exclusion of card-months where the minimum is at exact pounds, excepting that, due to the exclusion of frequent minimum repayments at £5 and £25, the proportion of repayments with the last digit equal to 5 decreases.

Notably, the height of the first bar indicates that in 71% of card-months the last digit of the repayment amount is 0 (i.e., repayments at multiples of £10 values). This indicates a strong preference for round numbers. This finding is consistent with stock prices clustering at the last digit of 0, as seen in previous studies (e.g., Kandel et al., 2001).

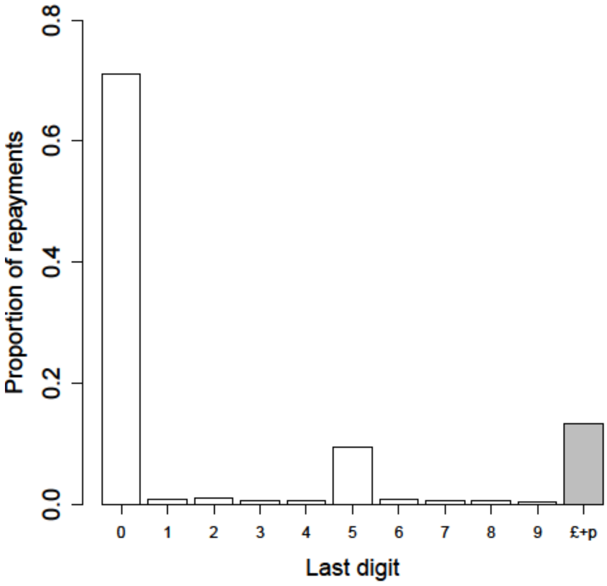


Figure 4.2. The distribution of repayments at exact pounds by the last digit (white) and the proportion of repayments with pennies (grey).

One explanation for repayments with the last digit of 0 (seen as the leftmost bar in Figure 4.2) may be rounding up the minimum payment to a nearest multiple of £10. Alternatively, this pattern may result from a preference for prominent numbers, irrespective of the level of the required minimum. For example, a card holder having £28.01 as a minimum payment may choose to repay £30.00. This repayment is likely to be due to rounding up of the minimum. On the other hand, if the card holder repays £200.00, the repayment is likely to be due to the preference for the prominent number (i.e., the prominence of 200.00). While both cases lead to the last digit of 0, the former case is more likely to be due to the preference for round numbers (i.e., rounding up the minimum to a nearest multiple of £10) and the latter case is more likely to be due to the preference for prominent numbers.

In order to distinguish both types of preference, we divided the repayments with the last digit of 0 by the distance between the repayment and the minimum. Among repayments with the last digit of 0, the proportion of repayments led by rounding up the minimum to a nearest multiple of £10 is 17%. This indicates that, although people prefer both round and prominent numbers, the preference for prominent numbers appears to be stronger than that for round numbers.

Next, in order to estimate the prevalence of rounding-up-the-minimum behavior, we calculate the proportion of repayments at exactly a multiple of £10, and explore how this varies as the minimum payment sweeps past the previous multiple of £10. For example, we

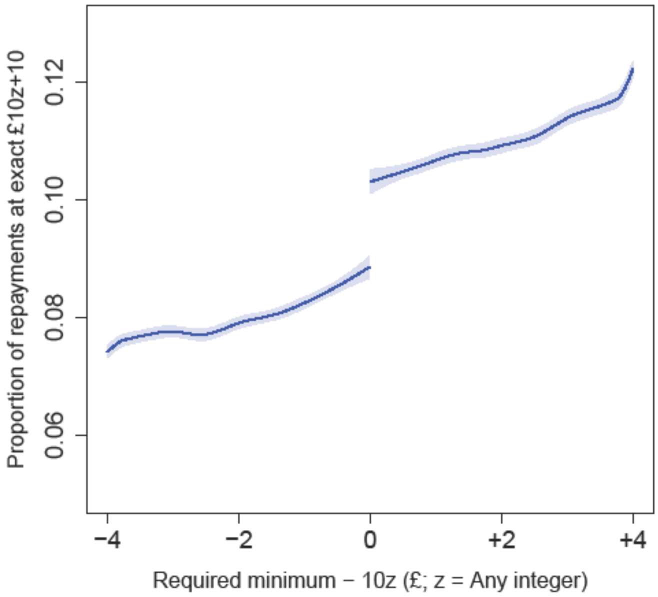


Figure 4.3. The jump of the likelihood of repayments at any multiple of £10 as the minimum crosses the previous multiple of £10. The observations where a balance is no more than 10*z*+10 were excluded. The shadow area represents 95% confidence intervals, corrected for clustering by cards.

calculated the proportion of repayments of exactly £30.00, and plotted this as a function of the minimum varying between £16.00 and £24.00, which included the previous multiple of £10 (i.e., £20.00). In Figure 4.3, the x-axis represents the minimum minus £10*z*, where *z* is any integer, and the y-axis represents the proportion of repayment at £10*z* plus 10. Continuing the example (i.e., *z* = 2), when x = -2, the minimum is £20 - £2 = £18.00. When x = 0 the minimum is exactly £20.00. When x = +2 the minimum is £20 + £2 = £22.00.

As seen in Figure 4.3, the likelihood of repayments at the next multiple of 10 jumps as the minimum crosses the previous multiple of £10. For example, the likelihood of a £30 repayment jumps as the minimum crosses £20: the likelihood of £30.00 repayments is discontinuously larger at the minimum of 20.01 than at the minimum of £19.99. This reflects the tendency of card holders rounding up the minimum to a nearest multiple of £10. The magnitude of this effect can be measured as the size of the jump in the local polynomial regression line at the discontinuity value (set at zero on the x-axis in the figure). In Figure 4.3 this jump is approximately 1.5 percentage points, against a baseline value of 8.8%. Hence the impact of marginally excluding the last round number due to a penny increase in the minimum repayment is to increase the likelihood of consumers choosing the next round number by 1.5 / 8.8 = 17%. This again indicates a strong preference of card holders rounding up the minimum.

As additional evidence of card holders' preference for round numbers, Appendix 3.2 shows a tendency of card holders mistakenly rounding down the minimum, leading to missed repayments, and a tendency of card holders rounding up the full balance, leading to overpayments.

4.3.3 Frequency of repayments at prominent numbers as a function of minimum

Next we explore more generally how the clustering of repayments at prominent numbers changes as a function of the minimum. We begin by showing Figure 4.4a, which plots the proportion of repayments at each of four most frequent repayment amounts—£100.00, £50.00, £200.00, and £150.00—as a function of the minimum. A feature of Figure 4.4a is that the likelihood of repayment at these prominent amounts increases as the minimum increases (this occurs mechanistically, reflecting larger balances due), but that the likelihood discontinuously increases at some points where the minimum crosses certain numbers. Why does the likelihood of choosing a prominent number discontinuously increases with minimum payment amounts? We consider two possible causes.

First, the discontinuities occur due to rounding. As seen in Figure 4.4a, there are a jump in the proportion of £50.00 repayments at the minimum of £40.00, a jump in the proportion of £100.00 repayments at the minimum of £90.00, and a jump of the proportion of £150.00 repayments at the minimum of £140.00. These jumps reflect rounding up the minimum to a nearest multiple of £10, consistent with the findings of Figure 4.3. However, this pattern of rounding up to unit of £10 does not occur in all cases. That is, we see a jump in the proportion of £200.00 repayments at £180.00 instead of at £190.00. This indicates that, when the minimum is just over £180.00, card holders prefer repaying £200.00 to repaying £190.00. This implies that the degree of rounding-up may increase as the absolute value of the minimum increases. In other words, the larger the number the lower the resolution of rounding up.

Figures 4.4b, c, d, and e more closely look at these discontinuities, using local regressions. Figure 4.4b shows the discontinuity of the proportion of £50.00 repayments at the threshold of £40.00. Figure 4.4c shows the discontinuity of the proportion of £100.00 repayments at the threshold of £90.00. Figure 4.4d shows the discontinuity of the proportion of £150.00 repayments at the threshold of £140.00. Figure 4.4e shows the discontinuity of the proportion of £200.00 repayments at the threshold of £180.00. Each panel shows that the proportion of repayments at a certain prominent number jumps at the corresponding threshold, supporting the effect of £10 rounding-up seen in Figure 4.4a.

Second, the large jumps in the proportion of repayments at a given prominent number could occur when the minimum is itself at that prominent number. For example, the proportion of £50.00 repayments is considerably larger when the minimum is £50.00 than

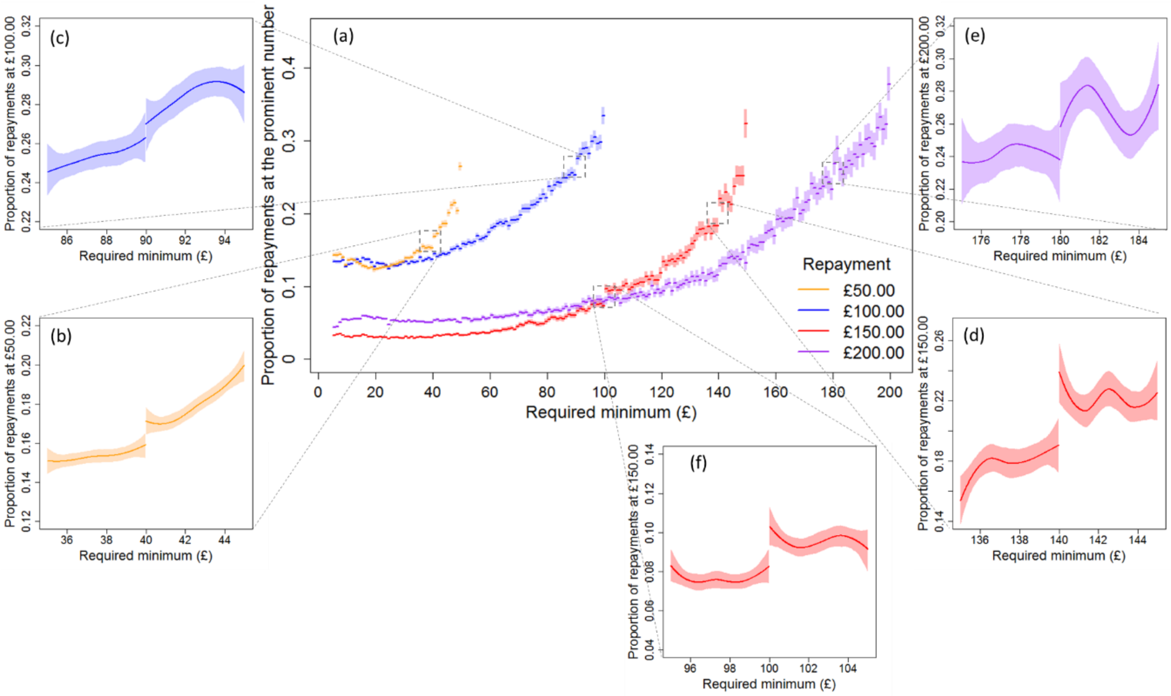


Figure 4.4. The proportion of repayments at four most frequent repayment amounts as a function of the minimum. The shadow area represents 95% confidence intervals, corrected for clustering by cards. Panel (a) shows an overview of the proportion of four most frequent repayment amounts. The yellow, blue, red, and purple lines represent the proportion of repayments at £50.00, £100.00, £150.00, and £200.00 among all partial repayments. The width of minimum bins on the x-axis is £1. Panels (b-f) present local regressions exploring discontinuities. In each panel, two local regressions were conducted separately on the minimum less than the threshold and on those greater than the threshold. The scale of the y-axis differs among panels. Panel (b) explores the discontinuity of the proportion of £50.00 repayments at the threshold of £40.00. Panel (c) explores the discontinuity of the proportion of £100.00 repayments at the threshold of £90.00. Panel (d) explores the discontinuity of the proportion of £150.00 repayments at the threshold of £140.00. Panel (e) explores the discontinuity of the proportion of £200.00 repayments at the threshold of £180.00. Panel (f) explores the discontinuity of the proportion of £150.00 repayments at the threshold of £100.00.

when the minimum is £49.99. This is an effect of the prominence of the minimum value itself.

In addition, the proportion of £150.00 repayments has a large jump at the minimum of £100.00. This indicates that, because £100.00 is the most popular repayment, a large part of repayments tend to shift to £150.00 once the minimum exceeds £100.00, and thus, £100.00 repayments are removed from the feasible set of repayment values. Figure 4.4f shows the discontinuity of the proportion of £150.00 repayments at the threshold of £100.00, using a local regression. This jump indicates that the popularity of £150.00 repayments is partially attributed to an absence of £100.00 rather than the prominence of £150.00 alone.

As seen above, the proportion of repayments at a certain prominent number is a function of the minimum because (1) individuals with a larger balance tend to repay more, (2) individuals round up the minimum, and (3) an increase in minimum excludes smaller prominent numbers from the feasible repayment set. In Section 4.3.5, we estimate genuine prominence of 10 most frequent repayment numbers after excluding the influence of the minimum and the balance.

4.3.4 Frequency of repayments as a function of the precision of the number value

As reviewed in Section 4.1, the theory of prominence (Albers, 1997) predicts that the greater the precision of a numerical answer the greater the cognitive effort required. In the theory, the precision of a number is measured as the relative exactness ratio that is the smallest prominent number used to derive the number divided by the absolute value of the number. The smaller the ratio the greater the precision of the repayment number.

Here we show that, as predicted by Albers (1997), repayment amounts with a greater precision (i.e., a smaller relative exactness ratio) are less likely to be chosen as a repayment than those with a smaller precision (i.e., a larger relative exactness ratio). To do this, we computed the proportion of repayments falling at each integer (i.e., exact pounds) up to 1000 and locally regressed those proportions on corresponding relative exactness ratios of the repayment numbers (Note that the 95th percentile repayment in our sample is £999.99, and so considering numbers up to £1,000 covers almost the entire dataset.) In the calculation, repayments at exactly the minimum and the nearest integer to the minimum were excluded because those repayments are likely to be due to the effect of an anchoring effect of the minimum.

Figure 4.5 plots the results. In the figure, each dot represents an integer repayment. The proportion of repayments at that integer is on the y-axis and the relative exactness ratio of the repayment number is on the x-axis. The blue line is the prediction from a local regression. The results show that the smaller the relative exactness ratio (i.e., the greater the precision) the smaller the likelihood of the number being chosen as a repayment, consistent with the prediction of Albers (1997).

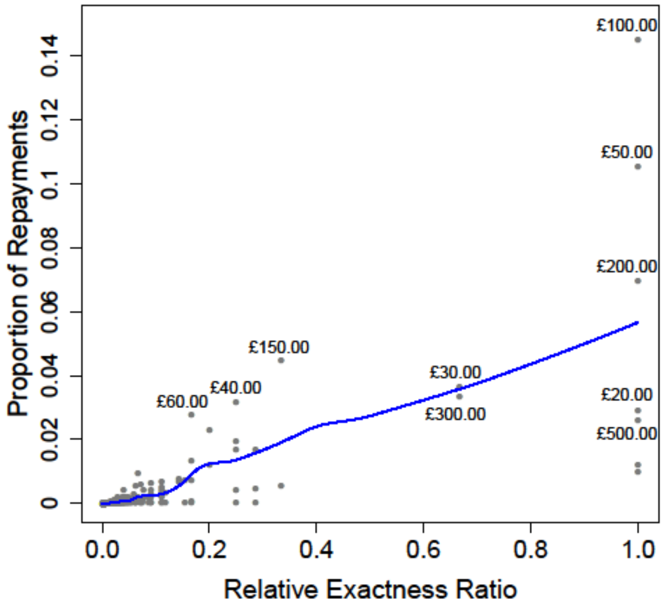


Figure 4.5. Proportion of repayments at one integer as a function of the relative exactness ratio. Each dot represents an integer repayment. The proportion of repayments at that integer is on the y-axis and the relative exactness ratio of the repayment number is on the x-axis. The blue line is the prediction from a local regression.

4.3.5 Estimation of relative prominences of top 10 prominent numbers

Finally, we estimate the relative prominences of the 10 most frequent repayment amounts (see Table 4.1). The estimation is conducted in two steps corresponding to two stages of mental process. In the Latent Repayment Stage, we assume that, when faced with a bill, people have in mind a latent repayment, somewhere between a minimum repayment and a full repayment. In the Rounding Stage, people are assumed to translate this latent repayment into an actual repayment reflecting prominence of candidate repayment numbers.

Consider a particular target card-month. How much does the card holder want to repay that month? In the first step of our estimation, we use the empirical distribution of actual repayments to approximate the distribution of latent relative repayments from Latent Repayment Stage. We select a set of card-months that are similar on card profile including minimum, balance, credit limit, utilization, total monthly purchase, merchant APR, cash APR, and charge-off rate. First, we conducted a principal component analysis on card-month profiles. The results showed that the first and the second principal components together explain 99% of the total variance. Then, we divided card-months into 10 groups with the k-means algorithm on the two principal components. (The number of card-month groups, 10, was determined at the number where increasing the number of groups has a limited impact on the reduction of within-group sum of squares. With these 10 card-month groups, the between-groups sum of square explains 92.3% of the total sum of square.)

Next we built a histogram of relative repayments with a bin-width of 1% for each group. In order to obtain a distribution of latent (absolute) repayments, we multiplied each card-month balance with mid points of each bin in the histogram of relative repayments for the group which the card-month belongs to. (Note that the distribution of latent relative repayments is identical for all card-months within a group. However, due to the multiplication with a card-month balance, the distribution of latent absolute repayments differs among card-months.) We denote the density of the distribution of latent absolute repayments for card-month i as $f_i(x)$, where x is a latent repayment. Note that, we set $f_i(x) = 0$, when $x < Minimum_i$ or $x > Balance_i$.

In the Rounding Stage, we assume that people are more likely to select a repayment that is more similar to their latent repayment. We also assume that they are more likely to select a repayment that has higher prominence. In the second step of the estimation procedure we find the optimal prominences for the 10 most frequent repayment amounts which best fit to the data. Assuming that the distribution of latent repayments, $f_i(x)$, obtained in the first step is a ‘true’ repayment in a card holder’s mind at the point of considering how much to repay, two elements affect the card holder’s choice of an actual repayment—the prominence of candidate numbers and the similarity to a latent repayment. Specifically, the model assumes that the larger the prominence of the candidate number and the smaller the distance between the candidate number and the latent repayment the larger the likelihood of the candidate number being chosen as an actual repayment.

We calculated the similarity between a candidate repayment and a latent repayment based on a distance between the two numbers in log space. The rationale for this approach is that it was well evident in cognitive science that reaction time for a comparison of two numbers negatively associates with the numerical distance between the numbers and that the distance of two numbers tends to be perceived by people in a logarithmic form rather than in a linear form (Hinrichs, Yurko, & Hu, 1981; Moyer & Landauer, 1967). The logarithmic perception for numbers is also supported by previous neural studies (Dehaene, 2003). For the calculation of the similarity, we used Shepard’s generalization function (Shepard, 1987) which predicts that the larger the distance between a candidate repayment and a latent repayment the smaller the probability of the candidate repayment being generalized as the latent repayment (i.e., the larger the probability of the candidate repayment being perceived as distinct from the latent repayment, and thus, not being chosen as an actual repayment). Equation 4.1 shows the Shepard’s generalization function.

$$g(x,z) = exp\left(-2\frac{|\log x - \log z|}{\mu}\right), \tag{4.1}$$

where x is a latent repayment, z is a candidate repayment, and μ is a scale parameter.

By integrating the density of latent repayments, $f_i(x)$, with the generalization function, $g(x,z)$, over x, we obtain the integrated density function, $h_i(z)$, for each card-month (Equation 4.2).

$$h_i(z) = \int_{Minimum_i}^{Balance_i} f_i(x)g(x,z)dx \tag{4.2}$$

We denote the prominence of a candidate number value, z_j, as $prominence(z_j)$. We consider 11 candidate repayments, $z_j, j = (1, 2, \dots, 11)$, including the 10 most frequent repayment amounts and all the other possible repayment amounts between the minimum and the full balance as one category. Then, the probability of z_j being chosen as an actual repayment in card-month i, given the integrated density function, $h_i(z_j)$, and $prominence(z_j)$ is given by Equation 4.3.

$$P(Repayment_i = z_j) = \frac{prominence(z_j) \times h_i(z_j)}{\sum_{k=1}^{11} prominence(z_k) \times h_i(z_k)} \tag{4.3}$$

Using the maximum likelihood estimation, the optimization with the Nelder-Mead algorithm finds the optimal, $prominence(z_j),\ j = (1, 2, \dots, 11)$, and the optimal scale parameter μ. The prominence of £100.00 was fixed at 1 as a reference without loss of generality. The optimization was conducted with randomly-sampled 10,000 card-months.

As seen in Section 4.3.3, the likelihood of a repayment at a certain prominent number is a function of the balance (or the minimum). First, in general, the larger the balance due the larger the average repayment. Second, an increase in the minimum excludes smaller prominent numbers from the feasible set of repayments. Using the distribution of latent repayments, $f_i(x)$, where $f_i(x) = 0$ when $x < Minimum_i$ or $x > Balance_i$, the optimization estimates genuine prominence of numbers by excluding these two mechanisms for the balance to influence repayments.

The results are shown in Figure 4.6. £50.00 and £100.00 are the most prominent repayment numbers with the similar level of prominence. Interestingly, the subsequent order of the estimated prominences differs from the order of the raw proportions of the repayments seen in Table 4.1. For example, the estimated prominences of £20.00, £25.00, and £30.00 (the ninth, the eighth, and the fifth most frequent prominent numbers in the raw proportions, respectively) are about the same as that of £200.00 (the third most frequent prominent number in the raw proportions) and are higher than that of £150.00 (the fourth most frequent prominent number in the raw proportions). This indicates that the popularity of £200.00 and £150.00 repayments in the raw proportions is partially due to the relationship between the minimum and the repayment where the repayments need to be no less than the minimum, and thus, the large prominent repayment amounts tend to occupy the large share of repayments when smaller prominent amounts less than the minimum are not available.

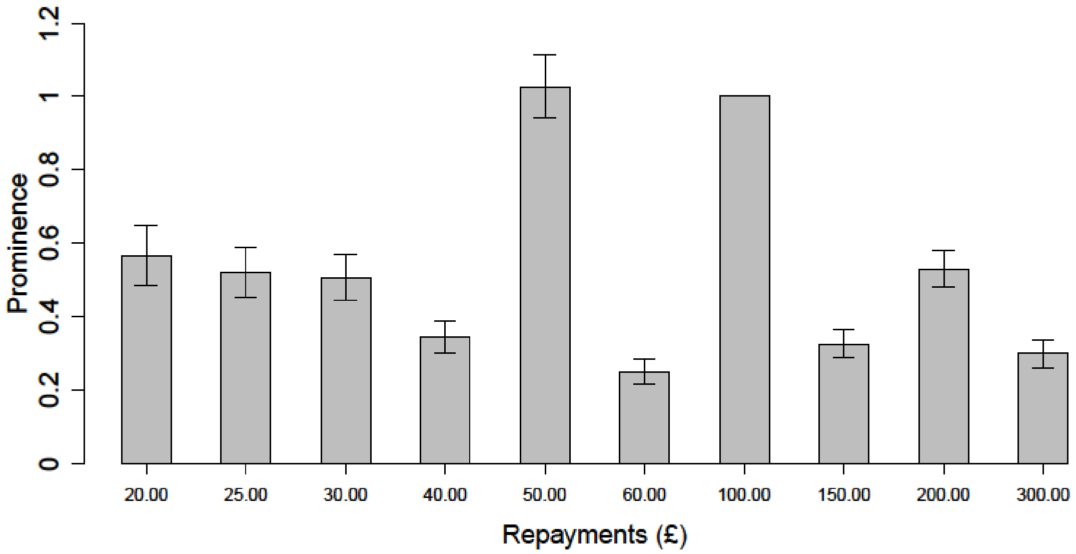


Figure 4.6. Estimated prominence of the 10 most frequent repayments. The prominences were estimated relative to that for £100.00 which was fixed at 1. The height of each bar represents the estimated prominence for each prominent number on the x-axis. The error bars are 95% confidence intervals. The optimal μ = 1.19, 95% CI [1.05, 1.33]. The log likelihood = -16160.09.

4.4 Conclusion

This chapter provides the first evidence of people’s preference for prominent and round numbers in the context of credit card repayments. This is a particularly interesting context as credit card holders face a regular number-choice problem in deciding how much to repay, where natural variation in the choice set of feasible numbers arises due to the convention of credit card companies requiring minimum repayments.

We found that credit card repayments highly cluster at prominent numbers. In particular, repayments exactly at £50.00, £100.00, £150.00, and £200.00 occupy more than 30% of partial repayments. We also find evidence for card holders’ preference for round numbers, exploiting quasi-experimental changes in the set of feasible repayment numbers which arises due to minimum repayment levels set by card issuers. At the point where the required minimum exceeds any multiple of £10, a large share of people choose to jump to the next multiple of £10. Previous studies in stock price clustering attribute the clustering to market makers' intention to reduce a cost in negotiating a price or to preserve wide bid-offer spreads. However, unlike the asset markets which most previous studies conducted on, credit cards repayments are completely individual decisions, and thus, price negotiations and bid-offer spread are irrelevant to card holders' decisions. Our study therefore indicates that the clustering of repayments at prominent numbers is likely to be due to people's natural preference led by the heuristic processing of numerical information. In addition, our analysis showed that, as predicted by Albers (1997), the likelihood of repayments falling at a certain integer (i.e., exact pounds) decreases as the precision of the repayment number increases (i.e., the relative exactness ratio of the repayment number decreases). We also estimated the relative prominence of 10 most prominent numbers. We are the first to provide such estimation. The results showed that £50.00 and £100.00 are the most prominent numbers.

Chapter 5 People incorrectly believe that most people make only the minimum payment on their credit card, and resist a social nudge to correct this belief

5.1 Background

The nudge is a policy tool which involves changing the choice architecture to help people make better decisions (Thaler & Sunstein, 2008). The social nudge guides people toward a particular behavior by informing them about the norm which most other people follow (Sunstein, 2014b). The social nudge is motivated by the theory of conformity suggesting that people tend to conform to a standard behavior which is popular among their peers because they are afraid that deviating from the social norm may hurt their status (Bernheim, 1994). For example, a descriptive norm message, ‘the majority of guests reuse their towels’, increases the towel reuse rate in the hotel (Goldstein, Cialdini, & Griskevicius, 2008, and see Scheibehenne, Jamil, & Wagenmakers, 2016, for a Bayesian reanalysis). The effect of the social nudge has been evident in previous studies in various fields including alcohol consumption (Haines & Spear, 1996), recycling (Cialdini, 2003), charity donation (Bartke et al., 2017), energy efficiencies (Schultz et al., 2007), and voting (Gerber & Rogers, 2009). Also, in practice, the social nudges are frequently used in marketing and advertisement campaign (Burchell, Rettie, & Patel, 2013).

The effect of the social nudge has been extensively studied in alcohol consumption. Many of those studies observed that college students tend to overestimate alcohol consumption level among their peers and that correcting the overestimation through a social nudge reduces their alcohol use (Burchell et al., 2013; Perkins & Berkowitz, 1986). For example, Perkins and Berkowitz (1986) asked college students their personal attitudes toward alcohol and their estimations about the general attitude among other students on campus (i.e., perceived norm). The results revealed that most students overestimated the proclivity for alcohol consumption among peers compared to the self-reports of those peers. Students who thought that their own drinking attitude was close to the perceived norm tended to consume more alcohol. Similarly, Haines and Spear (1996) found that students substantially overestimated the proportion of students engaging in binge drinking at parties and that correcting the overestimation through a social nudge campaign considerably reduced the number of students binge drinking.

People tend to falsely overestimate the commonness of one’s own behavior―the false consensus bias (Ross et al., 1977). One possible mechanism for the false consensus bias is based on the availability heuristic (Tversky & Kahneman, 1973)―people’s tendency to estimate the likelihood of events by the ease of retrieving them. The information most available in memory is not a representative sample of the population, but instead information about one's own behavior and the behaviors of others close to oneself. To the extent that similar others are more likely to share one's own behavior, using the availability heuristic with a limited number of observations of others' behaviors will lead people to believe their own behavior is more common than it is believed by those with a different behavior.

Another possible mechanism for the false consensus bias is driven by people's motivation to justify own behavior. That is, people may be motivated to believe that their own behavior is common because they want to justify their own behavior by confirming the commonness of their behavior among others (Ross et al., 1977). That is, a false consensus forms on the basis of people's desire for conformity to the majority. An interaction of the desire for conforming and the false consensus bias makes the behavior of the deviant minorities persistent because they are just comfortable with their deviant behavior which they mistakenly believe conforms to the majority of others. Therefore, correcting the false belief about the consensus helps people behave better, and social nudges may be one of effective tools to do so. That is, the social nudge is intended to correct the gap between the perceived norm and the actual norm (Berkowitz, 2004). To put this on the other way around, social nudges can work only conditional on the existence of a false belief to be corrected.

In this chapter, we examine the existence of the false consensus bias and the effect of the social nudge in the context of one frequent financial decision—credit card repayments. Many consumers use credit cards for daily purchases and financing. The US and the UK regulators require credit card companies to collect at least a certain proportion of the balance and interest in each month (known as the required minimum repayment). In the UK, the required minimum is normally interest and fees accrued within the month plus 1% of the card balance, or £5, whichever is the greater. The required minimum is intended to protect consumers from accumulating debts by decreasing the capital at least a little bit with each repayment. However, card holders repeating the required minimum repayments can reduce their debt only slowly. While minimum repayment is not necessarily problematic, minimum repayment may not be an optimal repayment decision for consumers who can afford to repay larger amounts. In the UK, about 10-12% of card holders usually repay only the minimum (including those with an introductory zero merchant APR), about 3-5% of card holders persistently repeat minimum repayments, and 50-60% of card holders always repay the balance in full (Financial Conduct Authority, 2015; The UK Cards Association, 2010, 2013). That is, the majority of people are full repayers and only a small fraction of people make repeated minimum repayments.

Previous studies have examined the effect of the numerical information on the credit card bill on people's repayments. Stewart (2009) and Navarro-Martinez et al. (2011)

showed in an experiment that an inclusion of the required minimum information in a mock bill increases the likelihood of people repaying only the minimum, and suggested that the minimum information in the bill may work as a psychological anchor (Tversky & Kahneman, 1974). In addition to the required minimum information, the US regulator introduced a new rule requiring credit card bills to present the total cost and the time duration for clearing the debt with two repayment scenarios. The first scenario assumes people keeping minimum repayments without further spending and the second scenario assumes people repaying a monthly repayment amount required to repay the balance in three years without further spending. This new rule was intended to nudge people to repay more than the minimum. However, empirical studies found an adverse effect of the presence of the three-year scenario in the bill. The three-year attractor reduces not only minimum repayments as desired, but also full repayments, suggesting that the scenario may act as another psychological anchor or that people may perceive that the scenario is recommended, and thus, is the most appropriate repayment (Hershfield & Roese, 2015; Wang & Keys, 2014).

In the present study, we are going to use the hypothetical bill repayment task to (a) replicate the effects of adding the minimum payment to bills, (b) estimate the effects of adding a higher repayment scenario to bills, and (c) estimate the effect of adding a social nudge (truthfully) explaining that most people make repayments higher than the scenario.

According to the literature reviewed above, we built the following four hypotheses. First, people who usually repay only the minimum falsely believe that minimum repayments are common among others (the false belief hypothesis). Second, the presence of the required minimum will increase repayments around the minimum (the minimum anchoring hypothesis). Third, the presence of a higher repayment scenario increases repayments around the high repayment (the high attractor anchoring hypothesis). Finally, conditional on the false belief hypothesis, informing repayers that most people repay at least the higher repayment will make people repay more (the social nudge hypothesis).

5.2 Method

An online experiment was conducted in collaboration with the consumer association Which? and was run by the market research agency, Populus.

5.2.1 Participants

2,020 adults who preregistered to the Populus Participants Panel voluntarily visited the online survey site. Of these, 594 participants did not have a credit card in their own name and were not allowed to join the experiment. The remaining 1,426 participants (735 males and 691 females; See Table A4.1 in Appendix 4.1) proceeded the experiment. All participants were over 18 years old (see Table A4.2 in Appendix 4.1 for the distribution of participants' age). Participants received £1 per 5 minutes for participation.

5.2.2 Procedure

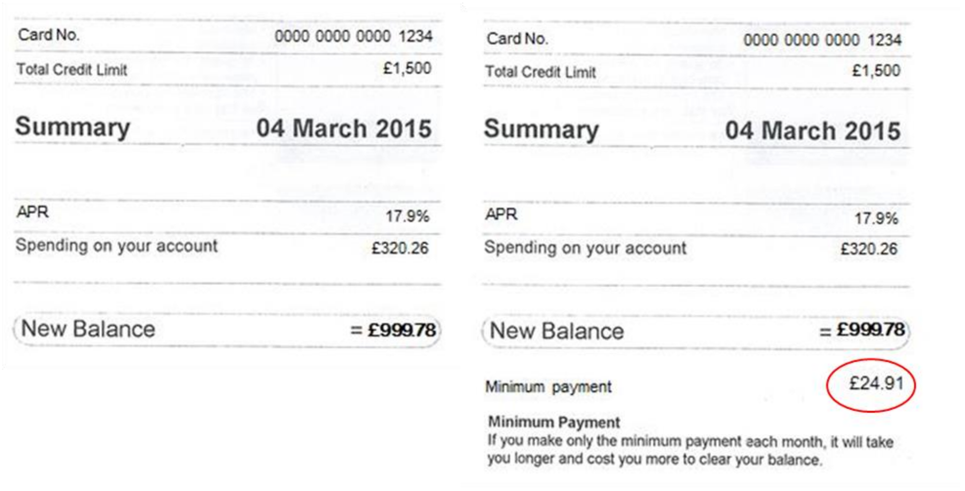
At the beginning of the experiment, participants were asked about their usual repayment behavior (the question about usual repayment behavior; see Appendix 4.2a for the exact phrases of the question). Six options were available—'minimum repayment', 'more than minimum but less than full balance', 'varying among months', 'full repayment', 'do not use a credit card', and 'do not know'. Participants selected one of the options which is most close to their own usual repayment behavior in real life.

Following the question about usual repayment behavior, participants were presented with the following sentences.

> 'Imagine that, this morning, you have opened your post and received a bill from your credit card company. We'll show you the bill on the next screen and you can read through it then. Obviously you might not really expect to get a bill like this. But if you did, bearing in mind your own personal financial situation including how much money you actually have and your normal expenses, what would you repay?'

At this point, participants were randomly assigned to one of three experimental conditions: *Missing-Minimum Condition*, *Minimum Condition*, *Minimum-and-High-Attractor Condition*. Those assigned to Minimum-and-High-Attractor Condition were further randomly divided to two conditions: *Minimum-and-High-Attractor-without-Social-Nudge Condition* and *Minimum-and-High-Attractor-with-Social-Nudge Condition*. Thus the experiments had four conditions: Missing-Minimum Condition (n = 477), Minimum Condition (n = 471), Minimum-and-High-Attractor-without-Social-Nudge Condition (n = 228) and Minimum-and-High-Attractor-with-Social-Nudge Condition (n = 250).

After the assignment to the experimental conditions, a mock bill was shown to participants. The conditions differ in a mock bill shown to participants. The mock bills for four conditions are presented in Figure 5.1. The bill in Missing-Minimum Condition (see Figure 5.1a) showed card number (0000 0000 0000 1234), total credit limit (£1,500), date (04 March 2015), APR (17.9%), spending of the month (£320.26), and new balance (£999.78). The required minimum repayment (£24.91) was added in the bill for Minimum Condition, Minimum-and-High-Attractor-without-Social-Nudge Condition, and Minimum-and-High-Attractor-with-Social-Nudge Condition (see the red circles in Figures 5.1b, c, and d; note that the mock bills used in the experiment did not include these colored circles). The mock bill for Minimum Condition resembles to the real credit card bill used in the UK where the minimum repayment amount is required to be presented by the regulator. In

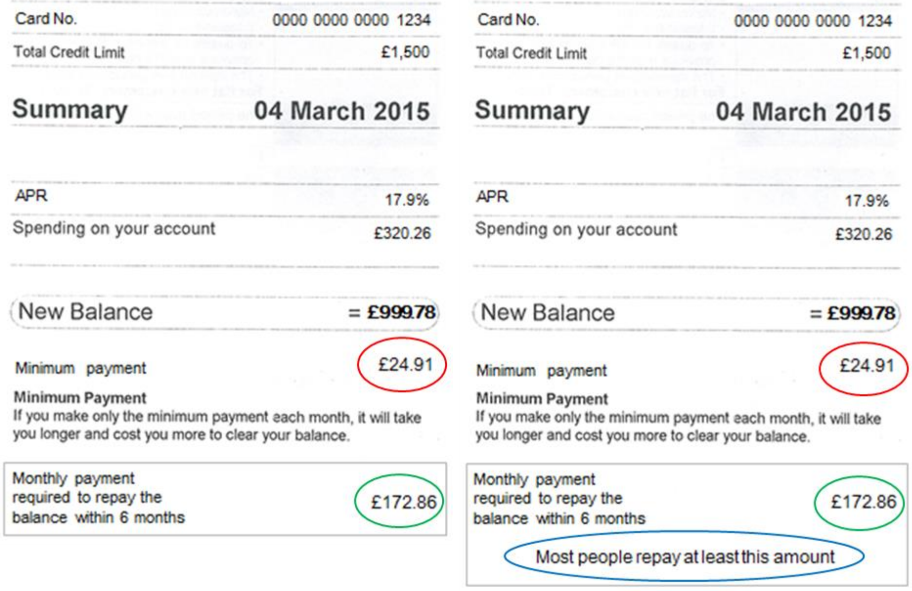


(a) Missing-Minimum Condition

Card No. 0000 0000 0000 1234
Total Credit Limit £1,500
Summary **04 March 2015**
APR 17.9%
Spending on your account £320.26
New Balance = **£999.78**

(b) Minimum Condition

Card No. 0000 0000 0000 1234
Total Credit Limit £1,500
Summary **04 March 2015**
APR 17.9%
Spending on your account £320.26
New Balance = **£999.78**
Minimum payment £24.91
Minimum Payment
If you make only the minimum payment each month, it will take you longer and cost you more to clear your balance.



(c) Minimum-and-High-Attractor-without-Social-Nudge Condition

Card No. 0000 0000 0000 1234
Total Credit Limit £1,500
Summary **04 March 2015**
APR 17.9%
Spending on your account £320.26
New Balance = **£999.78**
Minimum payment £24.91
Minimum Payment
If you make only the minimum payment each month, it will take you longer and cost you more to clear your balance.
Monthly payment required to repay the balance within 6 months £172.86

(d) Minimum-and-High-Attractor-with-Social-Nudge Condition

Card No. 0000 0000 0000 1234
Total Credit Limit £1,500
Summary **04 March 2015**
APR 17.9%
Spending on your account £320.26
New Balance = **£999.78**
Minimum payment £24.91
Minimum Payment
If you make only the minimum payment each month, it will take you longer and cost you more to clear your balance.
Monthly payment required to repay the balance within 6 months £172.86
Most people repay at least this amount

Figure 5.1. Mock bills used in the experiments. Panel (a) shows the mock bill used in Missing-Minimum Condition. Panel (b) shows the mock bill used in Minimum Condition. Panel (c) shows the mock bill used in Minimum-and-High-Attractor-without-Social-Nudge Condition. Panel (d) shows the mock bill used in Minimum-and-High-Attractor-with-Social-Nudge Condition. The red circles indicate the required minimum. The green circles indicate the high attractor. The blue circle indicates the social nudge. Note that the mock bills used in the experiment did not have these colored circles.

addition to the minimum repayment, the mock bill in Minimum-and-High-Attractor-without-Social-Nudge Condition and Minimum-and-High-Attractor-with-Social-Nudge Condition included monthly payment required to repay the balance within six months (£172.86; see the green circles in Figures 5.1c and d). We call this information a High Attractor. The mock bill in Minimum-and-High-Attractor-with-Social-Nudge Condition included an additional social nudge sentence—'Most people repay at least this amount' (see the blue circle in Figure 5.1d).

Following the presentation of a mock bill, participants entered their repayments in a free text response box (£xxx.xx). After, we asked participants' estimations about how many people out of 100 repay the minimum on a credit card bill (the estimation of the popularity of minimum repayments; the exact phrases shown to participants are presented in Appendix 4.2b) and their estimations about how many people out of 100 repay a credit card bill in full (the estimation of the popularity of full repayments; the exact phrases shown to participants are presented in Appendix 4.2c). Participants moved a slider ranging from 0 to 100 to answer to the both estimations.

In addition, we asked the current credit limit, the latest balance of participants' actual credit cards, and how much current liquidity (e.g., saving) they have. In addition, participants' demographic and socioeconomic data including gender, age, income, and educational level were collected (see Tables A4.1-A4.5 in Appendix 4.1 and Figures A4.1-A4.3 in Appendix 4.3 for details).

5.3 Results

5.3.1 False beliefs about the popularity of minimum and full repayments

Table 5.1 reports the distribution of participants' self-reported usual repayment behaviors, showing that about 9% of participants usually repay the minimum (usual minimum repayers) and over 60% of participants usually repay in full (usual full repayers) in their real life. The distribution is consistent with that seen in the previous empirical and survey data (Financial Conduct Authority, 2015; The UK Cards Association, 2010; 2013; see the literature review above). Participants answering 'Don't use' and 'Don't know' (54 participants) were excluded from the following analysis.

Table 5.1*. *The Prevalence of Self-reported Usual Repayment Behavior

Repayment Behavior (Type of repayers)	Prevalence
Minimum (Minimum repayers)	9.0%
Between minimum and full balance (Between repayers)	12.4%
Vary among months (Varying repayers)	12.8%
Full balance (Full repayers)	62.0%
Not use	3.5%
Don't know	0.3%

Next we see participants' estimations of the popularity of minimum repayments and those of the popularity of full repayments. Unsurprisingly, the estimation of the popularity of minimum repayments and that of the popularity of full repayments were negatively correlated (Pearson correlation = -.49, 95% CI [-.53, -.45]).

Figure 5.2 presents the distribution of participants' estimations about how many people out of 100 repay the minimum, showing that participants' estimations (*M* = 54.41, 95% CI [53.19, 55.65]; *Median* = 56, 95% CI [51, 60]; see Figure 5.2a) tended to be much higher than the actual proportion of minimum repayers seen in Table 5.1 (9.0%). That is, most participants greatly overestimated the popularity of minimum repayments. Interestingly, the extent of the overestimation is larger for participants who usually repay the minimum (*M* = 68.12, 95% CI [64.91, 71.36]; *Median* = 70, 95% CI [68, 71]; see Figure 5.2b) than for those who usually repay in full (*M* = 50.89, 95% CI [49.34, 52.49]; *Median* = 50, 95% CI [50, 51]; see Figure 5.2c). In addition, for participants who usually repay between the minimum and the full balance, the estimations are *M* = 59.92, 95% CI [56.98, 62.51]; *Median* = 60, 95% CI [59, 69.5]. For participants whose repayment behavior varies among months, the estimations are *M* = 56.42, 95% CI [53.50, 59.47]; *Median* = 59.5, 95% CI [50.5, 61]. Among four types of repayers, the degree of overestimation is largest for usual minimum repayers.

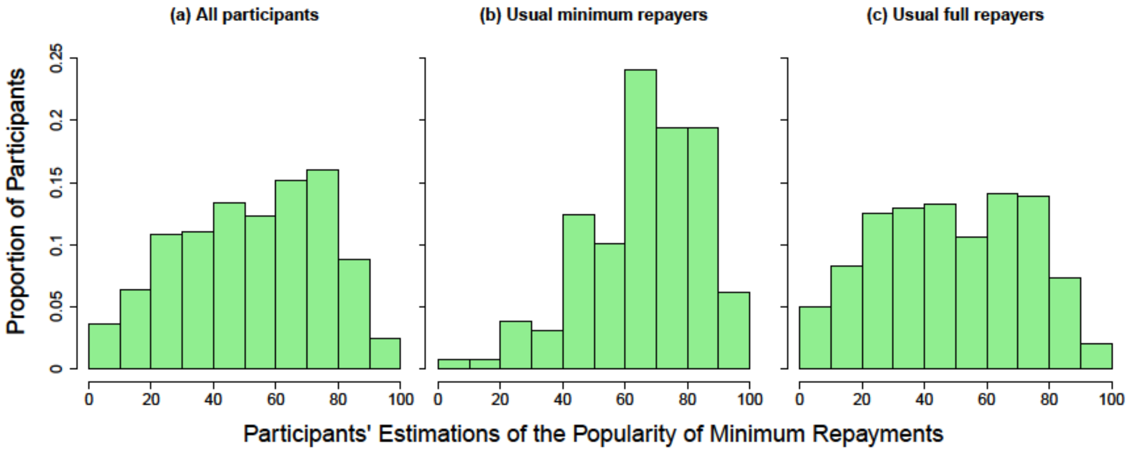


Figure 5.2. The distribution of participants' estimations of the popularity of minimum repayments. Panel (a) shows the distribution of estimations for all participants. Panel (b) shows the distribution of estimations for participants who usually repay the minimum. Panel (c) shows the distribution of estimates for participants who usually repay in full.

Figure 5.3 presents the distribution of participants' estimations about how many people out of 100 repay in full, showing that participants' estimations (*M* = 35.70, 95% CI [34.40, 36.86]; *Median* = 30, 95% CI [30, 30]; see Figure 5.3a) tended to be much lower than the actual proportion of full repayments seen in Table 5.1 (62.0%). That is, most participants underestimated the popularity of full repayments. The extent of the underestimation is smaller for participants who usually repay in full (*M* = 41.08, 95% CI [39.44, 42.64]; *Median* = 37.5, 95% CI [32, 40]; see Figure 5.3c) than those who usually repay the minimum (*M* = 24.04, 95% CI [20.69, 27.28]; *Median* = 20, 95% CI [13, 20]; see Figure 5.3b), while the estimations by the usual full repayers were still much lower than the actual proportion of full repayments. In addition, for participants who usually repay between the minimum and the full balance, the estimations are *M* = 25.73, 95% CI [22.89, 28.74]; *Median* = 20, 95% CI [19, 24.5]. For participants whose repayment behavior varies among months, the estimation are *M* = 27.49, 95% CI [24.77, 30.45]; *Median* = 20, 95% CI [20, 27]. Among four types of repayers, the degree of underestimation is smallest for usual full repayers.

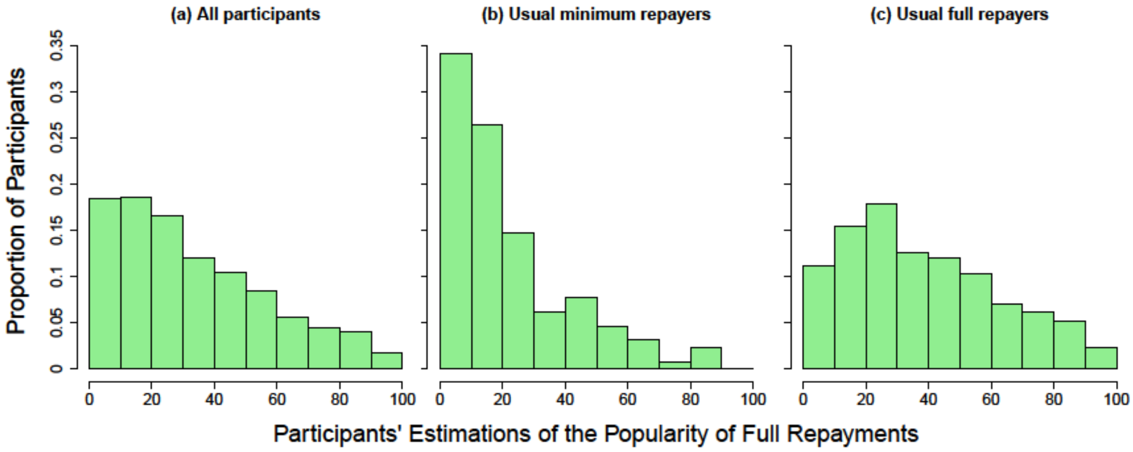


Figure 5.3. The distribution of participants’ estimations for the popularity of full repayments. Panel (a) shows the distribution of estimations for all participants. Panel (b) shows the distribution of estimations for participants who usually repay the minimum. Panel (c) shows the distribution of estimations for participants who usually repay in full.

To recap, participants, in general, tended to overestimate the popularity of minimum repayments and underestimate the popularity of full repayments. In particular, usual minimum repayers incorrectly believe that many more people are minimum repayers just like themselves than it really is. This is consistent with the false belief hypothesis. Because of the existence of the false belief about the commonness of minimum repayments, a social nudge may reduce the number of minimum repayments if it is successful in correcting the false belief.

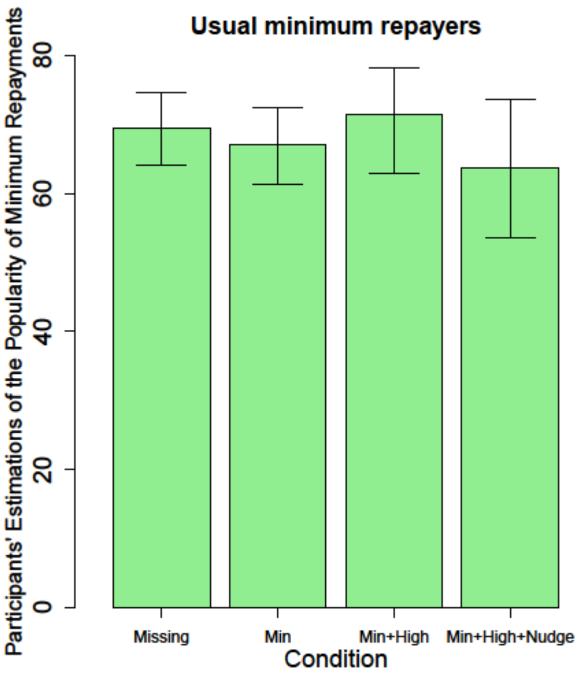


Figure 5.4. The mean of usual minimum repayers' estimations of the popularity of minimum repayments by the experimental conditions. On the x-axis, 'Missing' represents Missing-Minimum Condition, 'Min' represents Minimum Condition, 'Min+High' represents Minimum-and-High-Attractor-without-Social-Nudge Condition, and 'Min+High+Nudge' represents Minimum-and-High-Attractor-with-Social-Nudge Condition. The error bars are 95% confidence intervals computed by the bootstrap method with 1,000 resamples.

5.3.2 Did the social nudge correct the overestimation about the popularity of minimum repayments?

The above analysis showed that usual minimum repayers falsely overestimated the popularity of minimum repayments. If the social nudge did successfully correct this false belief, then the social nudge might reduce the number of minimum repayments. The mock bill in Minimum-and-High-Attractor-with-Social-Nudge Condition has a social nudge sentence—'Most people repay at least this amount' (note that 'this amount' in the social nudge means the amount of the high attractor which is larger than the minimum, see Figure 5.1). Just after looking at the mock bill, participants were asked their estimation of the popularity of minimum repayments. Therefore, if the social nudge worked, their estimation of the popularity of minimum repayments should have been influenced, at least to some extent, by the social nudge. Specifically, we expect that usual minimum repayers might reduce the extent of the overestimation about the popularity of minimum repayments in the presence of the social nudge. That is, the extent of the overestimation might be smaller in Minimum-and-High-Attractor-with-Social-Nudge Condition than in other conditions. Figure

5.4 shows the mean of usual minimum repayers' estimations of the popularity of minimum repayments by conditions. The 95% confidence intervals (the error bars in Figure 5.4) mostly overlap across four conditions, indicating that the social nudge did not influence minimum repayers' belief about the popularity of minimum repayments. (Note that the social nudge had no effect on beliefs of other types of repayers either, see Figure A4.4 in Appendix 4.4.)

In order to confirm the findings in Figure 5.4 in multivariate setting, we conducted a linear regression with Equation 5.1. In Equation 5.1, the dependent variables is *Estimation of the popularity of minimum repayments* representing the participant's estimation of the popularity of minimum repayments (a numerical variable ranging from 0 to 100). X_U is a vector of participant's usual repayment types in their real life with four levels: Minimum, Between, Varying, and Full. *Minimum in the bill* is a dichotomous variable having a value of 1 if the mock bill included the required minimum, otherwise 0. *High Attractor in the bill* is a dichotomous variable having a value of 1 if the mock bill included the high attractor, otherwise 0. *Social Nudge in the bill* is a dichotomous variable having a value of 1 if the mock bill included the social nudge, otherwise 0. We controlled for participants' self-reported credit card profile and their demographic and socioeconomic characters. *Latest balance*, *Current credit limit*, and *Current liquidity* are continuous variables representing the latest balance and the credit limit of participants' credit cards, and their available current liquidity, respectively. X_{DS} is a vector of participants' demographic and socioeconomic categories including gender (2 levels), age (6 levels), household income (13 levels), house-ownership status (6 levels), and educational level (6 levels) (see Tables A4.1-A4.5 in Appendix 4.1 and Figures A4.1-A4.3 in Appendix 4.3 for details of the control variables).

$$\begin{aligned} &Estimation\ of\ the\ popularity\ of\ minimum\ repayments \\ &\qquad = \beta_0 + B_U X_U + \beta_1 Minimum\ in\ the\ bill + \beta_2 High\ Attractor\ in\ the\ bill \\ &\qquad + \beta_3 Social\ nudge\ in\ the\ bill + \beta_4 Latest\ balance \\ &\qquad + \beta_5 Current\ credit\ limit + \beta_6 Current\ Liquidity + B_{DS} X_{DS} \end{aligned} \tag{5.1}$$

Table A4.6 in Appendix 4.6 reports the full results of the regression. First, *Usual repayment behavior* = "*Minimum*" positively associates with *Estimation of the popularity of minimum repayments* (*Beta* = 9.42, 95% CI [3.96, 14.87], *p* < .001). This means that participants who usually repay the minimum tended to believe that a larger proportion of other people are minimum repayers, consistent with the false belief hypothesis. Regarding the effect of the experimental conditions, all of *Minimum in the bill* (*Beta* = -.82, 95% CI [-3.9, 2.26], *p* = .602), *High Attractor in the bill* (*Beta* = -.55, 95% CI [-4.44, 3.34], *p* = 0.782), and *Social Nudge in the bill* (*Beta* = 3.40, 95% CI [-1.00, 7.80], *p* = .130) have no effect on *Estimation of the popularity of minimum repayments*. That is, the experimental conditions had no influence on participants' belief about the popularity of minimum repayments. In particular, the coefficient estimate for *Social Nudge in the bill* is positive, indicating that the social nudge failed to correct the false belief. The confidence interval indicates that if there is an effect it is very likely either a null effect or a small positive effect. Figure 5.5 shows the model predictions for the participants' estimations for the popularity of minimum repayments by the experimental conditions, which is nearly identical to Figure 5.4 and confirms no effect of the experimental conditions on participants' belief about the popularity of minimum repayments even when we control for individual differences. The social nudge failed to correct participants' false belief.

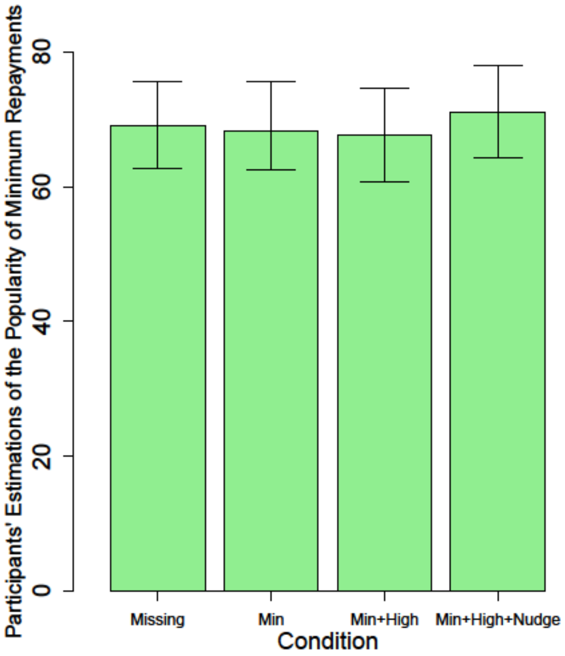


Figure 5.5. The model predictions (Equation 5.1) for participants' estimation of the popularity of minimum repayments. On the x-axis, 'Missing' represents Missing-Minimum Condition, 'Min' represents Minimum Condition, 'Min+High' represents Minimum-and-High-Attractor-without-Social-Nudge Condition, and 'Min+High+Nudge' represents Minimum-and-High-Attractor-with-Social-Nudge Condition. The error bars are 95% confidence intervals. In the predictions, X_U (usual repayment behavior) was set at Minimum. *Gender* was set as male. House ownership status was set as 'Owned with mortgage or loan'. Educational level was set at NVQ1-3. Income was set as £21,001-38,000. Age was set 45-54. The median values were applied to *Latest balance, Current credit limit, and Current liquidity.*

5.3.3 Consistency between usual repayment behavior and the experimental repayment

In the experiment, participants entered their repayment for the hypothetical bill task in a free text response box. We divided those repayments into eight categories (see Table 5.2 for exact definitions of categories). Categories of interest are *Around-Minimum*, *Around-High-Attractor*, and *Full*. *Around-Minimum* includes repayments equal to or greater than the minimum (£24.91) and no more than £30. We allowed this category to include slightly larger than the minimum rather than exactly the same amount to the minimum because participants might round up the minimum for a repayment and still think that they repaid the minimum. *Around-High-Attractor* includes repayments between £100 and £200 which are around the amount of the high attractor (£172.86). *Full* includes repayments equal to or greater than the full balance (£999.78).

Table 5.2. Categories of Experimental Repayments

Repayment Category	Repayment Amount
Missed	Repayment < £24.91
Around-Minimum	£24.91 ≤ Repayment ≤ £30
Between-Minimum-and-High-Attractor	£30 < Repayment ≤ £100
Around-High-Attractor	£100 < Repayment ≤ £200
Between-High-Attractor-and-Spending	£200 < Repayment ≤ £300
Around-Spending	£300 < Repayment ≤ £400
Between-Spending-and-Full	£400 < Repayment < £999.78
Full	Repayment ≥ £999.78

Figure 5.6 shows the distribution of experimental repayments by participants' usual repayment behavior types and experimental conditions. In Figure 5.6, each row represents participants' usual repayment behavior in real life and each column represents experimental condition which differ in information in the mock bill. Red bars indicate that the experimental repayment matched to participants' usual repayment behavior in real life. (Note that, because the required minimum did not exist in a mock bill for Missing-Minimum Condition, Minimum and Between repayments cannot be defined in the condition. From this reason, the first column in Figure 5.6 does not have a red bar, except the bottom rows which is for usual full repayers.) Interestingly, comparing the plots within each row, participants' repayments in the experiment were quite consistent with their usual repayment behavior in the real life, irrespective of the experimental conditions (i.e., the red bars occupy a quite large proportion within each panel). This indicates two things. First, it was likely that participants seriously made the hypothetical repayment decisions that reflect their real life repayment behavior. Second, the experimental conditions had little effect on their experimental repayments. We confirm the second point with a multivariate analysis in Section 5.3.4.

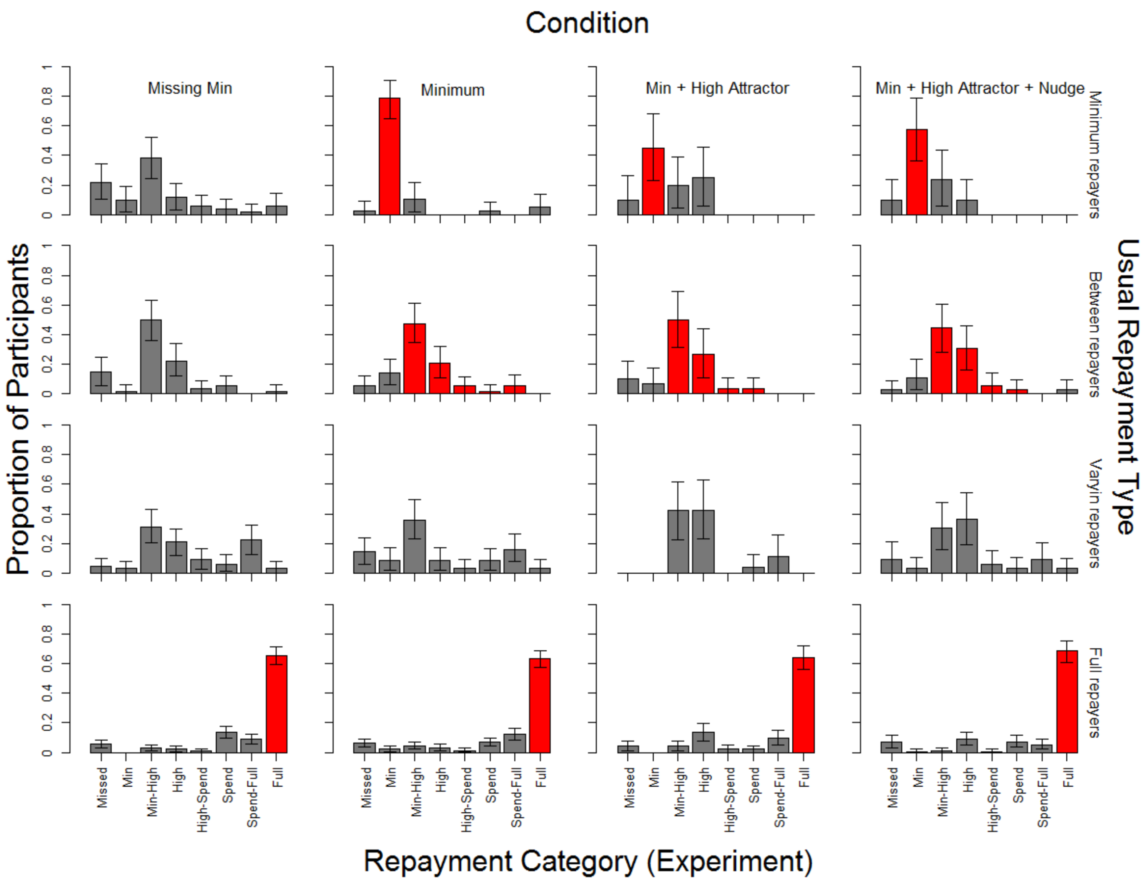


Figure 5.6. The distribution of participants' repayments to a mock bill. Each row represents participants' usual repayment behavior in real life. Each column represents an experimental condition which differ in information presented in the mock bill. In the heading, 'Missing Min' represents Missing-Minimum Condition, 'Minimum' represents Minimum Condition, 'Min + High Attractor' represents Minimum-and-High-Attractor-without-Social-Nudge Condition, and 'Min + High Attractor + Nudge' represents Minimum-and-High-Attractor-with-Social-Nudge Condition. The red bars indicate that the experimental repayment to the mock bill matched to participants' usual repayment behavior in real life. The error bars are 95% confidence intervals computed by the bootstrap method with 1,000 resamples.

5.3.4 Multivariate analysis on experimental repayments

The above analysis showed that usual minimum repayers tended to greatly overestimate the popularity of minimum repayments and that the social nudge failed to correct their false belief about the popularity of minimum repayments. We also saw that participants' experimental repayments were much influenced by their usual repayment behavior in real life. In particular, most usual minimum repayers repaid the minimum in the experiment, regardless of the experimental conditions, indicating a failure of the social nudge to change the minimum repayers' behavior.

In order to confirm the null effect of the social nudge on experimental repayments, we conducted a multinomial regression with Equation 5.2. In Equation 5.2, the dependent variable is the log-odds of the probability of participants' experimental repayments falling into each repayment category relative to the probability of a repayment falling into Around-Minimum category. The definition of other variables are identical to those in Equation 5.1.

$$\begin{aligned}\log\frac{P(Repayment\ Category = Category\ k)}{P(Repayment\ Category = Around\ Minimum)} &= \beta_0 + \beta_1 Minimum\ in\ the\ bill + \beta_2 High\ Attractor\ in\ the\ bill \\ &+ \beta_3 Social\ nudge\ in\ the\ bill\ +\ \beta_4 Latest\ balance \qquad (5.2) \\ &+ \beta_5 Current\ credit\ limit +\ \beta_6 Current\ Liquidity + B_{DS}X_{DS}\end{aligned}$$

Table A4.7 in Appendix 4.6 reports the full results of the regression. Figure A4.5 in Appendix 4.5 shows the model prediction for the distribution of repayments by experimental conditions.

First, *Minimum in the bill* has negative coefficients for all repayment categories (Beta = -2.49, 95% CI [-3.49, -1.49], p < .001 for Missed category; *Beta* = -2.23, 95% CI [-3.12, -1.34], *p* < .001 for Between-Minimum-and-High-Attractor category; *Beta* = -2.38, 95% CI [-3.34, -1.42], *p* < .001 for Around-High-Attractor category; *Beta* = -2.32, 95% CI [-3.55, -1.08], *p* < .001 for Between-High-Attractor-and-Spending category; *Beta* = -2.70, 95% CI [-3.68, -1.71], *p* < .001 for Around-Spending category; *Beta* = -1.95, 95% CI [-2.90, -1.01], *p* < .001 for Between-Spending-and-Full category; *Beta* = -2.36, 95% CI [-3.24, -1.49], *p* < .001 for Full category). These results mean that the presence of the required minimum in the bill increases the likelihood of repayments around the minimum by reducing the probability of repayments falling into all the other categories (note that, in the regression, the reference category is Around-Minimum category). This is consistent with the minimum anchoring hypothesis.

Second, *High Attractor in the bill* has a positive effect on Between-Minimum-and-High-Attractor category (*Beta* = 1.25, 95% CI [.35, 2.16], *p* = .007) and on Around-High-Attractor category (*Beta* = 2.22, 95% CI [1.28, 3.17], *p* < .001). These results mean that the presence of the high attractor in the bill shifts minimum repayments toward the high attractor by reducing the likelihood of around-minimum repayments. This is consistent with the high attractor anchoring hypothesis. In addition, *High Attractor in the bill* shows a positive coefficient on Full category (*Beta* = 1.14, 95% CI [.25, 2.03], *p* = .012). This is relative to the effect on Around Minimum category as a reference. Switching the reference repayment category in Equation 5.2 from Around-Minimum to Around-High-Attractor, *High Attractor in the bill* has a negative coefficients on Full category (*Beta* = -1.08, 95% CI [-

1.72, -.45], *p* < .001). The results are consistent with previous studies showing a negative effect of a high attractor on both minimum and full repayments.

Finally, the confidence intervals of *Social nudge in the bill* cross 0 for all repayment categories. Because the number of participants shown the social nudge in the bill is only about one sixth of all participants, it may be statistically difficult for *Social nudge in the bill* to have a significant effect in the regression. Having said that, crucially, the coefficient estimate of *Social nudge in the bill* for Around-High-Attractor category is negative (*Beta* = -.86, 95% CI [-1.89, .17], *p* = .100), indicating that the effect would be opposite to the intended direction even if we could have a larger sample. The null effect of the social nudge is expected from the findings in Figures 5.4 and 5.5 where the social nudge failed to correct participants' overestimations about the popularity of minimum repayments.

5.4 Discussion

Our experiment confirmed the findings of previous studies in anchoring effect of numerical information in a credit card bill. In addition, we found that participants who usually repay only the minimum greatly overestimated the popularity of minimum repayments. This is consistent with the false consensus bias. However the social nudge in the mock bill did not influence participants' belief about the popularity of minimum repayments and had no effect on experimental repayments.

5.4.1 Reasons behind the persistence of people's false beliefs

We consider why the social nudge did not work in our experiment. Some previous studies also found no effect of the social nudge. For example, Werch et al. (2000) found that the social nudge had no effect on college students' alcohol consumption. Berkowitz (2004) suggested that the social norm intervention by Werch et al. (2000) was conducted only over one month and was not long enough to influence the persistent misperception about alcohol consumption among students. In our experiment, the social norm message was presented to participants for a moment before they decided their experimental repayments and the presentation period might be too short to change participants' misperception which had been becoming persistent through their real life experience. If card companies conduct a social nudge campaign with their real credit card bill for a considerable time duration, it may be possible to have a positive effect of the social nudge on people's repayments.

Another possible reason of the null effect of the social nudge is a lack of the credibility of the social norm message. Thombs, Dotterer, Olds, Sharp, and Raub (2004) showed that some students with high alcohol consumption thought that the statistics used in the social nudge were not credible, suggesting that the lack of credibility about the statistics used in a social nudge is one of reasons that some social nudge programs have no effect on people’s behavior. It is possible that the social nudge in our mock bill did not have enough credibility to influence participants’ belief because participants knew that the mock bill was made for the experiment and was not a real one. In this sense, a social nudge like ‘50% of our clients repay in full’ in a real credit card bill may have an enough credibility to influence people’s belief. Field trials overcoming these possible shortfalls of our online experiment may find a positive effect of social nudges.

Chapter 6 Selling Winners or Losers: Two-Stage Decision Making and the Disposition Effect in Stock Trading

6.1 Introduction

One of the most well-evidenced behavioral biases in finance is the disposition effect, in which people are more likely to sell stocks that have gained value since they bought them than stocks that have lost value (Odean, 1998; Shefrin & Statman, 1985). More generally, the idea that people treat gains and losses differently is well established in psychology and economics (Kahneman & Tversky, 1979; Tversky & Kahneman, 1991) and is embodied in the concept of loss aversion which is core in behavioral economics (Camerer, 2005). The idea that outcomes are evaluated against a reference level, often taken to be the status quo, is also well established (Kőszegi & Rabin, 2006, 2007; Lopes & Oden, 1999). This chapter shows that, in the domain of finance, whether a stock has gained or lost value is psychologically elemental, such that (a) stocks are grouped together, with decisions taken about selling at this category level without reference to the magnitudes of the gains and losses, and (b) stocks in gain are considered separately from stocks in loss, and vice versa. As such we demonstrate that the disposition effect is, at least in the large part, a gain-loss-domain-level effect and not only an individual-stock-level effect.

The disposition effect is robust, and has been demonstrated using real stock trading data for private investors (Brown et al., 2006; Grinblatt & Keloharju, 2000; Odean, 1998), professional traders (Garvey & Murphy, 2004) and in laboratory experiments (Weber & Camerer, 1998). In many studies, the magnitude of the disposition effect is estimated using data from days upon which at least one stock is sold (sell-day portfolios) (e.g., Kaustia, 2010; Odean, 1998). Regression models are used to estimate the probability that a particular stock is sold while controlling for other properties of a given stock (e.g., return since purchase, price volatility, holding period). The disposition effect is observed when the probability that a stock is sold is higher when it is in gain than when it is in loss, other things being equal. The disposition effect is substantial. For example, Odean (1998) reported that gains are, on average, 1.5 times as much likely to be sold as losses in the US retail investors' portfolios. Similarly, Kaustia (2010) showed that gains are twice as much likely to be sold as losses when Finish investors sold a stock with a short holding period.

Here we propose that existing methods for estimating the disposition effect are inadequate because they make an erroneous assumption about the decision processes of individual investors. Consider an investor who is trying to decide on which stock to sell from his or her portfolio. The investor may consider all of the stocks in the portfolio, comparing their past performance and trying to predict their future outlook. If this investor exhibits the disposition effect, his or her decision will be swayed towards selling a stock in gain over a stock in loss. In this account, whether a stock is in gain or in loss is just one of many features used to assess each individual stock. This decision rule aligns well with the assumptions of the regression techniques used to estimate the disposition effect, in which the probability of each stock being sold is estimated simultaneously across domains of gains and losses. We refer to this approach as the one-stage model to reflect its implicit assumptions about the investors' decision process. Now, consider an alternative process in which an investor seeks to minimize the cognitive cost associated with the complex trade-offs of comparing stocks in gain with stocks in loss. Our investor therefore begins by answering a simple but important question: Do I sell a stock in gain, or do I sell a stock in loss? This decision is exogenously made without any consideration of individual stocks in the portfolio and its composition, but can be influenced by the investor's tendency to sell gains over losses. In the second stage of the decision process, the investor is left with one of two possible choice contexts: If he or she initially decided to sell a gain then he or she must now decide which gain to sell. Alternatively, if he or she initially decided to sell a loss, he or she must now decide which loss to sell. We refer to this process as the two-stage model, since the investors begin by selecting a domain from which they will sell in the first stage, and only then in the second stage do they evaluate the subset of stocks in the domain they chose in the first stage.

In Section 6.2 we argue that, from a psychological perspective, the two-stage model offers a plausible account of the investors' decision process. We propose that, in order to reduce decision complexity, people segregate outcomes into gains and losses and engage only in within-domain comparisons when evaluating individual stocks. In Section 6.3 we describe the Barber and Odean (2000) data set which we use to estimate the models. In Section 6.4 we outline the unique predictions that this two-stage model makes about how the size of the disposition effect should vary with the number of gains and losses in a portfolio. In Section 6.5 we show how the disposition effect is sensitive to the number of gains and losses in a portfolio, exactly as the two-stage model predicts. In Section 6.6 we show the implications for using regression models to estimate the disposition effect. In Section 6.7 we consider what the evidence for the two-stage model means for the origins of the disposition effect.

6.2 The Psychology of a Decision to Sell

When faced with a complex choice problem, individual decision makers tend to adapt and choose strategies that reflect a trade-off between decision accuracy and the cognitive cost of deciding—satisficing (Simon 1955, 1956). As a result, decision makers are likely to use sequential and non-compensatory decision rules (Gigerenzer & Gaissmaier, 2011; Payne, Bettman, & Johnson, 1993). A common feature of these strategies is that people attempt to reduce size of a choice set (i.e., the number of alternatives in consideration) using a single criterion at a time (Brandstätter et al., 2006; Tversky, 1972). Such models stand in stark contrast with the standard economic view, in which all available information is considered in making a decision. Here we focus on people's tendency to reduce the complexity of a decision context by first segregating choice objects into the domains of gains and losses, and then subsequently evaluating the options available within a domain.

The distinction between the positive and the negative is reflected in the psychological theories of language, attitude formation, attention allocation, reinforcement learning, and decision making (Cacioppo & Berntson, 1994; Rozin & Royzman, 2001). At the most rudimentary level, the common assumption is that people perceive different alternatives as advantages or disadvantages relative to some neutral reference point, often given by the current status quo (Kőszegi & Rabin, 2006; Novemsky & Kahneman, 2005; Thaler & Johnson, 1990). The majority of the existing work related to judgment and decision making under risk and uncertainty focused solely on the asymmetric weighting of gains and losses. It is widely accepted that the anticipated negative emotions associated with a loss are stronger than the anticipated positive emotions associated with a gain of an equal magnitude (Kermer, Driver-Linn, Wilson, & Gilbert, 2006). Demonstrations of such loss aversion (or negativity bias) apply to both monetary and nonmonetary domains (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). The existence of the disposition effect has been interpreted as support of the asymmetric weighing of gains and losses. People may avoid realizing a loss out of a concern for the intensity of negative feelings, and hence become more likely to sell a stock in gain (Weber & Camerer, 1998). Here the label of loss aversion is a purely descriptive concept that does not come with any assumptions about the underlying decision processes. The goal of the present work is to flesh out the decision rule that may underpin the decision to sell a gain or a loss by individual investors.

Psychological theory suggests that when people evaluate anticipated feelings of positive and negative events, they naturally engage in a within-domain comparison (Kahneman & Miller, 1986; McGraw et al., 2010). That is, people may choose whether a given situation or an outcome falls into category of gains and losses, and only then proceed to compare it with outcomes within the same domain. Such mechanisms are also consistent with many models of relative judgment, where the relative comparison context is often constructed by separating outcomes using a natural anchor, such as zero point or other neutral value (Marsh & Parducci, 1978; Parducci, 1983; Stewart, Chater, & Brown, 2006). For example, consider a situation in which you are trying to form an evaluative judgment about losing your baggage at an airport. In forming a relevant set of comparable events, one is likely to think of other negative things that might have happened in the past whilst traveling. It is unlikely however, that one would bring to mind both negative and positive events in order to evaluate an unpleasant experience. Studies of loss aversion in risky choice support the idea that gains are evaluated only against other gains and that losses are evaluated only against other losses. For example, Walasek and Stewart (2015) showed that people's reluctance to accept mixed lottery gambles is largely dependent on the ranges of possible gains and losses that people store in their memory. In their experiments, they found that people exhibit no loss aversion for symmetric 50-50 gambles as long as the gain appears attractive relative to other gains, and when the loss appears small relative to other losses. This strong context-sensitivity of loss aversion could not occur if people were making across-domain comparisons.

In sum, whether something is a gain or a loss is a psychologically salient category. Here we propose that complex decisions such as choosing which stock to sell rely on a separation of stocks that are in gains from those that are in loss. Additionally, we suggest that stocks in gains will be compared with others in gain, while stocks in loss will be compared with others in loss.

6.3 Data

Our data are historical stock transactions for individual investors in the US. The trades were completed through a large discount brokerage between January 1991 and November 1996. These data were previously used in studies of disposition effect by Barber and Odean (2000, 2001, 2002) and Hartzmark (2015). We merged trades with the historical prices retrieved from the Center for Research in Security Price (CRSP). Because the purchase prices of stocks bought before the beginning of the transaction data are unknown, we excluded all accounts which had positions at the end of January 1991 so that we have complete price data for all portfolios. Multiple intra-day trades conducted by the same investor on the same stock were aggregated with quantity weighted prices. We extracted sell trades which changed a net position from positive to non-negative (i.e., sell trades leading to short positions were excluded), and reconstructed the portfolios held by the corresponding accounts on these sell dates (sell-day portfolios). Short positions and positions opened on sell days were excluded from the remaining portfolios. The return since purchase was calculated by using a quantity weighted average purchase price of a stock for a given account and a closing price of the stock as of one day prior to the sell date. Commissions and dividends were not included in the calculation of returns. If a sell-day portfolio contained one or more stocks with missing variables in either the CRSP data or the transaction data, the whole sell-day portfolio was excluded. Because of this portfolio-based rather than stock-

Table 6.1. Notations and Descriptions of Variables Used in Sections 6.4, 6.5, and 6.6

Variable	Description
N_G	The number of gains in a sell-day portfolio
N_L	The number of losses in a sell-day portfolio
N_{G+L}	The total number of stocks in a sell-day portfolio
$Sold$	A dichotomous variable having a value of 1 if the stock was sold otherwise 0
$Gain$	A dichotomous variable having a value of 1 if the stock was in gain, otherwise 0
$Loss$	A dichotomous variable having a value of 1 if the stock was in loss, otherwise 0
$P(Sold)$	The probability that an individual stock is sold. For empirical data, this is a proportion
$P(Gain)$	The probability that an individual gain is sold. For empirical data, this is the average of $Sold$ over gains
$P(Loss)$	The probability that an individual loss is sold. For empirical data, this is the average of $Sold$ over losses
β	The size of the disposition effect at the individual-stock level (hence lower-case β)
B	The size of the disposition effect at the gain-loss-domain level (hence capital B)
$Return$	The stock's return since purchase
$Return_{20}$	The stock's return for 20 days prior the sell day
$Volatility_{20}$	The stock's volatility for 20 days prior the sell day
$Holding\ Days$	The number of days that the stock has been held for, from first purchase to the sell day

based exclusion, the compositions of all sell-day portfolios in our sample were exactly the same to those in actual investors' portfolios. (Note that we also conducted the analysis on the sample based on the stock-base exclusion. The results are nearly identical to those reported in this chapter.) Because we are interested in the investors' choice of stock for sale, we extracted sell-day portfolios consisting of two or more stocks. Sell-day portfolios consisting of only gains or only losses and those including stocks at a zero return were excluded. Further we extracted sell-day portfolios where exactly one stock was sold. These one-sale portfolios are 84.5% of all sell-day portfolios. The summary statistics for the portfolios used are presented in Tables A5.1, A5.2, and A5.3 in Appendix 5.1.

Table 6.1 summarizes the notation we use in the analysis. N_G is the number of gains in a portfolio and N_L is the number of losses, so that the total number of stocks in a portfolio is $N_{G+L} = N_G + N_L$. $Sell$, $Gain$, and $Loss$ are 0/1 dummy variables indicating whether a stock is sold, and whether it is in gain or loss. $P(Gain)$ is the average value of $Sell$ over the gains in portfolios. As such it represents the probability that a single individual stock in gain is sold. Analogously, $P(Loss)$ represents the probability that a single individual stock in loss is sold. Because we select only the sell-day portfolios where exactly one stock was sold, $P(Gain) \times N_G + P(Loss) \times N_L = 1$.

The measure of the disposition effect at the level of individual stocks is $\beta = P(Gain)/P(Loss)$. The measure of the disposition effect at the gain-loss domain level is $\mathrm{B} = \frac{[P(Gain) \times N_G]}{[P(Loss) \times N_L]} = \beta \frac{N_G}{N_L}$.

We also include control variables in our multivariate analyses for the return since purchase, $Return$, the return in the past 20 days, $Return_{20}$, the volatility in the past 20 days, $Volatility_{20}$, and the number of days that a stock has been held for, $Holding\ Days$.

6.4 Model Predictions

Taken together, the psychological literature suggests that investors may seek to simplify their decision by first choosing whether to sell a stock in gain or in loss and then choosing a particular stock from within either the domain of gains or losses. We contrast this two-stage choice with a single-stage choice where people compare all stocks (gains and losses) simultaneously to choose which stock to sell. The two-stage model offers unique predictions about the relationship between the portfolios' composition and the size of the disposition effect. If traders follow the two-stage model and choose the domain of either gains or losses before deciding which stock to sell, we should find that the probability of an individual gain being sold is sensitive to the number of gains in the portfolio, but not the number of losses. Similarly, the probability of an individual loss being sold should be sensitive to the number of losses in the portfolio, but not the number of gains. This prediction follows from the two-stage model because once a trader decides upon a domain (either gains or losses) only stocks within that domain will be in competition to be sold. In the one-stage model, on the other hand, the probability that a gain or a loss is sold will be with a function of all stocks in the portfolio.

To preempt the results in Section 6.5, our analysis shows that a mixture of the conventional one-stage model and the proposed two-stage model are required to fit the data. The implications are profound. First, this indicates that people take a category-level decision about whether to sell a gain or a loss independently of the properties of the individual stocks involved. This means that the disposition effect is, in large part, a portfolio-level phenomena rather than merely an individual-stock level phenomena. The second implication is that the current regression approaches to estimating the disposition effect must be corrected, which we address in Section 6.6.

6.4.1 The one-stage model

The conventional method for estimating the selling probability of individual stocks assumes that investors evaluate all stocks in their portfolio simultaneously to choose one stock to sell. The disposition effect is at the individual stock level. We consider the measure of the individual-stock-level disposition effect β which is the single free parameter in the one-stage model, and reflects the relative probabilities of selling an individual single gain, $P(Gain)$ rather than an individual single loss, $P(Loss)$.

Because we take only sell-day portfolios where exactly one stock is sold, by definition, we use our constraint that $P(Gain) \times N_G + P(Loss) \times N_L = 1$ (see the data-selection criteria described in Section 6.3). We also have, from the definition of β, that $\beta = P(Gain)/P(Loss)$. Substituting for $P(Loss)$ gives

$$P(Gain) = \frac{1}{N_G + \frac{N_L}{\beta}} \tag{6.1}$$

and substituting for $P(Gain)$ gives

$$P(Loss) = \frac{1}{\beta N_G + N_L} \tag{6.2}$$

Thus, according to the one-stage model, both $P(Gain)$ and $P(Loss)$ should be sensitive to both N_G and N_L. This is because investors are assumed to evaluate all of the stocks in a portfolio simultaneously, across both gains and losses.

Figure 6.1 shows the one-stage model predictions for $P(Gain)$ and $P(Loss)$ as a function of N_G and N_L using the best-fitting value of $\beta = 2.16$ (see Appendix 5.4). Otherwise, the selection of a stock for sale is assumed to be random. In Figure 6.1A, the *x*-axis represents N_G and each line represents different value of N_L. Given a fixed N_L (i.e., for a given line), the larger N_G the smaller $P(Gain)$. When $N_L = 1$, the curve in N_G will be relatively steep because changes of N_G in the denominator are large compared to N_L/β. Effectively, each extra gain in the portfolio takes a large share of the total probability of selling because the losses are taking only one share. When $N_L = 5$, the curve in N_G will be relatively flat because changes of N_G in the denominator are small compared to N_L/β. Effectively, each extra gain in the portfolio takes only a small share of the total probability of selling because the losses are taking five shares. Figure 6.1B replots Figure 6.1A exchanging the roles of N_G and N_L, which is useful for comparison with plots of the data later. Figure 6.1C shows $P(Loss)$ as a function of N_G and N_L. This is just a transformation of Figure 6.1A, but is useful later too. The curves are similar to those for $P(Gain)$ seen in Figure 6.1A. Figure 6.1D replots Figure 6.1C exchanging the roles of N_G and N_L.

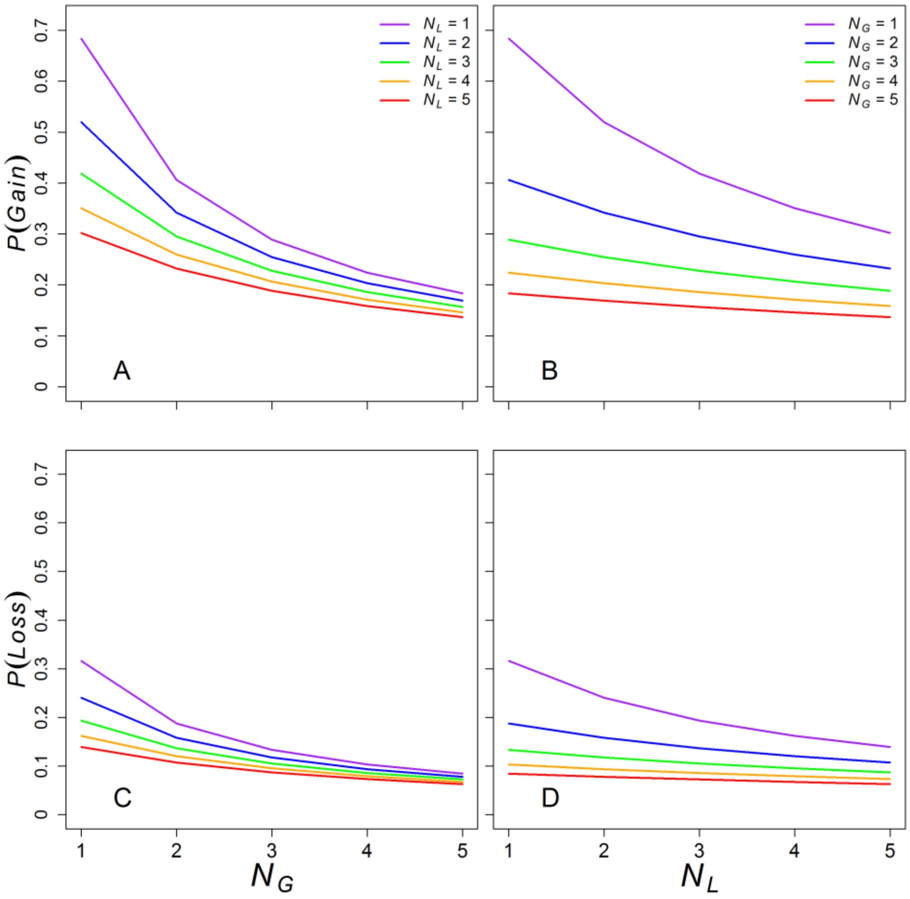


Figure 6.1. $P(Gain)$ and $P(Loss)$ as a function of N_G and N_L in the one-stage model. The right panels replot the data, swapping the roles of N_G and N_L.

6.4.2 The two-stage model

In the two-stage model, investors first choose whether to sell from the gain domain or the loss domain, before then choosing a specific stock from their chosen domain. The disposition effect is at the level of the gain-loss domain, and not at the level of individual stocks as it is in the one-stage model. In the two-stage model the single free parameter is the domain-level disposition effect B that is our free parameter.

Thus, we can begin again with our constraint that $P(Gain) \times N_G + P(Loss) \times N_L = 1$, but instead of substituting for β we substitute for $\mathrm{B} = \frac{[P(Gain) \times N_G]}{[P(Loss) \times N_L]}$ to get

$$P(Gain) = \frac{1}{N_G\left(1 + \frac{1}{\mathrm{B}}\right)} \tag{6.3}$$

and

$$P(Loss) = \frac{1}{N_L(1 + \mathrm{B})} \tag{6.4}$$

It is obvious from these equations that $P(Gain)$ depends only on N_G and that $P(Loss)$ depends only upon N_L in the two-stage model. Figure 6.2 shows the two-stage model predictions for $P(Gain)$ and $P(Loss)$ as a function of N_G and N_L. We use best-fitting value of $B = 2.04$ (see Appendix 5.4). Figures 6.2A and B show that $P(Gain)$ is inversely proportional to N_G but independent of N_L. Figures 6.2C and D show that $P(Loss)$ is inversely proportional to N_L but independent of N_G.

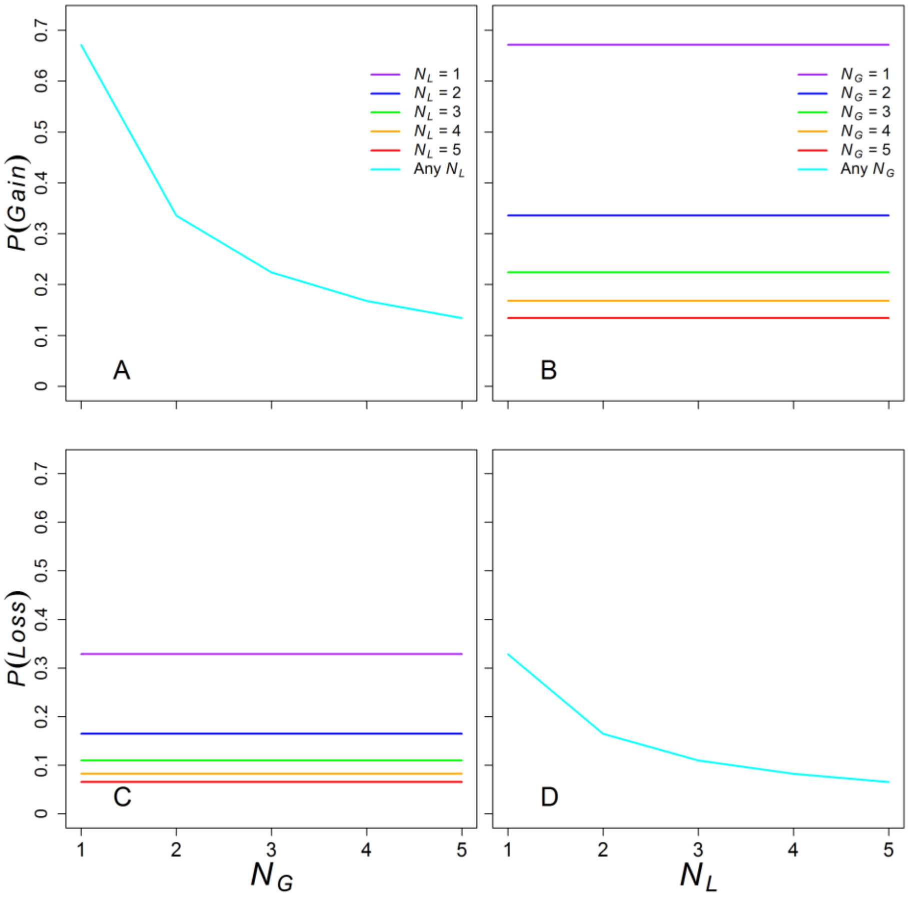


Figure 6.2. $P(Gain)$ and $P(Loss)$ as a function of N_G and N_L in the two-stage model. The right panels replot the data, swapping the roles of N_G and N_L.

6.5 Results

Below we test how the disposition effect is sensitive to the composition of the portfolio. First, we present some simple descriptive statistics of portfolios in our data, the disposition effect. Then, we explore how the disposition effect varies with portfolio composition. To preempt the findings, we see a pattern that looks remarkably like the signature from the two-stage model described above.

6.5.1 The disposition effect at individual stock level

First, we confirmed the presence of disposition effect in the data. Figure 6.3 compares *P(Gain)* (the grey bar) with *P(Loss)* (the red bar), showing that individual gains are on average about 1.8 times as much likely to be sold as individual losses (i.e., $\beta = 1.8$).

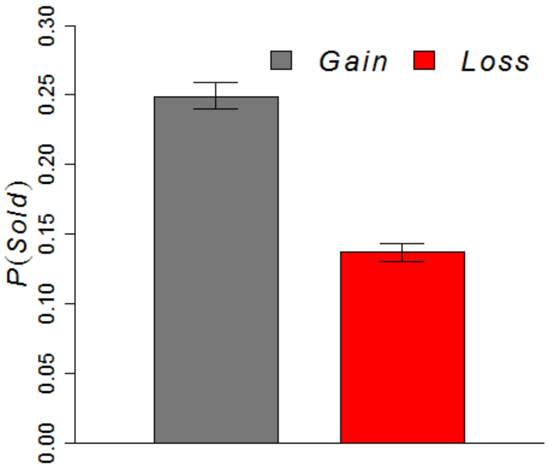


Figure 6.3. The disposition effect. The error bars are 95% bootstrapped confidence intervals computed with 1,000 resamples, corrected for clustering by accounts and sell dates.

6.5.2 Composition-sensitivity of the disposition effect

The degree of disposition effect depends on the composition of sell-day portfolios. In Figure 6.4, sell-day portfolios were divided into four bins depending on the ratio of the number of gains and losses in the portfolio. The size of the disposition effect (i.e., the difference between adjacent grey and red bars) reduces considerably as the ratio of the number of gains to the number of losses increases. For the Mostly Losses bin, individual gains are on average about 3.8 times more likely to be sold as individual losses, much larger than the 1.8 times for all portfolios. For the Mostly Gains bin, the disposition effect reverses such that losses are now more likely to be sold than gains. This very simple calculation of proportions is complemented with a multivariate analysis of composition sensitivity in Appendix 5.2, where we control for the returns, number of days held, and volatility of individual stocks, and include fixed effects for account and stock-by-date. The multivariate analysis confirms the pattern seen in Figure 6.4.

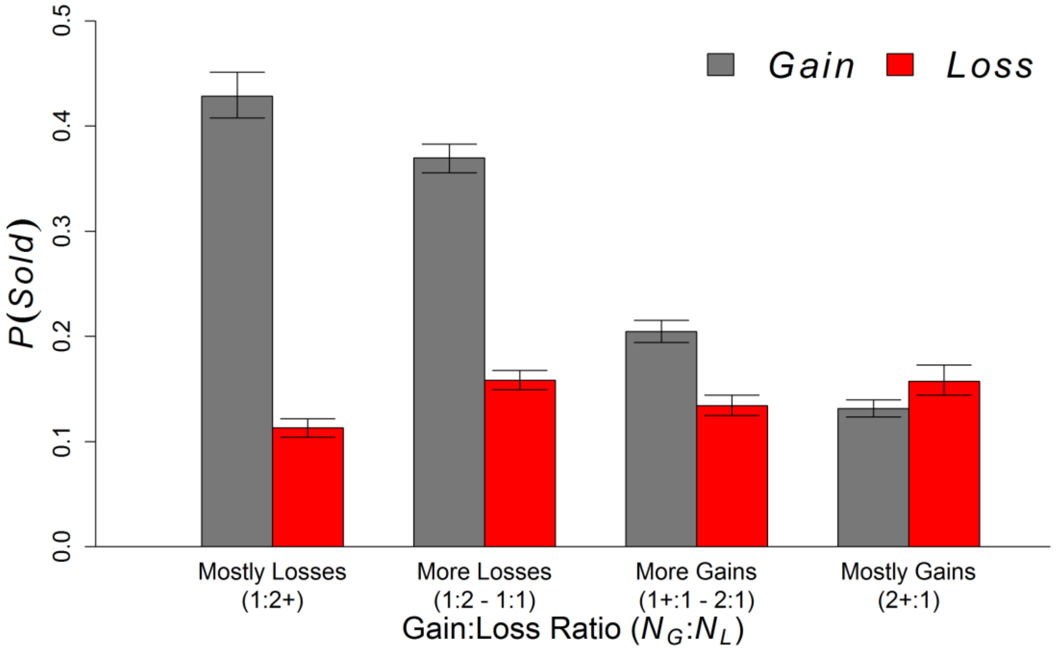


Figure 6.4. The disposition effect depends on the composition of the portfolio. The error bars are 95% confidence intervals computed with the bootstrap method with 1,000 resamples, corrected for clustering by accounts and sell dates.

6.5.3 Within-domain sensitivity

Here we show that the probability of an individual gain being sold is sensitive mostly to the number of gains but not the number of losses. And the probability of an individual loss being sold is sensitive mostly to the number of losses but not the number of gains. We call this the within-domain sensitivity. Figure 6.5A plots the proportion of sales taken by an individual gain, $P(Gain)$, as a function of the numbers of gains and losses in the portfolio, N_G and N_L. Figure 6.5B replots these data, swapping the roles of N_G and N_L. These two panels make it visually obvious that for the probability that an individual gain is sold, N_G has a large effect while N_L has, at most, only a small effect. $P(Gain)$ is nearly inversely proportional to N_G, but is unrelated to N_L. Figures 6.5C and D repeat these plots for the proportion of losses sold, $P(Loss)$. Now the pattern is reversed, with N_G having, at most, only a small effect while N_L has a large effect. $P(Loss)$ is nearly inversely proportional to N_L, but is unrelated to N_G.

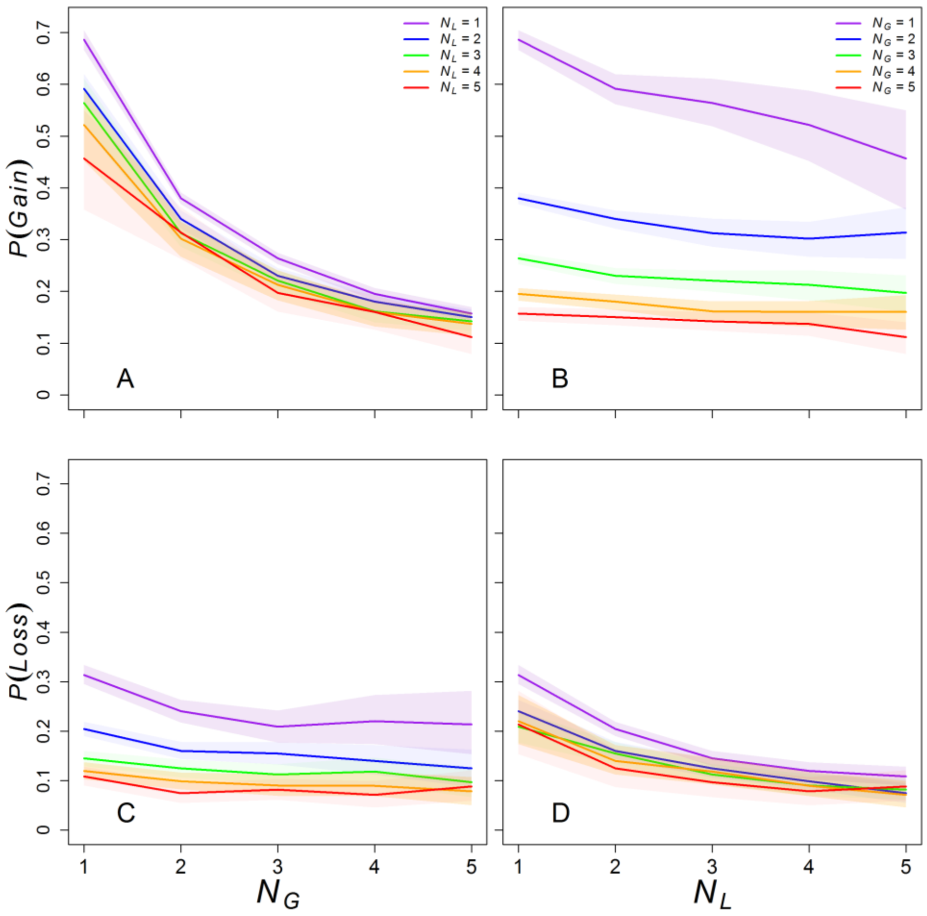


Figure 6.5. $P(Gain)$ and $P(Loss)$ as a function of N_G and N_L in the empirical data. The shaded areas are bootstrapped 95% confidence intervals, with clustering by accounts and sell dates. The right panels replot the data, swapping the roles of N_G and N_L.

The plot of the empirical data in Figure 6.5 bears a striking resemblance to the two-stage model predictions in Figure 6.2. To repeat the argument in Section 6.4.2, this within-domain sensitivity follows quite trivially from the two-stage model. Once the domain of gains is chosen for selling, the probability that any individual gain is sold is proportional to $1/N_G$, assuming the specific gain to be sold is selected at random. And once the domain of losses is chosen for selling, the probability that any individual loss is sold is simply proportional to $1/N_L$, assuming the specific loss to be sold is selected at random. Note that, for a robustness check, the Appendix 5.3 replicates Figures 6.4 and 6.5, using the sample of tax-exempt accounts (see Figures A5.1 and A5.2).

6.5.4 Estimating a mixture of the one-stage and two-stage models

In order to estimate what proportion of sell-day portfolios in our data follow the two-stage model, we conducted an optimization. The optimization finds what mixture probability of the one-stage and the two-stage models best fits the sell-day portfolios (see Appendix 5.4 for details). The results show that the composition of the optimized model is 43%, 95% CI [35%, 56%] of the one-stage model and 57%, 95% CI [44%, 65%] of the two-stage model. In the one-stage model, the individual-stock level disposition effect $\beta = 2.08$ 95% CI [1.12, 4.12], which represents individual gains being about 2.08 times more likely to be sold than individual losses. In the two-stage model, the domain-level disposition effect $\mathrm{B} = 2.09$, 95% CI [1.12, 3.21], which represents the gain domain is 2.09 times more likely than the loss domain to be chosen in the first stage. The optimized model fits the empirical data better than the one-stage model alone and the two-stage model alone.

6.6 Implications for Regression-Based Estimates of the Disposition Effect

We have shown that the disposition effect is strongly related to the composition of the portfolio. This within-domain sensitivity strongly implicates a two-stage model where an initial decision is taken about which domain to make a sale from before individual stocks are considered. It therefore follows that regression models estimating the probability of individual stocks being sold should properly control for the composition of a portfolio. This does not mean that the two stages of the decision process need to be implemented in the regression framework. Instead, with an appropriate control for the composition of a portfolio we can account for the within-domain sensitivity of the two-stage model. As a simple illustration, we compare four logistic models which differ from one another only in the way in which they control for N_G and N_L. The dependent variable which is common for all four models is the log-odds of the decision to sell a stock ($Sell$). The common covariates are: $Gain$, $Gain \times Return$, $Loss \times Return$, $\sqrt{Holding\ Days}$, $Gain \times Return \times \sqrt{Holding\ Days}$, $Loss \times Return \times \sqrt{Holding\ Days}$, $Gain \times Return_{20}$, $Gain \times Volatility_{20}$, $Loss \times Return_{20}$, and $Loss \times Volatility_{20}$. See Table 6.1 for the description of these variables. The models differ only in controls for N_G and N_L. Model 1 does not control for N_G and N_L. Model 2 controls for the reciprocals of the total number of stocks across gains and losses in a portfolio interacting separately with the gain and the loss domain: $\left(\frac{1}{N_{G+L}} \times Gain\right)$ and $\left(\frac{1}{N_{G+L}} \times Loss\right)$. Model 2 is very similar to the one-stage model, differing only in controlling for returns, volatility, and holding duration, and in having the logit link function as a logistic regression rather than directly modeling the probability of a sell. Model 3 includes separate interactions for the number of gains and for the number of losses: $(N_G \times Gain)$, $(N_L \times Loss)$, $(N_G \times Loss)$, and $(N_L \times Gain)$. Model 4 includes separate interactions for the reciprocals of the numbers of gains and losses: $\left(\frac{1}{N_G} \times Gain\right)$, $\left(\frac{1}{N_L} \times Loss\right)$, $\left(\frac{1}{N_G} \times Loss\right)$, and $\left(\frac{1}{N_L} \times Gain\right)$. Model 4 is very similar to the mixture-model, differing only in controlling for returns, volatility, and holding duration, and in having the logit link function, and having the cross-domain interactions $\left(\frac{1}{N_G} \times Loss\right)$ and $\left(\frac{1}{N_L} \times Gain\right)$.

Figure 6.6 compares the model predictions for $P(Gain)$. The predictions of Model 4 (bottom row) are close to those seen in the empirical data in Figure 6.5. On the other hand, the predictions of Models 1, 2, and 3 in the first three rows of Figure 6.6 all deviate from the empirical data. Model 1 does not concern the composition of a portfolio at all, leading to the worst fit among four models. Model 2 controls for $\left(\frac{1}{N_{G+L}} \times Gain\right)$ and $\left(\frac{1}{N_{G+L}} \times Loss\right)$. However, this control is on the total number of stocks across gains and losses and thus cannot capture the within-domain sensitivity. The prediction is similar to that of the one-stage model seen in Figure 6.1. Model 3 captures the within-domain sensitivity to some extent. However, as seen above, the relationship between $P(Gain)$ and N_G, and that between $P(Loss)$ and N_L is not linear but inversely proportional. Therefore, the control in Model 3 is not sufficient. In summary, Figure 6.6 shows that a clear advantage of Model 4 over Models 1, 2 and 3. That is, in order to capture the inverse proportionality within a domain, models should include the inverse of N_G and the inverse of N_L as control variables. Note that, because we used logistic models, Model 4 does not exactly control for the inverse proportional relationship between $P(Gain)$ and N_G. However, Model 4 sufficiently captures a non-linear relationship to offer a good fit. Model 4 offers the highest R^2, and is preferred by AIC and BIC.

Table A5.6 in Appendix 5.5 presents the full regression estimates. We note two things here about the coefficients. First, the coefficient for the $Gain$ dummy indicates the disposition effect, and varies considerably across the model specifications. Because Models 1-3 cannot capture the variation in the probability of selling a stock as a function of the number of gains and losses in the portfolio (compare the empirical effects in Figure 6.5 with the model predictions in Figure 6.6), there is substantial bias in the estimation of the disposition effect. Second, in Model 4, in line with the two-stage model and the within-domain sensitivity, the coefficient estimates for $\left(\frac{1}{N_G} \times Gain\right)$ and $\left(\frac{1}{N_L} \times Loss\right)$ (i.e., the within-domain effect) is much larger than those for $\left(\frac{1}{N_G} \times Loss\right)$ and $\left(\frac{1}{N_L} \times Gain\right)$ (i.e., the across-domain effect).

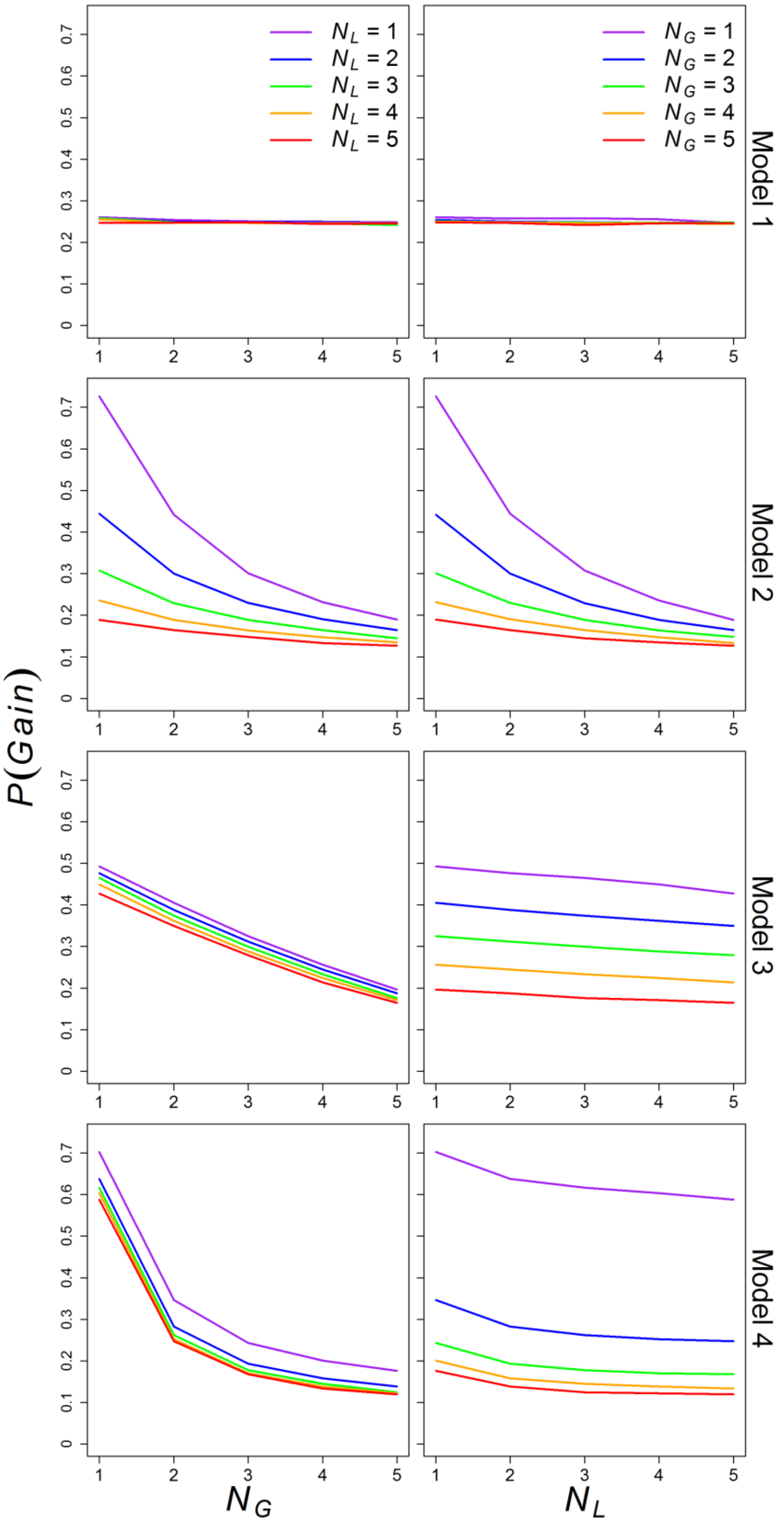


Figure 6.6. Comparison of the logistic regression model predictions for $P(Gain)$. Within each row, the right panels replot the data from the left panels, swapping the roles of N_G and N_L.

6.7 General Discussion

How do investors choose which stock to sell from their portfolio? We propose a two-stage decision rule, in which investors first decide whether to sell a stock in gain or a stock in loss without reference to the magnitudes of the gains or losses, and only then compare stocks individually within a given domain. This model is consistent with the existence of the disposition effect, but it also offers a new prediction about how the magnitude of this phenomenon should vary as a function of portfolio composition. More specifically, the two-stage model predicts that the probability of selling a particular stock in gain will depend only upon the number of stocks in gain in the portfolio and not the number of stocks in loss, and that the probability of selling a particular stock in loss will depend only upon the number of stocks in the portfolio in loss and not the number of stocks in gain. We tested this prediction using a large volume of stock trading data and found strong evidence for this within-domain sensitivity. Using a mixture model, we estimate that selling decisions are about a 50/50 mix of our two-stage model and the traditional one-stage model. Within-domain sensitivity must therefore be accounted for in the regression models used to estimate the disposition effect. We showed that a model in which we control for the reciprocals of the number of gains and losses in a portfolio offered a much better fit to the data.

6.7.1 Alternative explanations

We have deferred until now the discussion of other possible accounts of the composition-sensitivity of the disposition effect. For example, consider an alternative version of the two-stage model in which investors first evaluate each gain by comparing with other gains to identify one candidate gain to be sold. They also evaluate each loss by comparing with other losses and pick one candidate loss to be sold. Then, at the second stage, the candidate gain and the candidate loss are compared with one another and exactly one of them ends up being sold. Because the first stage of this alternative two-stage model requires only within-domain comparison, the model predicts the within-domain sensitivity and thus the composition-sensitivity of the disposition effect. But the interpretation of the disposition effect in the model is the same as the two-stage model described earlier: the disposition effect is a gain-loss-domain-level bias, and not an individual-stock-level bias.

We can also consider a model where the evaluation for gains and that for losses are completely independent. Depending on exogenous factors (e.g., feeling), investors evaluate only gains on one day to decide whether to sell one of gains and evaluate only losses on another day to decide whether to sell one of losses. The disposition effect may be represented by a difference in the number of days where gains or losses are evaluated. Because, in this model, the evaluation is completely independent for each domain, the model predicts the within-domain sensitivity and the composition-sensitivity of the disposition effect.

Our data do not allow us to test the exact cognitive process through which investors select a stock to sell. Without process data, it is difficult to identify which model is more valid. Further research, perhaps using carefully controlled lab experiments, may be necessary to disentangle the exact origins of the portfolio-composition sensitivity.

6.7.2 The origin of the disposition effect

We consider how our two-stage model relates to the existing accounts of the disposition effect. While the origin of the disposition effect has been continuing to be debated in the literature (Ben-David & Hirshleifer, 2012; Hens & Vlcek, 2011; Kaustia, 2010), there are three dominant explanations of the effect: prospect theory and loss aversion; a belief in mean reversion; and regret-avoidance (Shefrin & Statman, 1985; Zuchel, 2010).

In the simplest form of explanation based on prospect theory, investors are assumed to have an s-shaped value function, while the reference point is determined by the original stock’s purchase price. The gains portion of the value function is concave while the losses portion of the value function is convex. Under these assumptions, investors evaluate an individual stock by integrating over their expectation of the stock’s future distribution of returns after transforming them with the s-shaped value function. Given a nearly symmetrical distribution of expected future returns, when the stock is in loss, a large part of the distribution of expected future returns is in the convex part of the value function, leading to investors being risk-seeking and thus to hold the stock. When the stock is in gain, a large part of the distribution is in the concave part of the value function, leading to investors being risk-averse and thus to sell the stock. In this way, the prospect theory explains the disposition effect at individual stock level. In this prospect theory explanation, the disposition effect emerges as individual stocks are evaluated according to prospect theory. It is harder to see how prospect theory might account for the domain-level disposition effect we observe. One might assume that people evaluate all in a domain stocks and integrate over them to get a domain level expectation, but this does rather defeat the non-compensatory motivation described in Section 6.2.

The mean-reversion account proposes that people hold a belief that a stock price is negatively autocorrelated and therefore a stock’s price should revert to a ‘long-term’ mean (Andreassen, 1987; Kahneman & Tversky, 1973). The belief in mean reversion suggests that stocks which have recently depreciated are likely to go up to reach the long-term mean, and conversely, stock which have recently appreciated are likely to go down towards the long-term mean. Consequently, investors tend to hold stocks in loss which are likely to be oversold relative to the long-term mean and to sell stocks in gain which are likely to be overbought relative to the long-term mean. In this explanation, investors' decisions depend on how long the long-term is, how long they have held the stock, and how large the past price movement was. The latter two elements are individual stock specific characteristics and cannot explain the domain-level disposition effect. Having said that, it may be possible that people believe that gains as a category turn to losses and that losses as a category turn to gains, regardless of the duration of holding days and the magnitude of the return of individual stocks. While such a belief would be closer to the first stage of our two-stage model, it is distinct from the decision rule assumed in the mean-reversion account.

The theory of regret avoidance (Bell, 1982; Loomes & Sugden, 1982) suggests that people anticipate feeling regret about their past decision of purchasing the stock when they consider realizing a loss on the stock, but anticipate feeling pride when they consider realizing a gain on the stock. Therefore, if people are on average regret-averse and pride-seeking, they are more likely to sell gains than losses. This is consistent with the previous finding that people are risk seeking in the loss domain until they must realize the loss, after which they are risk averse (Imas, 2016). The degree of a regret and the degree of a pride may depend on the magnitude of a loss or a gain. In this sense, the regret avoidance also assumes to operate on individual stock level. However, it is possible that people hesitate to realize a loss because they do not want to feel bad at all, regardless of how large is the realized loss is. Equally, they may prefer to realize a gain because they seek to feel proud regardless of the size of the realized gain. If so, the regret avoidance may not be influenced by the size of a stock's return and may be based on a categorical thinking which conforms to the first stage of the two-stage model. People's happiness may be insensitive to the size of a gain when they make an earning on an investment decision (Kassam et al., 2011), which supports the idea that people think in categorical terms and therefore their regret avoidance will result in the disposition effect at a portfolio level.

We do not offer a definitive psychological origin for the disposition effect. But the relationship we report between the disposition effect and the composition of a portfolio in terms of the number of gains and losses strongly implicates a two-stage approach where an initial gain-loss domain-level decision is also strongly contributing to the disposition effect. Thus, existing accounts must take into account the fact that people often take domain-level decisions about whether to sell a winner or a loser. More pragmatically, our results show that the current methods for estimating disposition effect must be revised to account for the complexity of the portfolio composition sensitivity. Without such controls, the estimates of the magnitude of the disposition effect will be incorrect. Our results also indicate not just the primacy of gains and losses rather than absolute value in people's decision making, but that the gain-loss category alone, without reference to magnitude, drives a substantial component of the sell decision.

Chapter 7 Conclusions

In this thesis I have investigated psychology of financial decisions, using large transaction datasets. Traditional economic theories assume that people are rational agents who maximize their subjective value or utility resulting from their decisions. However, in the credit card repayments and the stock trading data, we found that people's decision are subject to decision heuristics and biases caused by them. We also found the cases where seemingly helpful nudges do not help people to make better decisions or even have a negative effect.

Chapter 2 showed an adverse effect of a default nudge where the automatic minimum credit card repayment leads card holders to neglect their bill and to rarely make additional manual repayments. While most existing critiques of default nudges are from ethical aspects, our findings suggest that the default nudge may bring about substantial economic costs. While the automatic repayment helps people not to forget minimum repayments, our findings suggest that card companies and regulators should design choice architecture which effectively reminds card holders using automatic repayments to make additional manual repayments.

Chapter 3 saw the automatic credit card repayment as a tool for adapting to experience of having a late payment fee. Our analysis showed that card holders tend to set up an automatic repayment just after forgetting a minimum repayment and being charged a late payment fee, resulting in a reduction in the subsequent fee likelihood. We found that the decline in the likelihood of card holders having a late payment fee over account tenure is completely attributed to those setting up the automatic repayment. The declining pattern was not observed on non-switchers. That is, unless you set up an automatic repayment, there is absolutely no evidence that the late payment fee helps you learn to avoid subsequent missed payments. Our study is the first to examine a role of automatic repayments as a tool for adapting to negative feedback of having a fee. In contrast, the decline in the likelihood of cash advance and over-limit fees are due to time-varying liquidity constraints rather than people learning from experience—the explanation is economic not psychological. The likelihood of cash advance and over limit fees declines as the liquidity needs ease over time. Our conclusions are quite different from those in a previous study in the US (Agarwal et al., 2013). Agarwal et al. interpreted the declining patterns in fees as evidence for people learning and adapting their behavior in subsequent months. However, the further analysis we have conducted rules out the interpretation that fees help people learn to use their credit cards.

Chapter 4 showed people’s preference for prominent numbers in the context of credit card repayments. Strikingly, repayments at the exact prominent numbers of £50.00, £100.00, £150.00, and £200.00 together occupy over 30% of all repayments where people are not selecting “full” or less than “minimum”. We also found evidence for people’s preference for round numbers, exploiting quasi-experimental changes in the set of feasible repayment numbers which arises due to minimum repayment levels set by card issuers. As the required minimum increases and passes a multiple of £10, a large share of people choose to jump to the next multiple of £10 as their repayment amount. In addition, our analysis showed that, as predicted by Albers (1997), the likelihood of repayments falling at a certain integer (i.e., exact pounds) decreases as the precision of the repayment number increases. Finally, assuming that card holders choose a repayment amount by rounding a latent level of repayment to prominent numbers, we estimated relative prominences of 10 most frequent repayment numbers. The results showed that £50.00 and £100.00 are the most prominent numbers. We are the first to provide such an estimation. While people’s preference for prominent numbers were evident in previous studies showing price clustering in asset markets where people interact with each other, our study was based on completely individual credit card repayment decisions, and thus, our findings indicate that people’s preference for prominent and round numbers is likely to be attributed to people’s heuristic processing of numerical numbers rather than the alternative explanations for clustering of prices at prominent numbers in markets, such as profit-maximizing or cost-minimizing strategies in the presence of counterparties.

Chapter 5 examined how the information on a credit card bill influences repayments. Specifically, we conducted an online experiment to investigate the effect of the inclusion of anchoring numbers and a social nudge in a mock bill. The results confirmed the findings of previous studies about the anchoring effect of numerical information in a credit card bill, and found the false consensus bias where people who usually repay only the minimum greatly overestimate the popularity of minimum repayments. However, the social nudge in our experiment failed to correct participants’ overestimation of the popularity of minimum repayments and had no effect on their repayments.

In Chapter 6 we moved to a new financial domain using data from individual portfolios of shares. We explored how people choose a stock to sell from a portfolio. It is well established in behavioral finance that people are more likely to sell stocks in gain than loss, a phenomenon labelled as the disposition effect. We introduced a two-stage model where investors first decide whether to sell a stock in the domain of gains or losses, and only then choose a stock to sell from within their chosen domain. We showed that the probability of individual gains being sold is inversely proportional to the number of gains in the portfolio, but is not associated with the number of losses. Similarly, the probability of individual losses being sold is inversely proportional to the number of losses in the portfolio, but is not associated with the number of gains. These patterns are predicted by our two stage model, but not by the standard accounts of the disposition effect. These patterns indicate that investors conduct within-domain comparisons rather than across-domains comparisons, consistent with the two-stage model. Sell decisions are about the domain of gains versus losses, not just about individual stocks. We argue that investors can save cognitive effort by conducting this two-stage decision making. The model conforms to consideration set heuristics where people first reduce the size of a choice set to just gains or just losses and only then evaluate individual options remaining in the reduced choice set. In addition, the model is consistent with psychological studies proposing different cognitive processing for the positivity and the negativity. Importantly, the two-stage model indicates that existing estimation methods of the disposition effect result in substantial biases because those estimations assume that all stocks in a portfolio are simultaneously evaluated across domains of gains and losses in a single decision stage.

Overall, our studies suggest that, in order to help people to make better financial decisions, policy makers should take people’s heuristic decision making into consideration and should be aware of possibilities of nudges backfiring.

Here we consider possible links among chapters. First, Chapter 2 shows an adverse effect of setting up autopay covering only the minimum. Why do card holders choose the minimum autopay rather than autopay covering larger amounts? Chapter 5 may provide one of possible reasons. That is, when people set up the autopay, their false belief that most others usually repay only the minimum may lead them to choose the minimum amount for the autopay. Second, people’s preference for round and prominent numbers seen in Chapter 4 may result in larger repayments for Non-Auto group (i.e., repayers who do not set up the autopay) seen in Chapter 2.

Conventionally, most psychological studies have been conducted in lab experiments with a limited number of participants. In the lab, environments are nicely controlled and researchers can prevent unwanted variables to influence test results. In this thesis I have concentrated upon an alternative approach, using large, real-world data sets collected by financial institutions as a record of human behavior. Research using field data is gradually more common in psychology. In recent years, due to collaboration between industry and academia, large-sized field data are increasingly available and high-speed computation helps researchers to process such big data.

Recent psychological research in consumer behavior has taken advantage of field data. For example, using purchase records of nearly 300,000 shoppers in a major UK supermarket chain, Riefer, Prior, Blair, Pavey, and Love (2017) found that the longer the repetition of purchases of the same product the smaller the likelihood of shoppers switching to an alternative product. That is, the longer the streak of exploiting the smaller the likelihood of exploring. On the other hand, lab experiments, where participants are provided with monetary payoffs as a reward resulting from either exploiting the current deck or exploring another deck, typically find the opposite—the longer the streak of exploiting the same deck the larger the likelihood of participants exploring another deck (e.g., Knox, Otto, Stone, & Love, 2011). Riefer et al. (2017) argue that, unlike in the lab experiments using objective monetary reward, people are required to subjectively evaluate their satisfaction with products in daily shopping and that the evaluation process tends to be influenced by desire to justify their own past choices. This leads shoppers to keep purchasing the same product without exploring alternatives. Such finding is unique for the research using field data which track actual purchase histories of a large number of shoppers for considerable duration.

In addition, research using field data may provide additional evidence for findings of previous small-sized research. For example, a well-known study by Prelec and Loewenstein (1998) tested a double-entry mental accounting model by conducting small surveys asking people how happy they think different consumption and repayment schedules would make them. The model assumes that the pain of paying is eased by thoughts of future consumption, and conversely, the pleasure of consumption is undermined by thoughts of future payments. Thus the model predicts that people tend to delay payments for durable goods because they can enjoy long-term pleasure of consumption, and tend to pay early for non-durable goods because the pleasure of consumption is short-lived. Recently, analyzing the large-sized credit card data, which are identical to those used in Chapters 2, 3, and 4 of this thesis, Quispe-Torreblanca and Stewart (2017) found that people are less likely to repay the card balance in full when the debt arises from a single purchase of durable goods than when it arises from a purchase of non-durable goods. Interestingly, this difference diminishes if multiple purchases across different product categories are confounded in the card balance because, after using the card multiple times without repaying in full, the one-to-one coupling between purchases and repayments is no longer possible for most card holders. These findings are consistent with those in Prelec and Loewenstein (1998). In this way, a study using field data contributes to providing additional quantitative evidence of an existing theory.

What the Riefer et al. (2017) and Quispe-Torreblanca and Stewart (2017) examples illustrate is how the methodology from economics of using available financial data can be used to investigate issues in behavioral science and test ideas and theories about judgment and decision making. In general, by maximizing benefits of field data, psychological research may greatly enhance research quality.

Finally, reflecting limitations of the presented studies, we conclude this thesis with some plans and suggestions for future studies in financial decisions. First, more precise estimation of long-time consequences of particular consumer behaviors which cover a broad range of costs and benefits may enhance research impact. For example, in Chapter 2, we estimated an overall cost of a minimum automatic repayment netting fees avoided and interest incurred. However, forgetting to make minimum repayments is likely to bring about a deterioration of credit score, leading to an increase in future borrowing cost. The estimation should also include those costs. Such an estimation can be done if regulators and credit agencies share consumers' long-period credit history with researchers. Closer and broader collaborations among researchers, industry, and regulators is required.

Second, the downside of research on field data is inevitable endogeneity issues that follow from the loss of experimental control in which people are randomly assigned to conditions. In order to help make statements about causality, it is possible to exploit techniques from econometrics to analyze "natural" experiments. For example, as seen in Chapter 2 where we addressed for the possible endogeneity issue that minimum automatic repayers might have ongoing intention to reduce repayments, quasi-experimental analyses are possible even with field data. Yet, we admit that this 'quasi' experiment did not perfectly exclude the endogeneity issue. While we cannot conduct pure randomized control trials to evaluate the effects of switching to minimum autopay because such experiments are not allowed by financial regulations, researchers may be able to conduct randomized trials to test effects of other interventions on consumer behaviors. For example, as discussed in Chapter 5, adding a 'credible' social norm nudge to randomly chosen real credit card bills may find an effect to increase the card holders' repayments.

Third, due to the lack of individual-level socioeconomic data, our studies might not capture individual heterogeneities. For example, as seen in Chapter 3, our analysis did not identify the reason that only a part of people experiencing a late payment fee switched to an automatic repayment but others did not. There must be individual differences in response to the fees. Gathergood, Sakaguchi, Stewart, and Weber (2017) attempted to investigate the heterogeneity among card holders using postcode-level geographic data. The results showed that switchers tend to live in areas with high income, low unemployment, and high education. If individual-level demographic data were available, we may improve the estimation of individual differences.

Fourth, we may not generalize our findings across different countries. That is, people's financial decisions may reflect cultural difference which the presented studies did not investigate because each dataset was taken from either the UK only or the US only. As seen in Chapter 3, the UK credit card market which our studies are based on may differ from the US market in some properties. For example, in the UK, automatic repayment facility has been available since 1990s while it was only recently introduced in the US. Chapter 3 showed that the declining pattern in late payment fees is completely attributed to card holders switching to automatic repayment. While, in the UK data, we found no evidence of people learning and forgetting as Agarwal et al. (2013) suggested, it is possible that the US card holders who are not aware of automatic repayment exhibit the learning and forgetting pattern. Also, due to a difference in commercial practices such as rebate programs associated with credit cards, US consumers tend to have more cards than UK consumers. It may be possible that card holders in the US are more likely to exceed their credit limit because having multiple cards may make them less aware of credit limit for each card. In addition, Chapter 4 showed people's preference for prominent numbers in the UK data. It is possible that people in the US may have a stronger preference for $25.00 because they use quarter coins in their daily life. Similar datasets taken from difference countries may show different behavioral patterns.

Lastly, while we focused on people's psychology in financial decision making, the same psychological effects may also be observed in non-financial domains. For example, an adverse effect of a default nudge seen in Chapter 3 may be found in non-financial situations where setting a default leads people to neglect individual decision opportunities, and optimal choices change over time. In addition, people's preference for prominent number seen in Chapter 4 may be observed in any non-financial choice of numbers. If future studies find similar results as ours in non-financial domains, our findings would be more generalize.

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Appendix 1 Supplemental Materials for Chapter 2

A1.1 Additional Manual Repayments for the Min-Auto Cards

Figure A1.1 compares the fraction of balance repaid for Non-Auto cards (the left panel) and for Min-Auto cards (the right panel), in months where cardholders repaid more than minimum. The analysis is based upon a sample of 270,264 Non-Auto cards with 4,434,364 card months and 20,743 Min-Auto cards with 133,941 card months.

Figure A1.1 shows that when Min-Auto cards did make additional repayments, the proportion of full repayments was similar to that for Non-Auto cards. Specifically, the proportion of repayments equal to or greater than the balance, given the repayment over the minimum, was 61.2% for Non-Auto cards and was 46.9% for Min-Auto cards. The different in the proportion is much smaller than that seen in the top panels of Figure 2.1 (57.5% for Non-Auto cards vs. 7.5% for Min-Auto cards) which includes months where Min-Auto card holders did not manually repay. Note that, in the right panel of Figure A1.1, the fraction of the balance repaid has multiple peaks near 1. This is caused by some Min-Auto cards repaying roughly in full rather than exactly by subtracting the minimum repayment from the full balance when making the additional manual repayment.

To further explore the difference between additional manual repayments for the Min-Auto cards and repayments for Non-Auto cards, we used the logistic regression in Equation A1.1. The dependent variable is a dichotomous indicator variable taking the value of 1 if the card was repaid in full (i.e. fraction equal to or greater than 1) and 0 otherwise. $Balance$, $Credit\ Limit$, $Utilization$, $Spending\ Amount$, $Merchant\ APR$, $Cash\ APR$, and $Charge\text{-}off\ Rate$ were controlled as continuous variables. $Min\text{-}Auto\ Card$ is a dichotomous variable having a value of 1 for Min-Auto cards, otherwise having a value of 0. Since a repayment is made against a balance in the previous month, all independent variables except $Min\text{-}Auto\ Card$ were lagged by one month. The data were restricted to repayment observations over minimum.

$$log\left(\frac{P(Full\ Repayment)}{1-P(Full\ Repayment)}\right) = \beta_0 + \beta_1 Balance(t-1) + \beta_2 Credit\ Limit(t-1) + \beta_3 Utilization(t-1) + \beta_4 Spending\ Amount(t-1) + \beta_5 Merchant\ APR(t-1) + \beta_6 Cash\ APR(t-1) + \beta_7 Charge\text{-}off\ Rate(t-1) + \beta_8 Min\text{-}Auto\ Card \qquad \text{(A1.1)}$$

Table A1.6 in Appendix 1.6 reports the coefficients. The coefficient for $Min\text{-}Auto\ Card$ is small and about zero. This means that the probability of a full repayment is essentially the same whether making only a manual repayment, or making a manual repayment in addition to a minimum auto payment, holding other covariates constant. The predicted probability of making a full repayment for Non-Auto cards is 63.9%, 95% CI [63.5, 64.2] and for Min-Auto cards is 63.2% 95% CI [61.4, 65.0]. (The median values were applied to covariates in the prediction. The standard errors were clustered by cards and calendar months.) The results imply that Min-Auto cardholders may not be that different from Non-Auto cardholders in terms of their ability to repay in full, but may merely neglect the bill in most months.

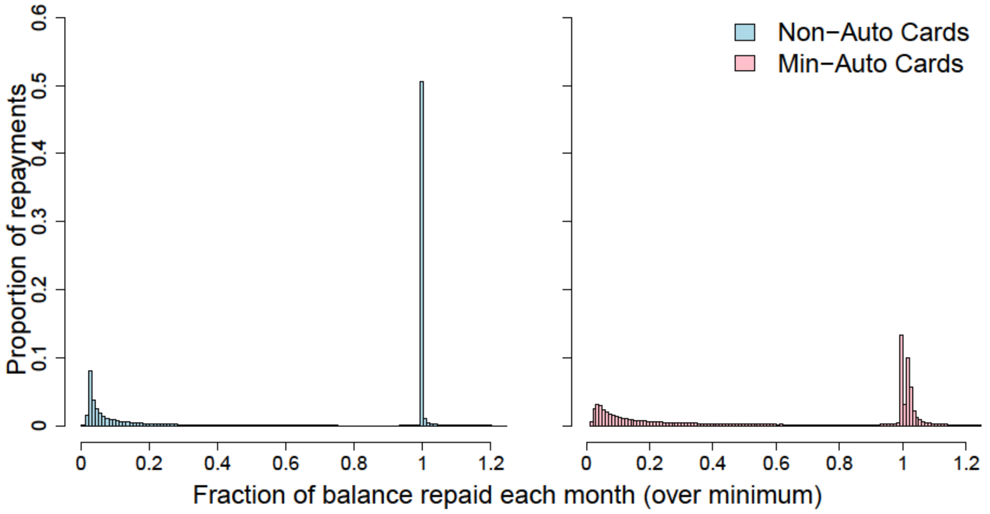

Figure A1.1. The fraction of the balance repaid for Non-Auto cards (left) and for Min-Auto cards (right) in months when additional repayments over the minimum were made.

A1.2 Additional Manual Repayments after Setting Min-Auto for the Within-Card Dataset

The analysis of additional manual repayments was repeated using the within-card dataset. Figure A1.2 compares the fraction of balance repaid, between before (the left panel) and after (the right panel) cards switched from a Non-Auto to a Min-Auto, in months where cards repaid more than minimum. The analysis is based upon a sample of 3,541 cards with 24,785 card months before setting a Min-Auto and 2,449 cards with 12,060 card months after.

Figure A1.2 shows that, when cardholders made a manual repayment, the proportion of full repayments was higher for additional manual repayments after the switch than for manual repayments before the switch. The proportion of repayments equal to or greater than the balance, given the repayment greater than the minimum, before the switch was 26.3%, rising to 43.2% after the switch.

In order to further investigate the findings of Figure A1.2, we conducted a linear regression with the fixed effects of card (Equation A1.2). The dependent variable is a dichotomous indicator variable taking the value of 1 if the card was repaid in full (i.e. fraction equal to or greater than 1) and 0 otherwise. $Balance$, $Credit\ Limit$, $Utilization$, $Spending\ Amount$, $Merchant\ APR$, $Cash\ APR$, and $Charge\text{-}off\ Rate$ were controlled as continuous variables. The independent variable of interest is $Before\ Min\text{-}Auto$ which is a dichotomous variable having a value of 1 if a cards had not started using a Min-Auto, otherwise having a value of 0. The data were restricted to repayment observations over minimum.

$$P(Full\ Repayment) = \beta_1 Balance + \beta_2 Credit\ Limit + \beta_3 Utilization + \beta_4 Spending\ Amount + \beta_5 Merchant\ APR + \beta_6 Cash\ APR + \beta_7 Charge\text{-}off\ Rate + \beta_8 Before\ Min\text{-}Auto\ + Fixed\ Effect(Card) \tag{A1.2}$$

Coefficients are reported in Table A1.8 in Appendix 1.6. The *Before Min-Auto* coefficient is about zero, indicating that the likelihood of full repayments is nearly identical between before and after the Min-Auto was established.

Figure A1.2 and Table A1.8 together suggest that cards' ability to repay in full may not be very different before and after the switch to a Min-Auto.

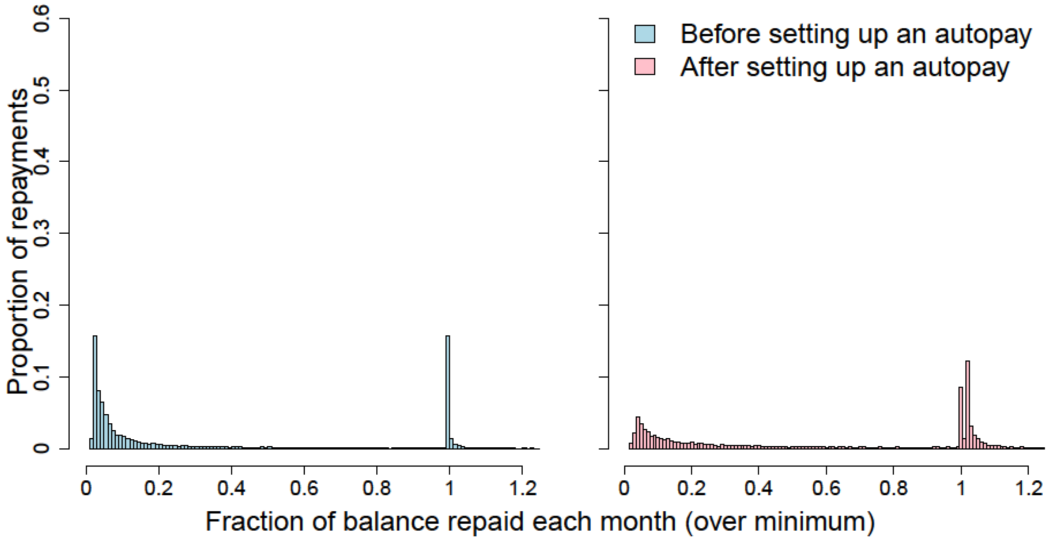

Figure A1.2. The fraction of the balance repaid for observations in the months before setting a Min-Auto (left) and for months afterwards (right).

A1.3 Addressing A Potential Concern about Endogeneity

One potential concern with our main analysis is that card holders may endogenously select into Min-Auto due to their future repayment intentions. In the between cards model, Min-Auto card holders may intend to pay less compared with manual repayers. In the within cards model, individuals switching to Min-Auto may do so because of an intention to reduce future repayments. An ideal research design would exploit random variation in Min-Auto status. However, firms are not permitted to vary the autopay status of customers in a way that would allow this experiment to be conducted.

In order to account for this concern, in an additional analysis we exploit shocks to consumer repayment plans as a source of variation in sign-up to Min-Auto. Specifically, when cardholders incur a late payment fee, they may communicate with the card company who may waive the fee to avoid losing the customer's account. Because card companies have an intention to prevent consumers who are aggrieved by incurring a late payment fee from cancelling the card, refunding the fee upon the cardholders' claim is quite common. (About 7% of late payment fees were refunded in our sample.) In claiming the refund, consumers were likely to be prompted to set up the autopay by the card company.

We exploit this natural experiment by identifying two types of cardholders who differently responded to the refund. The first type of cardholder received a refund, but did not set up the autopay and kept manually repaying throughout the data period (Remaining-as-Non-Auto cards). The second type of cardholders set up an autopay covering only the minimum within three months after a refund (Switched-to-Min-Auto cards). It is likely that Switched-to-Min-Auto cardholders set up the autopay as the result of experiencing a late payment and being prompted by the card company, and not as part of an ongoing intention to make small repayments.

We repeated the between-cards analysis on repayments of Remaining-as-Non-Auto cards following a first refund of a late payment fee and those of Switched-to-Min-Auto cards following a first automatic repayment.

Figure A1.3 shows the results. The top panels of Figure A1.3 show the distribution of repayments, expressed as a fraction of the card balance. In the Remaining-as-Non-Auto group, 55.1% of the cards are repaid in full each month, and only a small fraction pay only the minimum (top left). In the Switched-to-Min-Auto group, only 16.9% of cards are repaid in full each month, and 64.5% were the minimum repayments (top right; the sum of bars around 1-5% on the fraction of balance repaid). The distribution looks similar to that seen in Figure 2.1.

The bottom panels of Figure A1.3 show the results of a multinomial regression with Equation 2.1 (Table A1.9 in Appendix 1.6 reports the coefficients.) The pattern is similar to that seen in the main analysis (the bottom panels of Figure 2.1). That is, the probability of full and larger repayments are higher for Non-Auto cards than for Min-Auto cards, and the probability of minimum repayments is much higher for Min-Auto cards than for Non-Auto cards.

In summary, this analysis suggests that the effect of Min-Auto repayment is not attributed to Min-Auto cardholders' intentions to make small repayments in future.

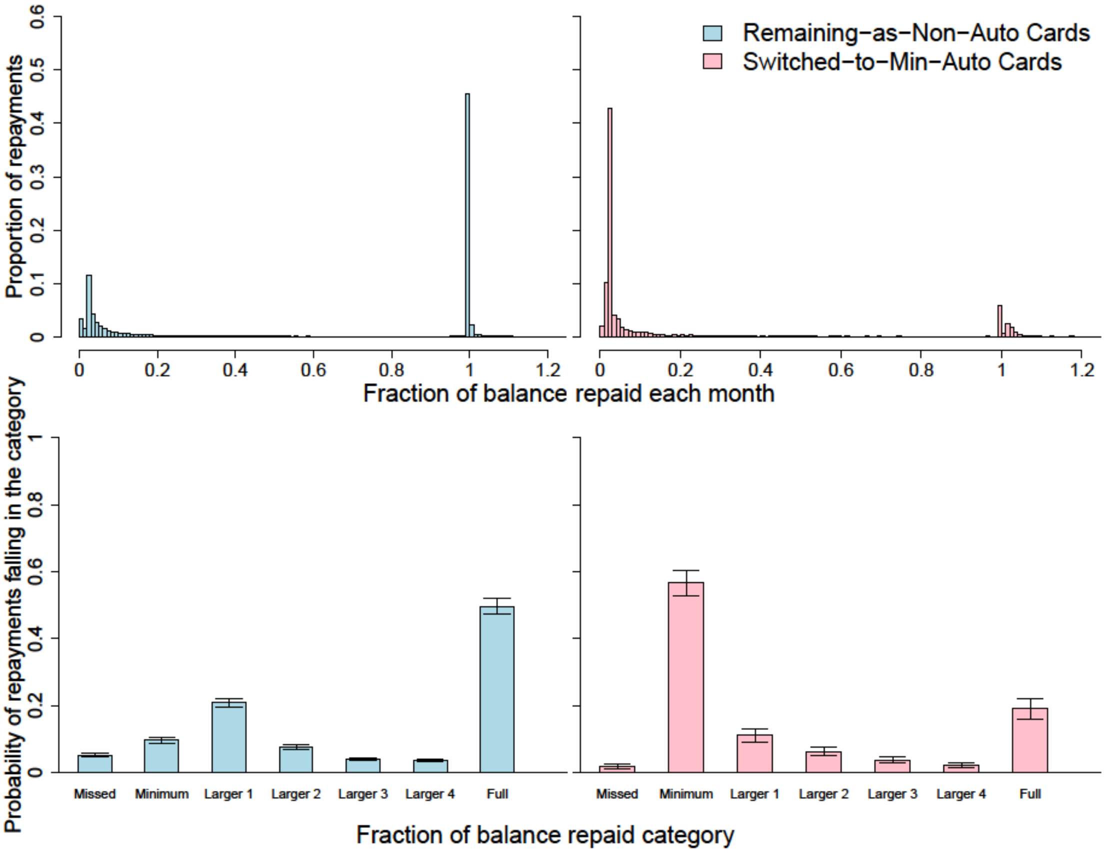

Figure A1.3. The fraction of the balance repaid each month for Remaining-as-Non-Auto cards and Switched-to-Min-Auto cards. The top panels show histograms of monthly credit card repayments expressed as fractions of the credit card balances due for Remaining-as-Non-Auto cards and Switched-to-Min-Auto and cards. The width of each bar is 0.01. The bottom panels show predicted probabilities from a multinomial logit model of seven different categories of repayment from missed (no payment made) to full (balance cleared in full). Values are predicted at the medians of covariates. The error bars are 95% confidence intervals.

A1.4 Robustness Check with an Alternative Definition of Min-Auto Cards

In our main analyses, Min-Auto cards were defined as the cards which repaid the minimum by the automatic payment every month with a positive balance throughout the data period for the between-cards analysis and in all months after a first automatic repayment for the within-card analysis. In this definition, additional manual repayments are allowed but cards need to have repaid the minimum by automatic repayment in order to be categorized as Min-Auto cards.

In the UK, if a card holder setting automatic repayment manually repays before the due date of the automatic repayment, the amount manually repaid is subtracted from the automatic payment taken in the month. For example, if a card holder with £60 of an automatic repayment due in a month repays £50 before the due date, only £10 is repaid through the automatic repayment in the month. (In our data, we see £50 of a manual repayment and £10 of an automatic repayment.) Therefore, in the case that a card holder with Min-Auto setting manually repaid before the due date of the Min-Auto, our definition of Min-Auto cards in the main analysis excluded the card from the Min-Auto group. Because we infer the automatic repayment status from repayment records in the data, we cannot know whether the card holder really switched from Min-Auto to Non-Auto or just manually repaid before the due date (thus we excluded them from Min-Auto group in the main analysis).

For the robustness check, what follows repeats the main analysis with an alternative (and broader) definition of Min-Auto cards. In the alternative definition of Min-Auto cards, cards were treated as a Min-Auto card if the repayment was the minimum or smaller than the minimum whenever the card was repaid by the automatic repayment. With this alternative definition, for example, a cards is treated as a Min-Auto card even if the minimum was repaid only once through the automatic repayment and was manually repaid in all the other months. We also included cards where the minimum repaid was equal to the full balance (i.e., very small balances) for all automatic repayments, in Min-Auto group. (Technically, those accounts might be Full-Auto cards and thus the main analysis excluded those accounts from Min-Auto group. We controlled the balance in the regressions and this inclusion of the small balances in the alternative definition is just for the robustness check.)

Figure A1.4 shows the results of the between-cards analysis with the alternative definition of Min-Auto cards (corresponding to Figure 2.1). The top panels of Figure A1.4 show the distribution of repayments, expressed as a fraction of the card balance. In the Non-Auto group, 58% of the cards are repaid in full each month, and only a small fraction pay only the minimum (top left). In the Min-Auto group, only 15% of cards are repaid in full each month, and more than 75% were the minimum repayments (shown as the sum of bars about from .01 to .05 on the x-axis in the top right panel). The distribution looks similar to that seen in Figure 2.1. The bottom panels of Figure A1.4 show the results of a multinomial regression with Equation 2.1. (Table A1.10 in Appendix 1.6 reports the coefficients.) The pattern is similar to that seen in the main analysis (the bottom panels of Figure 2.1). That is, the probability of full and larger repayments are higher for Non-Auto cards than for Min-Auto cards, and the probability of minimum repayments is much higher for Min-Auto cards than for Non-Auto cards.

In summary, our findings in the between-cards analysis do not change with the alternative definition of Min-Auto cards.

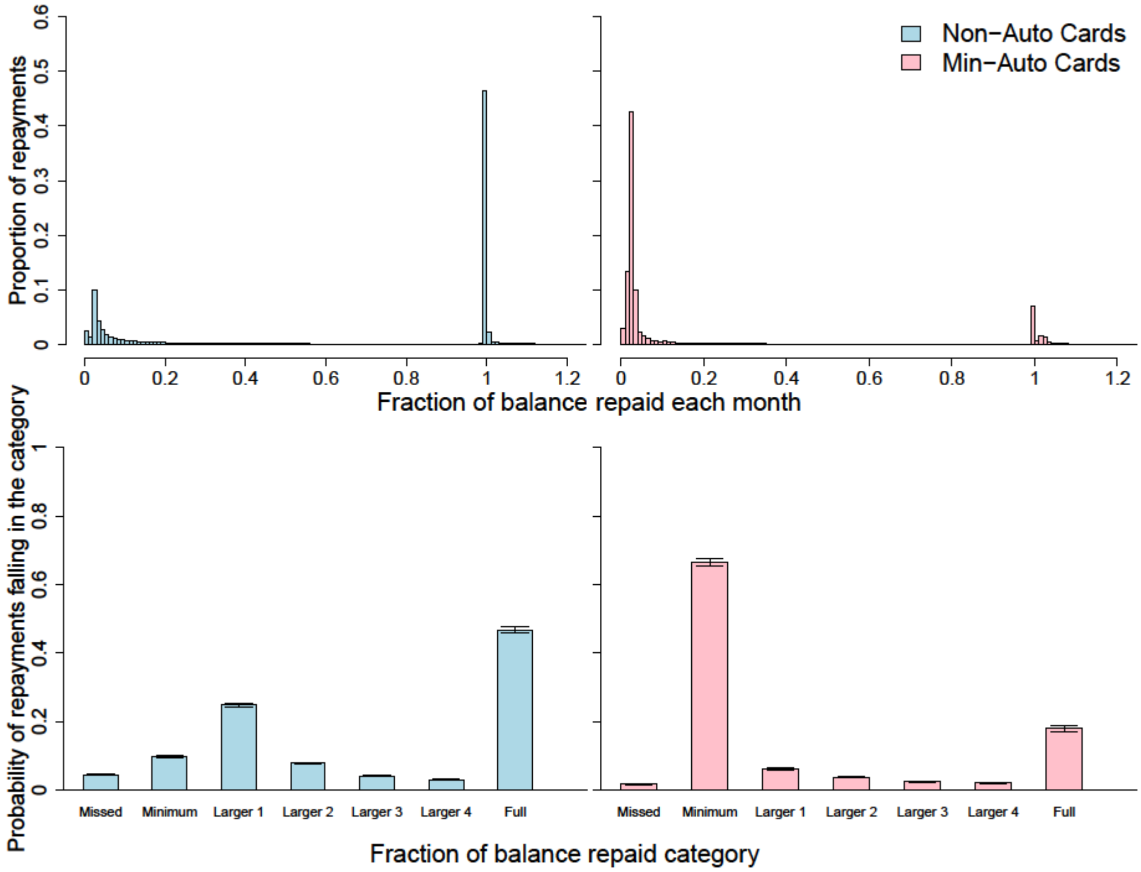

Figure A1.4. The fraction of the balance repaid each month with the alternative definition of Min-Auto cards. This figure corresponds to Figure 2.1 with the alternative definition of Min-Auto cards. The top panels show histograms of monthly credit card repayments expressed as fractions of the credit card balances due for Non-Auto cards and Min-Auto cards. The width of each bar is 0.01. The bottom panels show predicted probabilities from a multinomial logit model of seven different categories of repayment from missed (no payment made) to full (balance cleared in full). Values are predicted at the medians of covariates. The error bars are 95% confidence intervals.

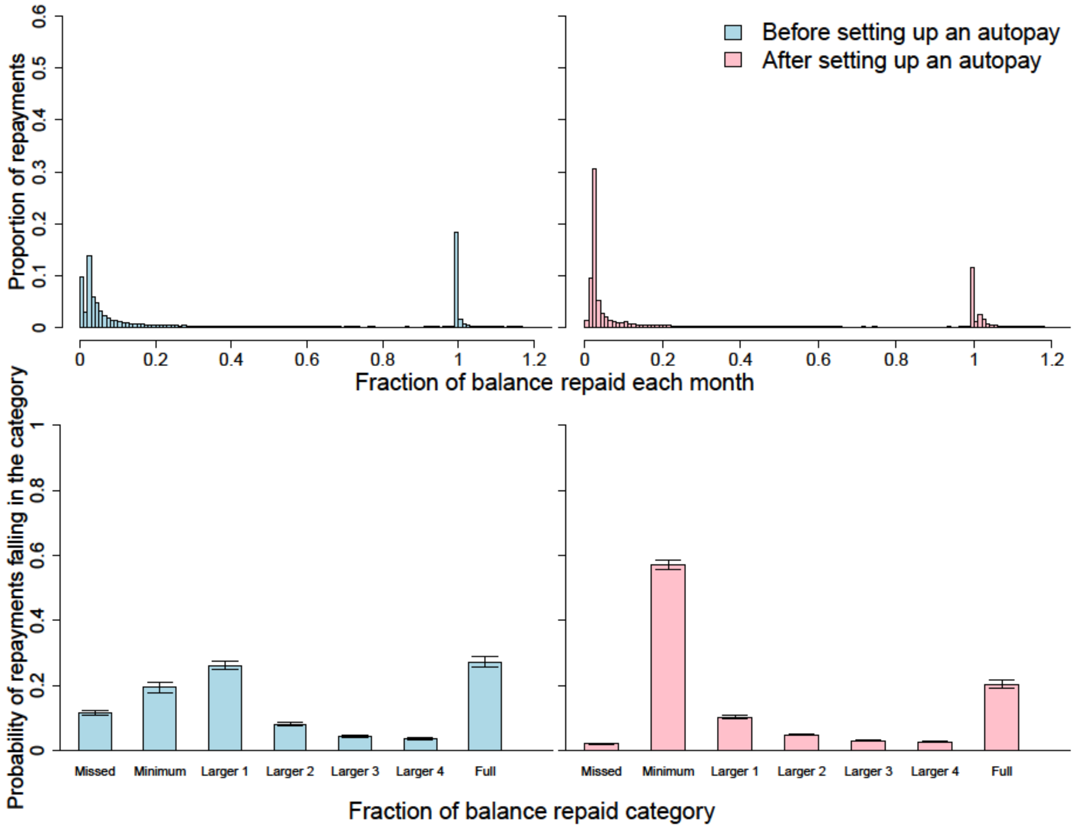

Figure A1.5. The fraction of the balance repaid each month before and after cards switch from Non-Auto to Min-Auto with the alternative definition of Min-Auto cards. This figure corresponds to Figure 2.2 with the alternative definition of Min-Auto cards. The top panels show histograms of monthly credit card repayments expressed as fractions of the credit card balance due. The width of each bar is 0.01. The bottom panels show predicted probabilities from a multinomial logit model of Before- and After-Min-Auto repayments falling in categories of fraction repaid from missed (no payment made) to full (balance cleared in full). Values are predicted at the medians of covariates. The error bars are 95% confidence intervals.

Figure A1.5 shows the results of the within-card analysis repeated with the alternative definition of Min-Auto cards (corresponding to Figure 2.2). As seen in the top panels, after the switch to a Min-Auto the share of minimum payments sharply increased from 18.3% to 51.7% (shown as the sum of bars about from .01 to .05 on the x-axis within each panel). The bottom panels of Figure A1.5 show the results of a multinomial regression with Equation 2.2. (Table A1.11 in Appendix 1.6 reports the coefficients.) Consistent with the finding in the top panels of Figure A1.5, after setting up Min-Auto the likelihood of paying only the minimum within the month increases sharply from 19.3%, 95% CI [17.8%, 20.9%] to 57.2%, 95% CI [55.8%, 58.6%], the likelihood of paying the full balance decreases from 27.1%, 95% CI [25.5%, 28.7%] to 20.3%, 95% CI [18.9%, 21.7%], and the likelihood of missing the minimum payment decreases from 11.6%, 95% CI [10.9%, 12.3%] to 2.0%, 95% CI [1.7%, 2.2%].

In summary, our findings in the within-card analysis do not change with the alternative definition of Min-Auto cards.

The above analysis showed that our findings are robust with the alternative definition of Min-Auto cards. However, we still have a potential problem caused by the limitation of the data. That is, because, as stated above, we inferred card holders' automatic repayment status from their repayment records and automatic repayments were not taken in the month where card holders manually repaid equal to or greater than the autopay amount before the due date, Non-Auto group may include cards which had an automatic repayment setting but were always manually repaid first at a level equal to or greater than the autopay amount throughout the data period (note that, if an automatic repayment covering the minimum was taken at least once during the data period, the alternative definition of Min-Auto card described above captures the card as a Min-Auto card). It is possible that card holders who had set automatic repayment manually repaid every month throughout 23 months. With our data, we cannot completely exclude this possibility that Non-Auto group includes those 'hidden' autopay cards. Having said that, we argue below that such cases are quite rare.

We extracted cards which had at least one automatic repayment and have repayment observations for 23 months (including the cards setting an automatic payment during the data period), and counted the number of months without an automatic repayment with a positive balance. Figure A1.6 shows the distribution of the number of months without an automatic repayment. For example, the high bar at zero on the x-axis means that over 60% of cards were repaid by the automatic repayment (or had a zero balance) throughout 23 months. Notably, the very low bar at 22 months on the x-axis means that only 0.8% of cards were repaid by Min-Auto once and were manually repaid in remaining 22 months. This indicates that the likelihood of card holders setting an automatic repayment making manual repayments for 22 out of 23 months is low. This further indicates that the likelihood of card holders setting the automatic repayment making manual repayments throughout 23 months is very low and the effect of the hidden autopay cards in Non-Auto group is likely to be small comparing with the size of the effect of Min-Auto on repayments seen in the analysis.

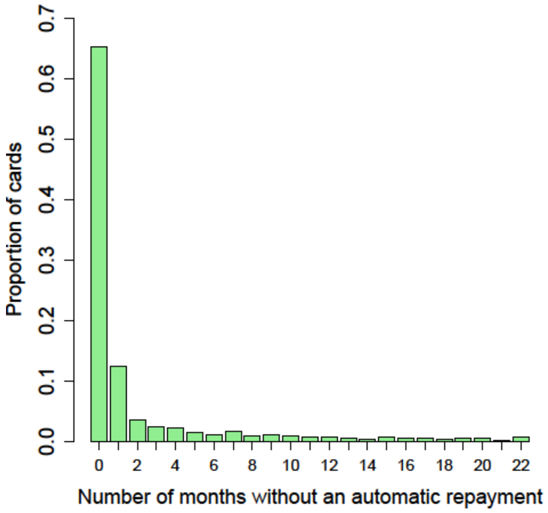

Figure A1.6. The distribution of the number of months without an automatic repayment for accounts with at least one automatic repayment during 23 months.

To recap, this section showed that our findings are robust with the broader alternative definition of Min-Auto cards and that a possible problem caused by hidden Auto cards in Non-Auto group cannot plausibly change the findings.

A1.5 Cost Simulations

We calculated the financial and time costs arising from lower repayments among card holders setting a Min-Auto. We have conducted two simulations. The first assumes no further purchases and represents people deciding to pay down their debt (Pay-Down-Only Simulation). The second assumes a steady continuation of purchases and repayments (Spending-and-Repayment Simulation). Both are Monte Carlo simulations, with repayments (and spending) drawn from their actual distributions, conditional on automatic payment status and balance, utilization, total monthly spending, and annual percentage rate (APR). We conducted the simulations separately for 1,000 sets of Non-Auto and Min-Auto cards.

In the Pay-Down-Only Simulation, the fraction of the balance repaid each month for an agent is drawn from cards with no spending and similar card profiles in the previous month and with the same Autopay status. A card profile consists of balance, utilization, and merchant APR. The credit limit and the merchant APR for initializing the agents were the median values in January 2013 (Month 1) in the data (£4,800 and 17.95%, respectively) and were assumed to be constant throughout a simulation.

In the Spending-and-Repayment Simulation, the total purchase amount and total cash advance amount for an agent were also drawn from cards with similar card profiles in the previous month and the same Autopay status. Here the card profile includes total purchase, total cash advance amount, and the cash APR (the cash APR was kept constant at a median value of 24.93%) in addition to balance, utilization, and merchant APR.

In both simulations, the weights used for sampling cards are based on the similarity between the agent card profile and the card month profile. Specifically, the similarity is a multivariate normal distribution with the agent card profile in the previous month as the mean and the covariance matrix given by the covariance of the variables in the data.

In both types of simulation, we consider two types of agents. The first type of agents have no Autopay setting in Month 1 while the second type of agents have a Min-Auto in Month 1. Both agents are allowed to change their Autopay status each month. These changes were simulated using a first-order transition matrix calculated from month-to-month transitions between Autopay states in the data. Note that the average probability of Non-Auto and Min-Auto status being unchanged from one month to the next month is 98% and 95% respectively. If an agent missed a repayment, £12 of a late fee was incurred in the next month. In the Spending-and-Repayment Simulation, if an agent made a cash advance or the utilization rate exceeded 1, a cash advance fee, which is £3 or 3% of the cash advance amount whichever is greater, and £12 of an over-limit fee were also incurred.

Each time step, the balance was updated reflecting a repayment, interest based on the merchant APR and any late fees in the Pay-Down-Only Simulation. In the Spending-and-Repayment Simulation, new purchases, any new cash advance amount and fee, and any over-limit fee were also added to the balance. A repayment made in a given month was first allocated to the balance for the cash advance, and then any remaining part was used to repay the balance on purchases. Interest on purchase and cash advances were separately calculated in each month with the merchant APR and the cash APR, respectively.

In the Pay-Down-Only Simulation, the simulation terminated when a balance became less than £10 (i.e., the balance was effectively cleared). In the Spending-and-Repayment Simulation, the simulation continued for 20 months. We ran simulations for three initial balances in Month 1: the median balance (£557), the mean balance (£1,414), and the 75th percentile balance (£1,711). We assumed that the whole initial balance was on purchases. The simulated results were averaged and the corresponding confidence intervals were calculated with the bootstrap method (1,000 resamples).

Table A1.1 presents the full results of the Pay-Down-Only Simulation. Min-Auto more than doubles the time duration and total costs (interest and fees) until clearing the balance compared with the Non-Auto group.

Table A1.1. The Time to Pay-Down the Debt to Less Than £10, and Total Cost of Pay-Down (Total Interest) in the Paydown-Only Simulation

Initial Balance	Autopay Status in Month 1	Total Time Until Clearing the Balance (Months)	Total Cost Until Clearing the Balance (£)
Median Balance	Non-Auto	7.94	40.45
(£557)		[7.47 : 8.41]	[38.5 : 42.38]
	Min-Auto	20.76	94.24
		[19.86 : 21.75]	[90.86 : 97.89]
Mean Balance	Non-Auto	8.12	104.75
(£1,414)		[7.72 : 8.56]	[98.15 : 113.75]
	Min-Auto	23.99	271.10
		[22.89 : 25.19]	[261.12 : 281.88]
75th Percentile Balance	Non-Auto	8.82	130.44
(£1,711)		[8.35 : 9.35]	[124.58 : 136.18]
	Min-Auto	24.34	347.66
		[23.19 : 25.51]	[334.69 : 361.61]

Note. The numbers in parentheses are 95% confidence intervals.

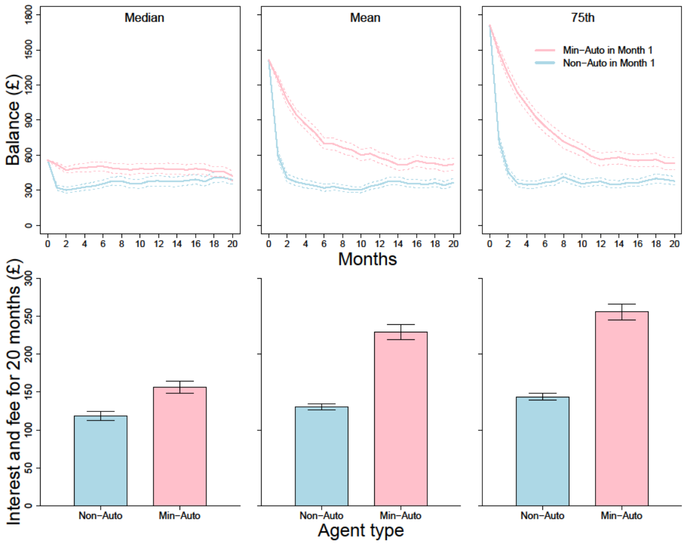

Figure A1.7. The balance trajectory and corresponding financial cost based on the Spending-and-Repayment Simulation. The top panels show a balance path over 20 months and the bottom panels show a total interest and fee accrued over those 20 months. The initial balance for the left, the middle, and the right panels are the median, the mean, and 75th percentile balances taken from the data.

Figure A1.7 shows the results of the Spending-and-Repayment Simulation where we see consistently higher balances and about double the total costs in the 20 month period. Therefore, even accounting for the higher prevalence of late fees among the Non-Auto group, the simulations show that Min-Auto creates far higher costs of debt for the consumer (about a 5% chance of incurring a £12 late fee for Non-Auto cards vs. £100 or more extra interest for Min-Auto cards).

We also conducted a final simulation estimating what proportion of total interest and fees incurred by all cards is due to Min-Auto. We randomly sampled 10,000 cards from the whole data (excluding cards with a balance transfer but including cards with a zero merchant APR) and categorized those cards into two groups. The first Never-Min-Auto group consists of 8,312 cards which were never repaid by Min-Auto, including Non-Auto cards and cards with an autopay covering more than the minimum. The second Some-Min-Auto group consists of 1,688 cards which were repaid by Min-Auto at least once in the data period. In the simulation the Some-Min-Auto cards were counterfactually repaid over time as if the cards were Never-Min-Auto cards: At each time-step in the simulation, the spending amount was drawn from the Some-Min-Auto cards but the fraction of the balance repaid was drawn from the Never-Min-Auto cards. The sampling methods are identical to those used in the Spending-and-Repayment Simulation, and were based on the specific the credit limit, the merchant APR, and the cash APR for each card. The balance, interest, and fees were then calculated for the month. The simulation continued up to the number of observations of the card in the data.

The simulation results showed that Some-Min-Auto cards could save about 36%, 95% CI [29, 44] of total interest and fees if they were repaid as Never-Min-Auto cards. Considering that the proportion of interest and fees for Some-Min-Auto cards among total interest and fees for all 10,000 cards is about 43%, we estimate that 15.5% of the total interest and fees for all cards is due to Min-Auto.

A1.6 Supplemental Tables

Table A1.2. Summary Statistics for the Between-Cards Dataset

Statistics	Non-Auto	Min-Auto
Number of observations	4,792,670	907,730
Number of cards	273,145	43,262
Median balance	687	2,081
Median credit limit	5,000	5,300
Median utilization	0.15	0.58
Median spending amount	220	0
Median merchant APR	0.179	0.200
Median cash APR	0.249	0.279
Median charged-off rate	0.002	0.013

Table A1.3. Summary Statistics for the Within-Card Dataset

Statistics	Before	After
Number of observations	35,191	47,914
Number of cards	4,001	4,001
Median balance	1,444	1,638
Median credit limit	4,475	4,400
Median utilization	0.517	0.618
Median spending amount	55	0
Median merchant APR	0.189	0.189
Median cash APR	0.249	0.260
Median charged-off rate	0.011	0.016

Table A1.4. Coefficients for Equation 2.1

IV	Estimate	LL	UL	Clustered SE	z value	Pr(>|z|)
Intercept:Minimum	1.167	0.846	1.488	0.164	7.1	0.00000
Intercept:Large1	2.134	1.829	2.438	0.155	13.7	0.00000
Intercept:Large2	1.523	1.211	1.835	0.159	9.6	0.00000
Intercept:Large3	1.141	0.831	1.450	0.158	7.2	0.00000
Intercept:Large4	0.559	0.229	0.888	0.168	3.3	0.00089
Intercept:Full	5.898	5.599	6.196	0.152	38.7	0.00000
Balance:Minimum	0.000	0.000	0.000	0.000	-2.0	0.05057
Balance:Large1	0.000	0.000	0.000	0.000	-2.6	0.01078
Balance:Large2	0.000	0.000	0.000	0.000	-15.2	0.00000
Balance:Large3	0.000	0.000	0.000	0.000	-20.5	0.00000
Balance:Large4	0.000	-0.001	0.000	0.000	-19.4	0.00000
Balance:Full	-0.002	-0.002	-0.002	0.000	-47.1	0.00000
Credit Limit:Minimum	0.000	0.000	0.000	0.000	13.0	0.00000
Credit Limit:Large1	0.000	0.000	0.000	0.000	17.7	0.00000
Credit Limit:Large2	0.000	0.000	0.000	0.000	10.4	0.00000
Credit Limit:Large3	0.000	0.000	0.000	0.000	10.2	0.00000
Credit Limit:Large4	0.000	0.000	0.000	0.000	13.3	0.00000
Credit Limit:Full	0.000	0.000	0.000	0.000	9.6	0.00000
Utilization:Minimum	2.539	2.347	2.730	0.098	26.0	0.00000
Utilization:Large1	1.924	1.745	2.104	0.091	21.0	0.00000
Utilization:Large2	-0.095	-0.306	0.117	0.108	-0.9	0.37991
Utilization:Large3	-0.399	-0.609	-0.190	0.107	-3.7	0.00019
Utilization:Large4	-0.118	-0.319	0.082	0.102	-1.2	0.24832
Utilization:Full	-2.072	-2.286	-1.859	0.109	-19.0	0.00000
Spending Amount:Minimum	-0.001	-0.001	-0.001	0.000	-24.9	0.00000
Spending Amount:Large1	0.000	0.000	0.000	0.000	-2.1	0.03327
Spending Amount:Large2	0.001	0.001	0.001	0.000	20.8	0.00000
Spending Amount:Large3	0.001	0.001	0.002	0.000	26.7	0.00000
Spending Amount:Large4	0.002	0.002	0.002	0.000	29.4	0.00000
Spending Amount:Full	0.003	0.003	0.003	0.000	49.7	0.00000
Merchant APR:Minimum	4.021	3.170	4.873	0.434	9.3	0.00000
Merchant APR:Large1	3.128	2.226	4.029	0.460	6.8	0.00000
Merchant APR:Large2	2.440	1.509	3.372	0.475	5.1	0.00000
Merchant APR:Large3	1.605	0.620	2.589	0.502	3.2	0.00140
Merchant APR:Large4	-0.848	-1.897	0.201	0.535	-1.6	0.11300
Merchant APR:Full	-7.265	-8.104	-6.425	0.428	-17.0	0.00000
Cash APR:Minimum	-3.041	-4.244	-1.838	0.614	-5.0	0.00000
Cash APR:Large1	-4.110	-5.268	-2.953	0.591	-7.0	0.00000
Cash APR:Large2	-4.430	-5.601	-3.259	0.598	-7.4	0.00000
Cash APR:Large3	-4.939	-6.155	-3.722	0.621	-8.0	0.00000
Cash APR:Large4	-3.650	-4.895	-2.406	0.635	-5.7	0.00000
Cash APR:Full	-4.946	-6.065	-3.828	0.570	-8.7	0.00000
Charge-off Rate:Minimum	-10.269	-10.975	-9.564	0.360	-28.5	0.00000
Charge-off Rate:Large1	-18.129	-19.451	-16.807	0.675	-26.9	0.00000
Charge-off Rate:Large2	-23.728	-26.531	-20.924	1.430	-16.6	0.00000
Charge-off Rate:Large3	-20.644	-23.848	-17.441	1.634	-12.6	0.00000
Charge-off Rate:Large4	-9.107	-10.412	-7.802	0.666	-13.7	0.00000
Charge-off Rate:Full	-37.502	-42.457	-32.548	2.528	-14.8	0.00000
Average Weekly Income :Minimum	-0.001	-0.001	-0.001	0.000	-7.0	0.00000
Average Weekly Income :Large1	-0.001	-0.001	0.000	0.000	-5.3	0.00000
Average Weekly Income :Large2	0.000	-0.001	0.000	0.000	-2.5	0.01285
Average Weekly Income :Large3	0.000	0.000	0.000	0.000	-1.2	0.24724
Average Weekly Income :Large4	0.000	0.000	0.000	0.000	-0.2	0.83185
Average Weekly Income :Full	0.000	0.000	0.000	0.000	0.9	0.3756
Proportion of Higher Education :Minimum	-1.415	-1.945	-0.885	0.271	-5.2	0.00000
Proportion of Higher Education :Large1	-0.992	-1.474	-0.510	0.246	-4.0	0.00006
Proportion of Higher Education :Large2	-0.691	-1.236	-0.146	0.278	-2.5	0.01294
Proportion of Higher Education :Large3	-0.986	-1.564	-0.407	0.295	-3.3	0.00084
Proportion of Higher Education :Large4	-0.666	-1.259	-0.073	0.303	-2.2	0.02780
Proportion of Higher Education :Full	-0.039	-0.514	0.437	0.242	-0.2	0.87352
Min-Auto Card:Minimum	3.705	3.489	3.922	0.110	33.5	0.00000
Min-Auto Card:Large1	0.007	-0.218	0.233	0.115	0.1	0.94967
Min-Auto Card:Large2	0.576	0.345	0.807	0.118	4.9	0.00000
Min-Auto Card:Large3	0.810	0.576	1.043	0.119	6.8	0.00000
Min-Auto Card:Large4	0.964	0.715	1.213	0.127	7.6	0.00000
Min-Auto Card:Full	0.018	-0.201	0.236	0.111	0.2	0.87409
R2 = .395						
Number of observations = 1,242,820						

Note. The standard errors were corrected, for clustering by cards and calendar months.

Table A1.5. Socioeconomic Status for Non-Auto and Min-Auto Cards in the Between-Cards Dataset

Postcode-Level Socioeconomic Variable	Autopay Status	Mean	25th Percentile	Median	75th Percentile
Median House Price (£)	Non-Auto	206,362	136,011	184,805	242,803
	Min-Auto	211,585	135,935	187,099	251,645
	Difference (Non - Min)	-5,223	76	-2,294	-8,842
Proportion of Jobless claimants among all adults (%)	Non-Auto	2.4	1.4	2.0	3.3
	Min-Auto	2.5	1.4	2.2	3.4
	Difference (Non - Min)	-0.1	-0.1	-0.1	-0.2
Average weekly income (£)	Non-Auto	749	630	724	846
	Min-Auto	755	631	729	859
	Difference (Non - Min)	-6	-1	-6	-13
Proportion of people having a post-high school educational qualification (%)	Non-Auto	28.3	22.3	27.4	33.1
	Min-Auto	28.7	22.4	27.7	33.5
	Difference (Non - Min)	-0.4	-0.1	-0.3	-0.4

Table A1.6. Coefficients for Equation A1.1

IV	Estimate	LL	UL	Clustered SE	z value	Pr(>|z|)
(Intercept)	4.063	3.997	4.129	0.034	120.7	0.00000
Balance	-0.002	-0.002	-0.002	0.000	-65.9	0.00000
Credit Limit	0.000	0.000	0.000	0.000	-36.0	0.00000
Utilization	-3.298	-3.368	-3.228	0.036	-92.8	0.00000
Spending Amount	0.003	0.003	0.003	0.000	104.8	0.00000
Merchant APR	-12.691	-12.969	-12.414	0.142	-89.6	0.00000
Cash APR	0.320	0.108	0.533	0.108	3.0	0.00314
Charge-off Rate	-14.613	-17.237	-11.990	1.339	-10.9	0.00000
Min-Auto Card	-0.027	-0.105	0.050	0.039	-0.7	0.48674
R2 = .472						
Number of observations = 4,533,224						

Note. The standard errors were corrected, for clustering by cards and calendar months.

Table A1.7. Coefficients for Equation 2.2

IV	Estimate	LL	UL	Clustered SE	z value	Pr(>|z|)
Intercept:Minimum	5.620	4.798	6.442	0.419	13.4	0.00000
Intercept:Large1	3.077	2.255	3.900	0.420	7.3	0.00000
Intercept:Large2	3.155	2.209	4.100	0.482	6.5	0.00000
Intercept:Large3	2.705	1.791	3.620	0.467	5.8	0.00000
Intercept:Large4	2.594	1.538	3.651	0.539	4.8	0.00000
Intercept:Full	7.591	6.693	8.490	0.458	16.6	0.00000
Balance:Minimum	0.000	0.000	0.000	0.000	0.7	0.47460
Balance:Large1	0.000	0.000	0.000	0.000	0.0	0.97014
Balance:Large2	0.000	0.000	0.000	0.000	-4.3	0.00002
Balance:Large3	0.000	0.000	0.000	0.000	-3.6	0.00032
Balance:Large4	0.000	0.000	0.000	0.000	-2.4	0.01814
Balance:Full	-0.001	-0.001	-0.001	0.000	-11.4	0.00000
Credit Limit:Minimum	0.000	0.000	0.000	0.000	2.4	0.01653
Credit Limit:Large1	0.000	0.000	0.000	0.000	4.5	0.00001
Credit Limit:Large2	0.000	0.000	0.000	0.000	2.2	0.02895
Credit Limit:Large3	0.000	0.000	0.000	0.000	1.9	0.06079
Credit Limit:Large4	0.000	0.000	0.000	0.000	1.1	0.25764
Credit Limit:Full	0.000	0.000	0.000	0.000	-1.6	0.10776
Utilization:Minimum	0.853	0.566	1.139	0.146	5.8	0.00000
Utilization:Large1	0.810	0.499	1.122	0.159	5.1	0.00000
Utilization:Large2	-0.737	-1.177	-0.297	0.224	-3.3	0.00103
Utilization:Large3	-0.903	-1.448	-0.358	0.278	-3.2	0.00117
Utilization:Large4	-1.172	-1.635	-0.709	0.236	-5.0	0.00000
Utilization:Full	-2.752	-3.185	-2.319	0.221	-12.5	0.00000
Spending Amount:Minimum	-0.001	-0.001	-0.001	0.000	-7.9	0.00000
Spending Amount:Large1	0.000	0.000	0.000	0.000	2.9	0.00404
Spending Amount:Large2	0.001	0.001	0.001	0.000	11.5	0.00000
Spending Amount:Large3	0.001	0.001	0.001	0.000	11.8	0.00000
Spending Amount:Large4	0.001	0.001	0.001	0.000	14.2	0.00000
Spending Amount:Full	0.002	0.002	0.002	0.000	21.1	0.00000
Merchant APR:Minimum	1.200	-0.471	2.871	0.853	1.4	0.15939
Merchant APR:Large1	-3.169	-4.997	-1.340	0.933	-3.4	0.00068
Merchant APR:Large2	-5.393	-7.570	-3.215	1.111	-4.9	0.00000
Merchant APR:Large3	-5.544	-7.868	-3.221	1.185	-4.7	0.00000
Merchant APR:Large4	-4.276	-7.392	-1.160	1.590	-2.7	0.00715
Merchant APR:Full	-8.055	-10.247	-5.862	1.118	-7.2	0.00000
Cash APR:Minimum	-8.153	-11.115	-5.192	1.511	-5.4	0.00000
Cash APR:Large1	-4.035	-7.164	-0.906	1.596	-2.5	0.01149
Cash APR:Large2	-3.579	-7.330	0.172	1.914	-1.9	0.06146
Cash APR:Large3	-3.297	-7.037	0.442	1.908	-1.7	0.08397
Cash APR:Large4	-4.606	-8.459	-0.752	1.966	-2.3	0.01915
Cash APR:Full	-8.989	-12.232	-5.745	1.655	-5.4	0.00000
Charge-off Rate:Minimum	-6.376	-7.399	-5.354	0.521	-12.2	0.00000
Charge-off Rate:Large1	-8.168	-9.572	-6.763	0.716	-11.4	0.00000
Charge-off Rate:Large2	-12.313	-16.159	-8.466	1.962	-6.3	0.00000
Charge-off Rate:Large3	-11.218	-16.846	-5.590	2.872	-3.9	0.00009
Charge-off Rate:Large4	-9.369	-14.581	-4.157	2.659	-3.5	0.00043
Charge-off Rate:Full	-24.579	-32.307	-16.851	3.943	-6.2	0.00000
Before Min-Auto:Minimum	-3.506	-3.808	-3.204	0.154	-22.8	0.00000
Before Min-Auto:Large1	-1.205	-1.500	-0.911	0.150	-8.0	0.00000
Before Min-Auto:Large2	-1.706	-2.020	-1.392	0.160	-10.7	0.00000
Before Min-Auto:Large3	-1.936	-2.260	-1.612	0.165	-11.7	0.00000
Before Min-Auto:Large4	-1.884	-2.210	-1.558	0.166	-11.3	0.00000
Before Min-Auto:Full	-1.931	-2.212	-1.649	0.144	-13.5	0.00000
R2 = .256						
Number of observations = 82,360						

Note. The standard errors were corrected, for clustering by cards and calendar months.

Table A1.8. Coefficients for Equation A1.2

IV	Estimate	LL	UL	Clustered SE	t value	Pr(>|t|)
Balance	0.000	0.000	0.000	0.000	-0.3	0.74064
Credit Limit	0.000	0.000	0.000	0.000	-1.0	0.29469
Utilization	-0.345	-0.400	-0.290	0.028	-12.2	0.00000
Spending Amount	0.000	0.000	0.000	0.000	0.4	0.68712
Merchant APR	0.588	-0.206	1.382	0.405	1.5	0.14658
Cash APR	-0.770	-1.659	0.119	0.453	-1.7	0.08955
Charge-off Rate	0.188	0.076	0.300	0.057	3.3	0.00100
Before Min-Auto	-0.007	-0.019	0.005	0.006	-1.1	0.26797

R2 = .682

Number of observations = 36,660

Note. The fixed effect of card was included in the linear regression. The standard errors were corrected, for clustering by cards and calendar months.

Table A1.9. Coefficients for Equation 2.1 on Remaining-as-Non-Auto and Switched-to-Min-Auto Cards

IV	Estimate	LL	UL	Clustered SE	z value	Pr(>|z|)
Intercept:Minimum	1.378	0.706	2.049	0.343	4.0	0.00006
Intercept:Large1	2.075	1.433	2.718	0.328	6.3	0.00000
Intercept:Large2	1.915	1.194	2.635	0.368	5.2	0.00000
Intercept:Large3	0.830	0.127	1.533	0.359	2.3	0.02073
Intercept:Large4	0.307	-0.477	1.091	0.400	0.8	0.44334
Intercept:Full	5.582	4.970	6.194	0.312	17.9	0.00000
Balance:Minimum	0.000	0.000	0.000	0.000	1.4	0.15931
Balance:Large1	0.000	0.000	0.000	0.000	1.4	0.15843
Balance:Large2	0.000	0.000	0.000	0.000	-4.9	0.00000
Balance:Large3	0.000	0.000	0.000	0.000	-5.7	0.00000
Balance:Large4	0.000	-0.001	0.000	0.000	-7.3	0.00000
Balance:Full	-0.002	-0.002	-0.001	0.000	-18.1	0.00000
Credit Limit:Minimum	0.000	0.000	0.000	0.000	0.9	0.37822
Credit Limit:Large1	0.000	0.000	0.000	0.000	4.0	0.00007
Credit Limit:Large2	0.000	0.000	0.000	0.000	1.8	0.07942
Credit Limit:Large3	0.000	0.000	0.000	0.000	1.8	0.06544
Credit Limit:Large4	0.000	0.000	0.000	0.000	3.9	0.00010
Credit Limit:Full	0.000	0.000	0.000	0.000	1.8	0.06445
Utilization:Minimum	2.033	1.623	2.444	0.209	9.7	0.00000
Utilization:Large1	1.376	0.980	1.773	0.202	6.8	0.00000
Utilization:Large2	-0.383	-0.930	0.165	0.279	-1.4	0.17091
Utilization:Large3	-0.625	-1.177	-0.072	0.282	-2.2	0.02669
Utilization:Large4	-0.549	-1.029	-0.069	0.245	-2.2	0.02505
Utilization:Full	-2.255	-2.744	-1.766	0.249	-9.0	0.00000
Spending Amount:Minimum	-0.001	-0.001	-0.001	0.000	-9.8	0.00000
Spending Amount:Large1	0.000	-0.001	0.000	0.000	-2.7	0.00750
Spending Amount:Large2	0.001	0.001	0.001	0.000	7.0	0.00000
Spending Amount:Large3	0.001	0.001	0.001	0.000	10.0	0.00000
Spending Amount:Large4	0.001	0.001	0.002	0.000	11.9	0.00000
Spending Amount:Full	0.003	0.002	0.003	0.000	18.9	0.00000
Merchant APR:Minimum	4.072	1.912	6.232	1.102	3.7	0.00022
Merchant APR:Large1	2.573	0.530	4.617	1.043	2.5	0.01359
Merchant APR:Large2	1.018	-1.569	3.604	1.320	0.8	0.44054
Merchant APR:Large3	0.855	-1.966	3.675	1.439	0.6	0.55251
Merchant APR:Large4	-3.296	-6.308	-0.285	1.537	-2.1	0.03194
Merchant APR:Full	-4.814	-6.739	-2.888	0.982	-4.9	0.00000
Cash APR:Minimum	-2.547	-4.653	-0.442	1.074	-2.4	0.01773
Cash APR:Large1	-3.485	-5.413	-1.557	0.984	-3.5	0.00039
Cash APR:Large2	-3.637	-5.920	-1.354	1.165	-3.1	0.00179
Cash APR:Large3	-3.458	-6.008	-0.908	1.301	-2.7	0.00787
Cash APR:Large4	-0.085	-2.320	2.150	1.140	-0.1	0.94068
Cash APR:Full	-5.803	-7.321	-4.285	0.774	-7.5	0.00000
Charge-off Rate:Minimum	-9.051	-10.283	-7.820	0.628	-14.4	0.00000
Charge-off Rate:Large1	-12.872	-15.686	-10.059	1.435	-9.0	0.00000
Charge-off Rate:Large2	-16.261	-22.771	-9.751	3.321	-4.9	0.00000
Charge-off Rate:Large3	-13.633	-21.810	-5.457	4.172	-3.3	0.00108
Charge-off Rate:Large4	-4.840	-6.321	-3.359	0.756	-6.4	0.00000
Charge-off Rate:Full	-33.412	-43.278	-23.547	5.033	-6.6	0.00000
Average Weekly Income :Minimum	-0.001	-0.001	0.000	0.000	-2.3	0.02194
Average Weekly Income :Large1	0.000	-0.001	0.000	0.000	-1.5	0.14184
Average Weekly Income :Large2	-0.001	-0.002	0.000	0.000	-2.6	0.00839
Average Weekly Income :Large3	0.000	-0.001	0.000	0.000	-0.7	0.49505
Average Weekly Income :Large4	0.000	-0.001	0.001	0.000	0.5	0.60139
Average Weekly Income :Full	0.000	-0.001	0.001	0.000	0.1	0.94162
Proportion of Higher Education :Minimum	-1.839	-3.153	-0.525	0.670	-2.7	0.00609
Proportion of Higher Education :Large1	-1.405	-2.617	-0.193	0.618	-2.3	0.02308
Proportion of Higher Education :Large2	-0.133	-1.760	1.494	0.830	-0.2	0.87280
Proportion of Higher Education :Large3	-0.826	-2.182	0.530	0.692	-1.2	0.23265
Proportion of Higher Education :Large4	-1.445	-3.110	0.221	0.850	-1.7	0.08920
Proportion of Higher Education :Full	0.254	-0.828	1.336	0.552	0.5	0.64495
Min-Auto Card:Minimum	2.946	2.478	3.415	0.239	12.3	0.00000
Min-Auto Card:Large1	0.530	0.047	1.013	0.246	2.2	0.03156
Min-Auto Card:Large2	0.953	0.478	1.428	0.242	3.9	0.00008
Min-Auto Card:Large3	1.137	0.649	1.625	0.249	4.6	0.00000
Min-Auto Card:Large4	0.613	0.109	1.117	0.257	2.4	0.01706
Min-Auto Card:Full	0.203	-0.255	0.660	0.233	0.9	0.38463
R2 = .310						
Number of observations = 78,106						

Note. The standard errors were corrected, for clustering by cards and calendar months.

Table A1.10. Coefficients for Equation 2.1 with the Alternative Definition of Min-Auto Cards

IV	Estimate	LL	UL	Clustered SE	z value	Pr(>|z|)
Intercept:Minimum	1.201	0.847	1.556	0.181	6.6	0.00000
Intercept:Large1	2.267	1.921	2.614	0.177	12.8	0.00000
Intercept:Large2	1.721	1.369	2.072	0.179	9.6	0.00000
Intercept:Large3	1.272	0.901	1.643	0.189	6.7	0.00000
Intercept:Large4	0.670	0.280	1.060	0.199	3.4	0.00077
Intercept:Full	5.967	5.620	6.314	0.177	33.7	0.00000
Balance:Minimum	0.000	0.000	0.000	0.000	-2.5	0.01301
Balance:Large1	0.000	0.000	0.000	0.000	-2.3	0.02192
Balance:Large2	0.000	0.000	0.000	0.000	-13.0	0.00000
Balance:Large3	0.000	0.000	0.000	0.000	-17.0	0.00000
Balance:Large4	0.000	0.000	0.000	0.000	-16.4	0.00000
Balance:Full	-0.002	-0.002	-0.001	0.000	-46.9	0.00000
Credit Limit:Minimum	0.000	0.000	0.000	0.000	12.6	0.00000
Credit Limit:Large1	0.000	0.000	0.000	0.000	15.0	0.00000
Credit Limit:Large2	0.000	0.000	0.000	0.000	10.0	0.00000
Credit Limit:Large3	0.000	0.000	0.000	0.000	9.5	0.00000
Credit Limit:Large4	0.000	0.000	0.000	0.000	10.5	0.00000
Credit Limit:Full	0.000	0.000	0.000	0.000	8.2	0.00000
Utilization:Minimum	2.405	2.164	2.645	0.123	19.6	0.00000
Utilization:Large1	1.922	1.698	2.146	0.114	16.8	0.00000
Utilization:Large2	0.009	-0.231	0.249	0.122	0.1	0.94237
Utilization:Large3	-0.241	-0.496	0.014	0.130	-1.9	0.06387
Utilization:Large4	-0.158	-0.425	0.109	0.136	-1.2	0.24630
Utilization:Full	-1.957	-2.224	-1.691	0.136	-14.4	0.00000
Spending Amount:Minimum	-0.001	-0.001	-0.001	0.000	-23.2	0.00000
Spending Amount:Large1	0.000	0.000	0.000	0.000	-1.9	0.05862
Spending Amount:Large2	0.001	0.001	0.001	0.000	24.9	0.00000
Spending Amount:Large3	0.001	0.001	0.001	0.000	28.6	0.00000
Spending Amount:Large4	0.001	0.001	0.002	0.000	31.7	0.00000
Spending Amount:Full	0.003	0.003	0.003	0.000	54.9	0.00000
Merchant APR:Minimum	3.859	2.885	4.834	0.497	7.8	0.00000
Merchant APR:Large1	2.319	1.288	3.349	0.526	4.4	0.00001
Merchant APR:Large2	1.900	0.870	2.930	0.525	3.6	0.00030
Merchant APR:Large3	1.077	0.037	2.117	0.531	2.0	0.04248
Merchant APR:Large4	-1.260	-2.391	-0.130	0.577	-2.2	0.02891
Merchant APR:Full	-8.264	-9.183	-7.345	0.469	-17.6	0.00000
Cash APR:Minimum	-3.754	-4.968	-2.541	0.619	-6.1	0.00000
Cash APR:Large1	-4.380	-5.535	-3.224	0.590	-7.4	0.00000
Cash APR:Large2	-5.278	-6.490	-4.066	0.618	-8.5	0.00000
Cash APR:Large3	-5.502	-6.746	-4.258	0.635	-8.7	0.00000
Cash APR:Large4	-3.842	-5.116	-2.568	0.650	-5.9	0.00000
Cash APR:Full	-4.861	-5.969	-3.753	0.565	-8.6	0.00000
Charge-off Rate:Minimum	-10.833	-11.783	-9.883	0.485	-22.3	0.00000
Charge-off Rate:Large1	-18.083	-19.769	-16.396	0.860	-21.0	0.00000
Charge-off Rate:Large2	-23.300	-26.528	-20.072	1.647	-14.1	0.00000
Charge-off Rate:Large3	-23.965	-27.481	-20.448	1.794	-13.4	0.00000
Charge-off Rate:Large4	-9.841	-11.498	-8.184	0.845	-11.6	0.00000
Charge-off Rate:Full	-39.238	-45.201	-33.275	3.042	-12.9	0.00000
Average Weekly Income :Minimum	-0.001	-0.001	-0.001	0.000	-5.8	0.00000
Average Weekly Income :Large1	-0.001	-0.001	-0.001	0.000	-5.5	0.00000
Average Weekly Income :Large2	0.000	-0.001	0.000	0.000	-2.9	0.00399
Average Weekly Income :Large3	0.000	-0.001	0.000	0.000	-2.3	0.02267
Average Weekly Income :Large4	0.000	-0.001	0.000	0.000	-2.1	0.03829
Average Weekly Income :Full	0.000	0.000	0.000	0.000	-0.1	0.92299
Proportion of Higher Education :Minimum	-1.069	-1.644	-0.495	0.293	-3.6	0.00026
Proportion of Higher Education :Large1	-0.457	-1.008	0.094	0.281	-1.6	0.10434
Proportion of Higher Education :Large2	-0.441	-1.037	0.154	0.304	-1.5	0.14641
Proportion of Higher Education :Large3	-0.350	-1.044	0.344	0.354	-1.0	0.32257
Proportion of Higher Education :Large4	0.305	-0.394	1.004	0.357	0.9	0.39295
Proportion of Higher Education :Full	0.468	-0.086	1.021	0.282	1.7	0.09767
Min-Auto Card:Minimum	2.893	2.762	3.025	0.067	43.1	0.00000
Min-Auto Card:Large1	-0.459	-0.597	-0.322	0.070	-6.5	0.00000
Min-Auto Card:Large2	0.192	0.058	0.325	0.068	2.8	0.00490
Min-Auto Card:Large3	0.430	0.290	0.569	0.071	6.0	0.00000
Min-Auto Card:Large4	0.570	0.418	0.722	0.078	7.3	0.00000
Min-Auto Card:Full	0.003	-0.128	0.134	0.067	0.0	0.96520

R2 = .377

Number of observations = 1,058,203

Note. The standard errors were corrected, for clustering by cards and calendar months.

Table A1.11. Coefficients for Equation 2.2 with the Alternative Definition of Min-Auto Cards

IV	Estimate	LL	UL	Clustered SE	z value	Pr(>|z|)
Intercept:Minimum	3.304	2.470	4.138	0.426	7.8	0.00000
Intercept:Large1	2.222	1.401	3.042	0.419	5.3	0.00000
Intercept:Large2	2.542	1.715	3.368	0.422	6.0	0.00000
Intercept:Large3	2.327	1.488	3.166	0.428	5.4	0.00000
Intercept:Large4	2.485	1.605	3.365	0.449	5.5	0.00000
Intercept:Full	6.112	5.320	6.904	0.404	15.1	0.00000
Balance:Minimum	0.000	0.000	0.000	0.000	-3.8	0.00017
Balance:Large1	0.000	0.000	0.000	0.000	-2.7	0.00663
Balance:Large2	0.000	0.000	0.000	0.000	-6.6	0.00000
Balance:Large3	0.000	0.000	0.000	0.000	-6.9	0.00000
Balance:Large4	0.000	0.000	0.000	0.000	-7.3	0.00000
Balance:Full	-0.001	-0.001	-0.001	0.000	-18.6	0.00000
Credit Limit:Minimum	0.000	0.000	0.000	0.000	7.4	0.00000
Credit Limit:Large1	0.000	0.000	0.000	0.000	8.0	0.00000
Credit Limit:Large2	0.000	0.000	0.000	0.000	4.7	0.00000
Credit Limit:Large3	0.000	0.000	0.000	0.000	4.4	0.00001
Credit Limit:Large4	0.000	0.000	0.000	0.000	4.7	0.00000
Credit Limit:Full	0.000	0.000	0.000	0.000	2.0	0.05061
Utilization:Minimum	1.139	0.909	1.369	0.117	9.7	0.00000
Utilization:Large1	1.235	0.998	1.472	0.121	10.2	0.00000
Utilization:Large2	-0.148	-0.466	0.169	0.162	-0.9	0.35996
Utilization:Large3	-0.422	-0.820	-0.025	0.203	-2.1	0.03742
Utilization:Large4	-0.741	-1.113	-0.369	0.190	-3.9	0.00009
Utilization:Full	-2.222	-2.501	-1.944	0.142	-15.6	0.00000
Spending Amount:Minimum	0.000	0.000	0.000	0.000	-3.6	0.00035
Spending Amount:Large1	0.000	0.000	0.000	0.000	4.6	0.00001
Spending Amount:Large2	0.001	0.001	0.001	0.000	13.4	0.00000
Spending Amount:Large3	0.001	0.001	0.001	0.000	15.7	0.00000
Spending Amount:Large4	0.001	0.001	0.001	0.000	15.7	0.00000
Spending Amount:Full	0.002	0.001	0.002	0.000	23.4	0.00000
Merchant APR:Minimum	1.338	0.009	2.668	0.678	2.0	0.04843
Merchant APR:Large1	0.803	-0.531	2.137	0.681	1.2	0.23827
Merchant APR:Large2	1.478	0.034	2.922	0.737	2.0	0.04489
Merchant APR:Large3	0.593	-1.020	2.205	0.823	0.7	0.47116
Merchant APR:Large4	-0.207	-1.995	1.580	0.912	-0.2	0.82004
Merchant APR:Full	-5.132	-6.498	-3.765	0.697	-7.4	0.00000
Cash APR:Minimum	-2.906	-5.861	0.050	1.508	-1.9	0.05396
Cash APR:Large1	-5.583	-8.505	-2.660	1.491	-3.7	0.00018
Cash APR:Large2	-7.770	-10.866	-4.673	1.580	-4.9	0.00000
Cash APR:Large3	-7.653	-10.888	-4.419	1.650	-4.6	0.00000
Cash APR:Large4	-8.160	-11.335	-4.984	1.620	-5.0	0.00000
Cash APR:Full	-6.065	-9.013	-3.117	1.504	-4.0	0.00006
Charge-off Rate:Minimum	-7.629	-9.114	-6.144	0.758	-10.1	0.00000
Charge-off Rate:Large1	-11.062	-12.887	-9.238	0.931	-11.9	0.00000
Charge-off Rate:Large2	-20.589	-25.634	-15.544	2.574	-8.0	0.00000
Charge-off Rate:Large3	-21.111	-28.811	-13.410	3.929	-5.4	0.00000
Charge-off Rate:Large4	-12.282	-17.494	-7.071	2.659	-4.6	0.00000
Charge-off Rate:Full	-28.189	-34.007	-22.371	2.968	-9.5	0.00000
Before Min-Auto:Minimum	-2.850	-2.996	-2.704	0.075	-38.3	0.00000
Before Min-Auto:Large1	-0.823	-0.970	-0.675	0.075	-11.0	0.00000
Before Min-Auto:Large2	-1.255	-1.445	-1.065	0.097	-13.0	0.00000
Before Min-Auto:Large3	-1.402	-1.599	-1.206	0.100	-14.0	0.00000
Before Min-Auto:Large4	-1.440	-1.683	-1.198	0.124	-11.6	0.00000
Before Min-Auto:Full	-1.477	-1.639	-1.315	0.083	-17.9	0.00000

R2 = .221

Number of observations = 190,882

Note. The standard errors were corrected, for clustering by cards and calendar months.

Appendix 2 Supplemental Materials for Chapter 3

A2.1 Credit Card Fee Types

Late payment fees are incurred when the consumers miss to repay at least the required minimum by the due date. Late payment fees are usually £12 per month. Late payment fees also lead to a deterioration in the consumer's credit score and hence have an indirect cost in terms of future access to credit. Cash advance fees are incurred when a customer borrows cash on their credit card or transfers monies from their credit card account to their deposit account. Cash advances incur a fixed fee typically of 3%, with a £3 minimum. Over-limit fees are usually £12 and are incurred when a consumer exceeds their credit limit. These fees can be incurred at any point in a card-month and a consumer may have several over-limit fees in a single card-month. Both cash advance and over-limit events are reported to credit files. Thus, all of three fee types have indirect costs through the impact on future credit availability via credit reporting, and therefore, the negative effects of fees extend beyond the immediate fee amount.

A2.2 Supplemental Figures and Tables

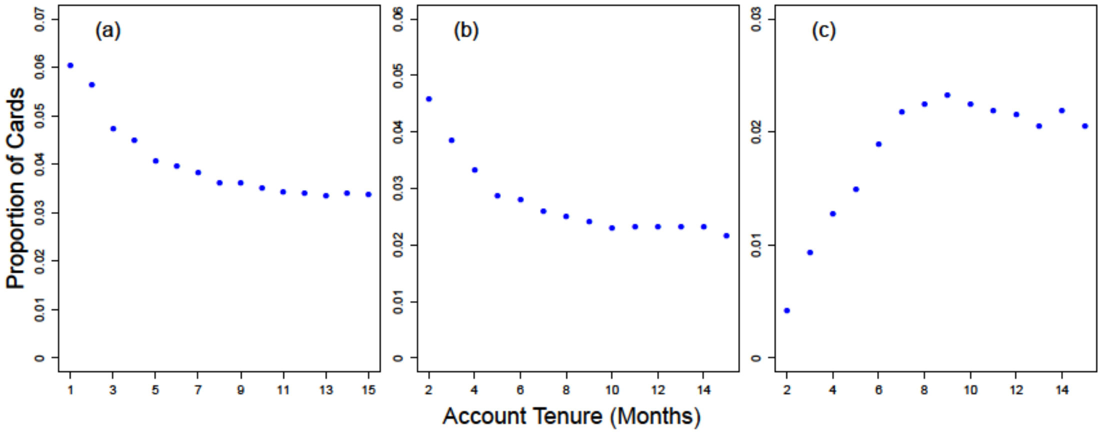

Figure A2.1. The proportion of cards with the fee over account tenure (Balanced panel). Panel (a) shows the proportion of cards with a late payment fee. Panel (b) shows the proportion of cards with a cash advance fee. Panel (c) shows the proportion of cards with an over-limit fee. The scale of the y-axis differs among panels. In Panel (a) the x-axis variable was adjusted one month forward.

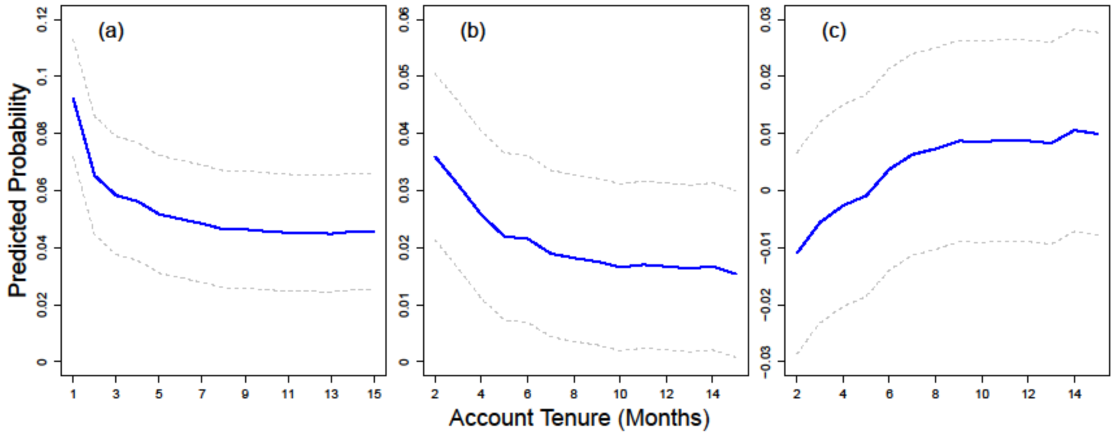

Figure A2.2. The probability of cards having the fee as a function of account tenure (Balanced panel). Predictions are from a linear probability model at covariates medians (Equation 3.1). Panel (a) shows the probability of cards having a late payment fee. Panel (b) shows the probability of cards having a cash advance fee. Panel (c) shows the probability of cards having an over-limit fee. The scale of the y-axis differs among panels. In Panel (a), the x-axis variable was adjusted one month forward. The dashed lines are 95% confidence intervals. The standard errors were corrected, for clustering by cards.

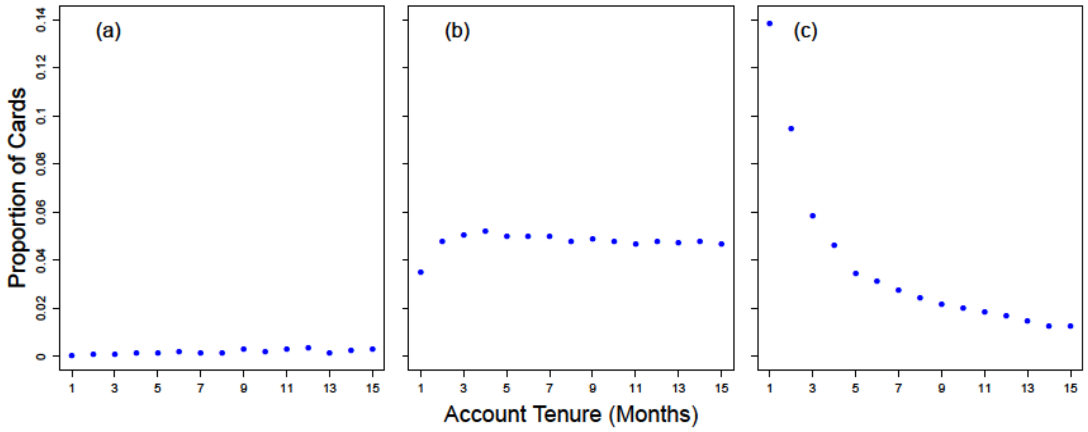

Figure A2.3. The proportion of cards with a late payment fee over account tenure by autopay status (Balanced panel). Panel (a) is for Always-Autopay Cards. Panel (b) is for Always-Non-Autopay Cards. Panel (c) is for Switched-To-Autopay Cards. The x-axis variable was adjusted one month forward.

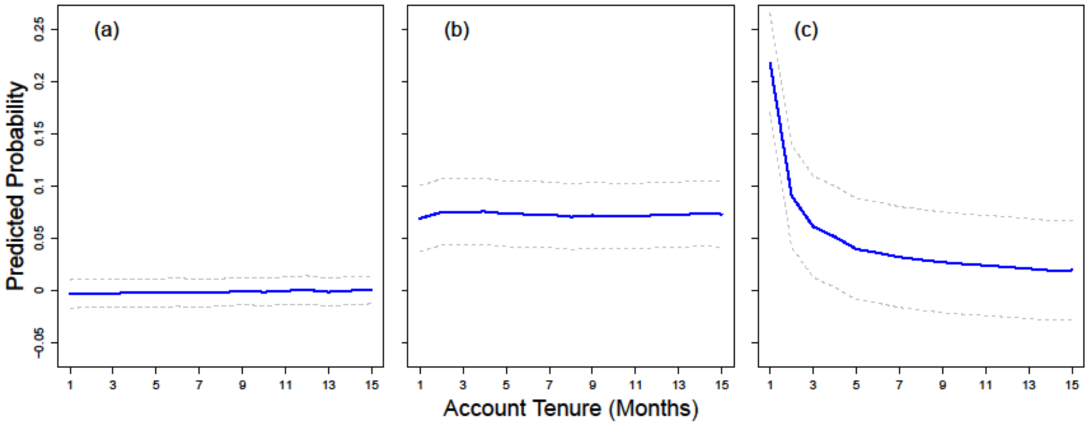

Figure A2.4. The probability of cards having a late payment fee as a function of account tenure by autopay status (Balanced panel). Predictions are from a linear probability model at covariates medians (Equation 3.1). Panel (a) is for Always-Autopay Cards. Panel (b) is for Always-Non-Autopay Cards. Panel (c) is for Switched-To-Autopay Cards. The x-axis variable was adjusted one month forward. The dashed lines are 95% confidence intervals. The standard errors were corrected, for clustering by cards.

Table A2.1. Summary Statistics

Statistics	Mean	SD	10th %tile	25th %tile	Median	75th %tile	90th %tile
Merchant APR (%)	9.28	0.09	0.00	0.00	6.89	17.95	19.94
Merchant APR$ (given %>0)	18.25	0.03	15.75	16.94	17.95	18.94	21.94
Cash APR (%)	24.79	0.04	17.95	24.89	24.93	27.95	27.95
Credit Limit (£)	4645.32	3126.98	1250.00	2250.00	4050.00	6300.00	8900.00
Monthly Purchase (£)	226.41	605.37	0.00	0.00	0.00	194.57	688.97
Monthly Purchase (given £>0)	542.56	837.13	34.49	97.57	278.98	660.66	1302.62
Monthly Cash Advance (£)	7.74	117.18	0.00	0.00	0.00	0.00	0.00
Monthly Cash Advance (given £>0)	240.68	608.87	20.00	49.05	100.00	260.00	510.00
Repayment (£)	236.92	648.97	0.00	19.50	50.00	170.00	564.41
Repayment (given balance>$0 (£))	286.51	703.12	20.00	33.91	80.00	210.29	700.00
Balance (£)	1692.55	2033.93	0.00	120.51	1005.06	2529.46	4413.41
Utilization (%)	39.83	36.12	0.00	3.48	31.74	75.05	93.39
Charge-off Rate (%)	1.25	3.33	0.14	0.21	0.40	1.20	2.92
Number of cards	242,899						
Number of card-months	2,669,259						

Table A2.2.Summary Statistics (Balanced Panel)

Statistics	Mean	SD	10th %tile	25th %tile	Median	75th %tile	90th %tile
Merchant APR (%)	8.50	0.09	0.00	0.00	0.00	17.95	18.94
Merchant APR$ (given %>0)	18.51	0.03	15.90	16.94	17.95	18.94	21.94
Cash APR (%)	25.41	0.03	21.94	24.93	24.93	27.95	27.95
Credit Limit (£)	4683.10	3108.20	1250.00	2300.00	4100.00	6300.00	8700.00
Monthly Purchase (£)	225.39	591.65	0.00	0.00	0.00	193.94	691.88
Monthly Purchase (given £>0)	540.21	814.39	34.35	97.40	279.00	663.59	1300.59
Monthly Cash Advance (£)	6.93	118.45	0.00	0.00	0.00	0.00	0.00
Monthly Cash Advance (given £>0)	231.62	645.82	20.00	40.00	100.00	250.00	500.00
Repayment (£)	246.60	663.35	0.00	22.65	50.00	182.41	600.00
Repayment (given balance>$0 (£))	295.16	713.36	23.11	35.00	80.00	223.00	725.00
Balance (£)	1749.15	2030.11	0.00	169.66	1090.96	2635.00	4474.16
Utilization (%)	40.82	35.97	0.00	4.70	33.79	76.00	93.28
Charge-off Rate (%)	1.19	3.07	0.13	0.19	0.36	1.20	2.92
Number of cards	82,661						
Number of card-months	1,239,915						

Table A2.3. Coefficient Estimates for the Probability of Cards Having a Late Payment Fee (Equation 3.1)

IV	All	Cards Type		
		Always-Autopay	Always-Non-Autopay	Switched-To-Autopay
Tenure 2	-0.015	0.000	0.005	-0.113
	[-0.017, -0.013]	[-0.001, 0.001]	[0.003, 0.007]	[-0.121, -0.105]
Tenure 3	-0.019	0.001	0.008	-0.143
	[-0.021, -0.017]	[0.000, 0.002]	[0.005, 0.011]	[-0.150, -0.136]
Tenure 4	-0.021	0.001	0.009	-0.156
	[-0.023, -0.019]	[-0.001, 0.003]	[0.006, 0.012]	[-0.163, -0.149]
Tenure 5	-0.023	0.002	0.008	-0.164
	[-0.025, -0.021]	[0.000, 0.004]	[0.005, 0.011]	[-0.172, -0.156]
Tenure 6	-0.025	0.002	0.007	-0.170
	[-0.028, -0.022]	[-0.001, 0.005]	[0.003, 0.011]	[-0.178, -0.162]
Tenure 7	-0.024	0.002	0.010	-0.172
	[-0.027, -0.021]	[-0.002, 0.006]	[0.005, 0.015]	[-0.180, -0.164]
Tenure 8	-0.026	0.002	0.009	-0.174
	[-0.029, -0.023]	[-0.002, 0.006]	[0.004, 0.014]	[-0.182, -0.166]
Tenure 9	-0.025	0.002	0.011	-0.176
	[-0.029, -0.021]	[-0.003, 0.007]	[0.005, 0.017]	[-0.184, -0.168]
Tenure 10	-0.025	0.003	0.011	-0.177
	[-0.029, -0.021]	[-0.002, 0.008]	[0.005, 0.017]	[-0.186, -0.168]
Tenure 11	-0.026	0.003	0.010	-0.179
	[-0.031, -0.021]	[-0.003, 0.009]	[0.003, 0.017]	[-0.188, -0.170]
Tenure 12	-0.025	0.004	0.012	-0.179
	[-0.030, -0.020]	[-0.003, 0.011]	[0.005, 0.019]	[-0.188, -0.170]
Tenure 13	-0.025	0.002	0.014	-0.180
	[-0.030, -0.020]	[-0.005, 0.009]	[0.006, 0.022]	[-0.190, -0.170]
Tenure 14	-0.024	0.003	0.014	-0.181
	[-0.030, -0.018]	[-0.005, 0.011]	[0.005, 0.023]	[-0.191, -0.171]
Tenure 15	-0.024	0.004	0.015	-0.180
	[-0.030, -0.018]	[-0.004, 0.012]	[0.006, 0.024]	[-0.191, -0.169]
Tenure 16+	-0.022	0.004	0.018	-0.180
	[-0.029, -0.015]	[-0.006, 0.014]	[0.007, 0.029]	[-0.192, -0.168]
$Balance^3$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Balance^2$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Balance$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Credit\ Limit^3$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Credit\ Limit^2$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Credit\ Limit$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Utilization^3$	0.000	0.004	-0.001	-0.001
	[0.000, 0.000]	[-0.003, 0.011]	[-0.001, -0.001]	[-0.001, -0.001]
$Utilization^2$	-0.007	0.000	-0.010	-0.006
	[-0.010, -0.004]	[-0.006, 0.006]	[-0.021, 0.001]	[-0.008, -0.004]
$Utilization$	0.047	0.003	0.059	0.041
	[0.041, 0.053]	[-0.006, 0.012]	[0.045, 0.073]	[0.032, 0.050]
$Charge-off\ Rate^3$	-1.304	-1.432	-1.602	-3.704
	[-1.696, -0.912]	[-2.693, -0.171]	[-2.098, -1.106]	[-5.540, -1.868]
$Charge-off\ Rate^2$	1.202	1.259	1.601	3.482
	[0.860, 1.544]	[0.181, 2.337]	[1.154, 2.048]	[2.262, 4.702]
$Charge-off\ Rate$	-0.119	0.098	-0.339	-0.520
	[-0.192, -0.046]	[-0.039, 0.235]	[-0.444, -0.234]	[-0.694, -0.346]
$Monthly\ Purchase^3$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Monthly\ Purchase^2$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Monthly\ Purchase$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
R2	0.254	0.252	0.268	0.218
Number of observations	2,392,275	273,532	1,338,862	501,489
Number of cards	230,531	31,735	131,318	47,188

Note. The numbers inside the parentheses are 95% confidence intervals. The standard errors were corrected, for clustering by cards.

Table A2.4. Coefficient Estimates for the Probability of Cards Having a Cash Advance or an Over-Limit Fees (Equation 3.1)

	Dependent Variable			
	P(Cash Advance Fee)			P(Over-Limit Fee)
IV	Cards Type			
	All	Low-risk cards (Low charge-off rate)	High-risk cards (High charge-off rate)	All
Tenure 3	-0.004	0.002	-0.015	0.004
	[-0.005, -0.003]	[0.000, 0.004]	[-0.018, -0.012]	[0.003, 0.005]
Tenure 4	-0.010	0.000	-0.024	0.008
	[-0.011, -0.009]	[-0.002, 0.002]	[-0.027, -0.021]	[0.007, 0.009]
Tenure 5	-0.013	0.000	-0.029	0.009
	[-0.015, -0.011]	[-0.002, 0.002]	[-0.033, -0.025]	[0.008, 0.010]
Tenure 6	-0.014	-0.001	-0.035	0.013
	[-0.016, -0.012]	[-0.004, 0.002]	[-0.040, -0.030]	[0.011, 0.015]
Tenure 7	-0.015	-0.001	-0.038	0.015
	[-0.017, -0.013]	[-0.004, 0.002]	[-0.043, -0.033]	[0.013, 0.017]
Tenure 8	-0.016	-0.001	-0.039	0.015
	[-0.018, -0.014]	[-0.005, 0.003]	[-0.045, -0.033]	[0.013, 0.017]
Tenure 9	-0.017	-0.003	-0.040	0.015
	[-0.020, -0.014]	[-0.007, 0.001]	[-0.047, -0.033]	[0.013, 0.017]
Tenure 10	-0.017	-0.003	-0.039	0.015
	[-0.020, -0.014]	[-0.008, 0.002]	[-0.046, -0.032]	[0.012, 0.018]
Tenure 11	-0.017	-0.003	-0.040	0.015
	[-0.020, -0.014]	[-0.008, 0.002]	[-0.048, -0.032]	[0.012, 0.018]
Tenure 12	-0.018	-0.004	-0.040	0.014
	[-0.022, -0.014]	[-0.010, 0.002]	[-0.049, -0.031]	[0.011, 0.017]
Tenure 13	-0.018	-0.005	-0.041	0.014
	[-0.022, -0.014]	[-0.011, 0.001]	[-0.050, -0.032]	[0.010, 0.018]
Tenure 14	-0.018	-0.004	-0.040	0.015
	[-0.022, -0.014]	[-0.011, 0.003]	[-0.050, -0.030]	[0.011, 0.019]
Tenure 15	-0.019	-0.007	-0.040	0.014
	[-0.024, -0.014]	[-0.015, 0.001]	[-0.051, -0.029]	[0.009, 0.019]
Tenure 16+	-0.019	-0.006	-0.041	0.016
	[-0.024, -0.014]	[-0.015, 0.003]	[-0.054, -0.028]	[0.011, 0.021]
$Balance^3$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Balance^2$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Balance$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Credit\ Limit^3$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Credit\ Limit^2$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Credit\ Limit$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Utilization^3$	0.000	0.000	-0.001	0.002
	[0.000, 0.000]	[0.000, 0.000]	[-0.003, 0.001]	[0.000, 0.004]
$Utilization^2$	-0.008	-0.002	-0.029	0.048
	[-0.014, -0.002]	[-0.005, 0.001]	[-0.066, 0.008]	[0.002, 0.094]
$Utilization$	0.017	0.016	0.035	0.102
	[0.009, 0.025]	[0.009, 0.023]	[-0.011, 0.081]	[0.056, 0.148]
$Charge-off\ Rate^3$	4.380	4.433	4.758	-0.165
	[4.094, 4.666]	[3.891, 4.975]	[4.208, 5.308]	[-0.487, 0.157]
$Charge-off\ Rate^2$	-5.203	-4.906	-5.234	-0.537
	[-5.463, -4.943]	[-5.412, -4.400]	[-5.718, -4.750]	[-0.848, -0.226]
$Charge-off\ Rate$	1.178	1.065	1.057	0.917
	[1.120, 1.236]	[0.958, 1.172]	[0.949, 1.165]	[0.833, 1.001]
$Monthly\ Purchase^3$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Monthly\ Purchase^2$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Monthly\ Purchase$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
R2	0.362	0.301	0.388	0.367
Number of observations	2,273,923	740,566	499,526	2,273,923
Number of cards	222,956	57,243	53,534	222,956

Note. The numbers inside the parentheses are 95% confidence intervals. The standard errors were corrected, for clustering by cards.

Table A2.5. Coefficient Estimates for the Probability of Cards Having a Late Payment Fee (Equation 3.1; Balanced Panel)

		Cards Type		
IV	All	Always-Autopay	Always-Non-Autopay	Switched-To-Autopay
Tenure 2	-0.027	0.001	0.006	-0.127
	[-0.030, -0.024]	[0.000, 0.002]	[0.002, 0.010]	[-0.138, -0.116]
Tenure 3	-0.034	0.001	0.006	-0.157
	[-0.037, -0.031]	[0.000, 0.002]	[0.003, 0.009]	[-0.166, -0.148]
Tenure 4	-0.036	0.001	0.007	-0.166
	[-0.039, -0.033]	[0.000, 0.002]	[0.004, 0.010]	[-0.175, -0.157]
Tenure 5	-0.041	0.001	0.004	-0.178
	[-0.044, -0.038]	[0.000, 0.002]	[0.001, 0.007]	[-0.187, -0.169]
Tenure 6	-0.042	0.002	0.004	-0.182
	[-0.045, -0.039]	[0.001, 0.003]	[0.001, 0.007]	[-0.191, -0.173]
Tenure 7	-0.044	0.001	0.004	-0.186
	[-0.047, -0.041]	[0.000, 0.002]	[0.001, 0.007]	[-0.195, -0.177]
Tenure 8	-0.046	0.001	0.002	-0.188
	[-0.049, -0.043]	[0.000, 0.002]	[-0.001, 0.005]	[-0.197, -0.179]
Tenure 9	-0.046	0.003	0.003	-0.191
	[-0.049, -0.043]	[0.002, 0.004]	[0.000, 0.006]	[-0.200, -0.182]
Tenure 10	-0.047	0.002	0.002	-0.192
	[-0.050, -0.044]	[0.001, 0.003]	[-0.001, 0.005]	[-0.201, -0.183]
Tenure 11	-0.047	0.003	0.002	-0.194
	[-0.050, -0.044]	[0.002, 0.004]	[-0.001, 0.005]	[-0.203, -0.185]
Tenure 12	-0.047	0.004	0.003	-0.195
	[-0.050, -0.044]	[0.002, 0.006]	[0.000, 0.006]	[-0.204, -0.186]
Tenure 13	-0.047	0.002	0.003	-0.197
	[-0.050, -0.044]	[0.001, 0.003]	[0.000, 0.006]	[-0.206, -0.188]
Tenure 14	-0.047	0.003	0.005	-0.198
	[-0.050, -0.044]	[0.001, 0.005]	[0.002, 0.008]	[-0.207, -0.189]
Tenure 15	-0.047	0.004	0.004	-0.198
	[-0.050, -0.044]	[0.002, 0.006]	[0.001, 0.007]	[-0.207, -0.189]
$Balance^3$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Balance^2$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Balance$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Credit\ Limit^3$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Credit\ Limit^2$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Credit\ Limit$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Utilization^3$	0.000	0.006	0.000	0.009
	[0.000, 0.000]	[0.000, 0.012]	[-0.001, 0.001]	[0.005, 0.013]
$Utilization^2$	-0.008	0.002	-0.005	-0.107
	[-0.011, -0.005]	[-0.006, 0.010]	[-0.017, 0.007]	[-0.144, -0.070]
$Utilization$	0.050	-0.002	0.058	0.152
	[0.043, 0.057]	[-0.011, 0.007]	[0.043, 0.073]	[0.110, 0.194]
$Charge-off\ Rate^3$	-1.486	-2.954	-1.806	-4.330
	[-2.198, -0.774]	[-5.903, -0.005]	[-2.627, -0.985]	[-6.495, -2.165]
$Charge-off\ Rate^2$	1.028	2.856	1.527	2.668
	[0.476, 1.580]	[0.664, 5.048]	[0.844, 2.210]	[1.208, 4.128]
$Charge-off\ Rate$	0.080	-0.153	-0.189	0.070
	[-0.025, 0.185]	[-0.330, 0.024]	[-0.337, -0.041]	[-0.150, 0.290]
$Monthly\ Purchase^3$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Monthly\ Purchase^2$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
$Monthly\ Purchase$	0.000	0.000	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]
R2	0.220	0.179	0.229	0.215
Number of observations	1,139,044	99,492	639,956	239,598
Number of cards	81,005	6,728	45,835	17,237

Note. The numbers inside the parentheses are 95% confidence intervals. The standard errors were corrected, for clustering by cards.

Table A2.6. Coefficient Estimates for the Probability of Cards Having a Cash Advance or an Over-Limit Fees (Equation 3.1; Balanced Panel)

IV	Dependent Variable	
	P(Cash Advance Fee)	P(Over-Limit Fee)
Tenure 3	-0.005	0.005
	[-0.007, -0.003]	[0.004, 0.006]
Tenure 4	-0.010	0.008
	[-0.012, -0.008]	[0.007, 0.009]
Tenure 5	-0.014	0.010
	[-0.016, -0.012]	[0.009, 0.011]
Tenure 6	-0.014	0.015
	[-0.016, -0.012]	[0.014, 0.016]
Tenure 7	-0.017	0.017
	[-0.019, -0.015]	[0.016, 0.018]
Tenure 8	-0.018	0.018
	[-0.020, -0.016]	[0.017, 0.019]
Tenure 9	-0.018	0.020
	[-0.020, -0.016]	[0.019, 0.021]
Tenure 10	-0.019	0.020
	[-0.021, -0.017]	[0.019, 0.021]
Tenure 11	-0.019	0.020
	[-0.021, -0.017]	[0.019, 0.021]
Tenure 12	-0.019	0.020
	[-0.021, -0.017]	[0.019, 0.021]
Tenure 13	-0.020	0.019
	[-0.022, -0.018]	[0.018, 0.020]
Tenure 14	-0.019	0.022
	[-0.021, -0.017]	[0.021, 0.023]
Tenure 15	-0.021	0.021
	[-0.023, -0.019]	[0.020, 0.022]
$Balance^3$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Balance^2$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Balance$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Credit\ Limit^3$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Credit\ Limit^2$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Credit\ Limit$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Utilization^3$	0.000	0.001
	[0.000, 0.000]	[-0.001, 0.003]
$Utilization^2$	-0.007	0.032
	[-0.014, 0.000]	[-0.019, 0.083]
$Utilization$	0.008	0.134
	[-0.002, 0.018]	[0.078, 0.190]
$Charge-off\ Rate^3$	5.106	-0.458
	[4.581, 5.631]	[-0.970, 0.054]
$Charge-off\ Rate^2$	-5.860	-0.281
	[-6.290, -5.430]	[-0.732, 0.170]
$Charge-off\ Rate$	1.311	0.883
	[1.225, 1.397]	[0.780, 0.986]
$Monthly\ Purchase^3$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Monthly\ Purchase^2$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Monthly\ Purchase$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
R2	0.332	0.343
Number of observations	1,087,827	1,087,827
Number of cards	81,005	81,005

Note. The numbers inside the parentheses are 95% confidence intervals. The standard errors were corrected, for clustering by cards.

Table A2.7.Coefficient Estimates for the Probability of Cards Having a Late Payment Fee after a First Fee (Equation 3.2)

IV	Always-Non-Autopay	Switched-To-Autopay
Months fr 1st Late Fee 2	0.017	-0.051
	[0.011, 0.023]	[-0.058, -0.044]
Months fr 1st Late Fee 3	0.009	-0.076
	[0.002, 0.016]	[-0.084, -0.068]
Months fr 1st Late Fee 4	0.005	-0.088
	[-0.003, 0.013]	[-0.096, -0.080]
Months fr 1st Late Fee 5	0.008	-0.094
	[-0.002, 0.018]	[-0.103, -0.085]
Months fr 1st Late Fee 6	0.008	-0.097
	[-0.004, 0.020]	[-0.106, -0.088]
Months fr 1st Late Fee 7	0.009	-0.103
	[-0.005, 0.023]	[-0.113, -0.093]
Months fr 1st Late Fee 8	0.014	-0.107
	[-0.002, 0.030]	[-0.118, -0.096]
Months fr 1st Late Fee 9	0.018	-0.110
	[0.000, 0.036]	[-0.121, -0.099]
Months fr 1st Late Fee 10	0.013	-0.113
	[-0.007, 0.033]	[-0.125, -0.101]
Months fr 1st Late Fee 11	0.024	-0.112
	[0.002, 0.046]	[-0.125, -0.099]
Months fr 1st Late Fee 12	0.023	-0.115
	[-0.001, 0.047]	[-0.129, -0.101]
Months fr 1st Late Fee 13+	0.028	-0.119
	[-0.001, 0.057]	[-0.135, -0.103]
$Balance^3$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Balance^2$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Balance$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Credit\ Limit^3$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Credit\ Limit^2$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
Credit Limit	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Utilization^3$	-0.020	-0.004
	[-0.031, -0.009]	[-0.007, -0.001]
$Utilization^2$	-0.072	0.035
	[-0.117, -0.027]	[0.004, 0.066]
$Utilization$	0.171	-0.013
	[0.104, 0.238]	[-0.049, 0.023]
$Charge - off\ Rate^3$	-1.509	-5.741
	[-2.058, -0.960]	[-7.540, -3.942]
$Charge - off\ Rate^2$	1.673	5.936
	[1.124, 2.222]	[4.616, 7.256]
$Charge - off\ Rate$	-0.702	-1.419
	[-0.851, -0.553]	[-1.647, -1.191]
$Monthly\ Purchase^3$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Monthly\ Purchase^2$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
$Monthly\ Purchase$	0.000	0.000
	[0.000, 0.000]	[0.000, 0.000]
R2	0.326	0.279
Number of observations	284,857	147,715
Number of cards	35,095	14,420

Note. The numbers inside the parentheses are 95% confidence intervals. The standard errors were corrected, for clustering by cards.

Table A2.8 Coefficient Estimates for Monthly Purchase before and after a Last Over-Limit Fee (Equation 3.3)

IV	Dependent Variable
	Monthly Purchase
Months fr Last OL Fee -11	-7.518
	[-27.562, 12.527]
Months fr Last OL Fee -10	8.384
	[-15.354, 32.123]
Months fr Last OL Fee -9	12.787
	[-15.125, 40.700]
Months fr Last OL Fee -8	31.510
	[-0.944, 63.963]
Months fr Last OL Fee -7	35.320
	[-1.021, 71.661]
Months fr Last OL Fee -6	46.598
	[5.157, 88.038]
Months fr Last OL Fee -5	52.079
	[6.770, 97.389]
Months fr Last OL Fee -4	75.178
	[24.710, 125.646]
Months fr Last OL Fee -3	88.226
	[32.815, 143.637]
Months fr Last OL Fee -2	120.286
	[59.636, 180.936]
Months fr Last OL Fee -1	217.521
	[151.071, 283.971]
Months fr Last OL Fee 0	275.926
	[203.803, 348.048]
Months fr Last OL Fee 1	24.136
	[-52.145, 100.418]
Months fr Last OL Fee 2	-35.510
	[-116.758, 45.738]
Months fr Last OL Fee 3	-56.535
	[-142.756, 29.685]
Months fr Last OL Fee 4	-76.926
	[-167.825, 13.973]
Months fr Last OL Fee 5	-90.253
	[-187.076, 6.570]
Months fr Last OL Fee 6	-103.492
	[-205.388, -1.595]
Months fr Last OL Fee 7	-129.699
	[-237.769, -21.629]
Months fr Last OL Fee 8	-134.928
	[-247.412, -22.445]
Months fr Last OL Fee 9	-139.185
	[-257.521, -20.850]
Months fr Last OL Fee 10	-175.677
	[-299.601, -51.753]
Months fr Last OL Fee 11	-160.814
	[-289.868, -31.759]
Months fr Last OL Fee 12+	-184.964
	[-326.451, -43.478]
$Balance^3$	0.000
	[0.000, 0.000]
$Balance^2$	0.000
	[0.000, 0.000]
$Balance$	0.151
	[0.111, 0.190]
$Credit\ Limit^3$	0.000
	[0.000, 0.000]
$Credit\ Limit^2$	0.000
	[0.000, 0.000]
Credit Limit	0.118
	[0.010, 0.226]
$Utilization^3$	-0.007
	[-0.009, -0.005]
$Utilization^2$	23.690
	[17.672, 29.707]
$Utilization$	-530.719
	[-575.371, -486.067]
$Charge-off\ Rate^3$	-1782.695
	[-2,289.564, -1,275.827]
$Charge-off\ Rate^2$	2637.753
	[2,086.610, 3,188.896]
$Charge-off\ Rate$	-1213.712
	[-1,382.190, -1,045.234]
R2	0.553
Number of observations	234,232
Number of cards	17,606

Note. The numbers inside the parentheses are 95% confidence intervals. The standard errors were corrected, for clustering by cards.

Appendix 3 Supplemental Materials for Chapter 4

A3.1 Descriptive Statistics

Table A3.1. Statistics

Statistics	Mean	S.D.	25th percentile	Median	75th percentile
Minimum (£)	54.23	62.30	18.00	32.00	67.26
Balance (£)	2558.87	2704.58	707.24	1637.00	3426.66
Credit limit (£)	5577.16	4011.22	2500.00	4600.00	7750.00
Utilization (%)	52.22	34.79	19.84	50.64	86.14
Merchant APR (%)	17.81	7.93	16.70	18.32	22.45
Cash APR (%)	24.50	4.64	22.94	24.93	27.95
Monthly purchase (£)	238.58	587.74	0.00	12.30	233.58
Repayment (£)	247.52	564.50	50.00	100.00	200.00

Note. N = 5,634,840 for 526,365 cards.

A3.2 Underpaying, Overpaying, and Rounding Behavior

Our main analysis focused on card holders rounding up the minimum to round or prominent numbers. However, a part of card holders erroneously rounded ‘down’ the minimum, leading to missing the minimum repayment and having a late payment fee. We found that 5.6% of all missed repayments were due to rounding down the minimum to a nearest pounds, a nearest multiple of £5, or a nearest multiple of £10. For example, someone might repay £10 in response to a minimum payment of £11.32. Because the difference between the minimum and the repaid round number is small, the missed repayments resulting from the rounding-down behavior are unlikely to be due to card holders’ financial difficulty. Therefore, the rounding-down behavior is likely to be because, under the constraints of time or the lack of attention, card holders mistakenly rounded down the minimum just following their preference for round numbers without a serious consideration. Alternatively, card holders might misunderstand the minimum as only a recommended repayment amount.

If misunderstanding the required minimum is the main source of the rounding-down behavior, we expect that the rounding-down behavior are mostly seen for relatively new cards because card holders’ understanding of the minimum is likely to be corrected over time. However, the median card age is 70 months among cards with at least one rounding-down behavior. This means that even experienced card holders mistakenly round down the minimum. Thus the rounding-down behavior is likely to be due to a lack of attention possibly due to the constraints of time and cognitive effort. (Note that 81% and 13% of card holders with at least one rounding-down behavior did so only once and twice, respectively.

This indicates that card holders tend to learn from the experience and did not repeat the rounding-down behavior many times.)

Also, we found that 28% of repayments over the full balance (i.e., overpaying) were due to rounding up the balance to a nearest pounds, a nearest multiple of £5, or a nearest multiple of £10. Similarly, 36% of over-repayments were made at any multiple of £10. These findings show another evidence for people’s preference for round numbers.

Appendix 4 Supplemental Materials for Chapter 5

A4.1 Demographic Information about Participants

Table A4.1. The Distribution of Participants' Gender

Gender	Num. of participants	Proportion (%)
Male	735	45.0%
Female	691	42.3%

Note. In a regression, *Gender* is a categorical variable with two levels.

Table A4.2. The Distribution of Participants' Age

Age	Num. of participants	Proportion (%)
18 - 24	104	6.4%
25 - 34	253	15.5%
35 - 44	224	13.7%
45 - 54	220	13.5%
55 - 64	234	14.3%
65+	391	23.9%

Note. In a regression, *Age* is a categorical variable with six levels.

Table A4.3. The Distribution of Participants' Annual Household Income

Income	Num. of participants	Proportion (%)
Up to £7,000	47	2.9%
£7,001 - £14,000	148	9.1%
£14,001 - £21,000	256	15.7%
£21,001 - £28,000	252	15.4%
£28,001 - £34,000	216	13.2%
£34,001 - £41,000	147	9.0%
£41,001 - £48,000	88	5.4%
£48,001 - £55,000	49	3.0%
£55,001 - £62,000	39	2.4%
£62,001 - £69,000	13	0.8%
£69,001 - £76,000	14	0.9%
£76,001 - £83,000	5	0.3%
£83,001 or more	18	1.1%
Prefer not to answer	134	8.2%
Don't know	0	0.0%

Note. In a regression, *Income* is a categorical variable with 13 levels. ('Prefer not to answer' and 'Don't know' were excluded.)

Table A4.4. The Distribution of Participants' House Ownership Status

House Ownership	Num. of participants	Proportion (%)
Owned outright	627	38.3%
Owned with a mortgage or loan	482	29.5%
Rented from the council	43	2.6%
Rented from a housing association	66	4.0%
Rented from a someone else	188	11.5%
Rent free	20	1.2%
Refused	0	0.0%

Note. In a regression, *House* is a categorical variable with six levels. ('Refused' was excluded.)

Table A4.5. The Distribution of Participants' Education Level

Education	Num. of participants	Proportion (%)
No formal education	11	0.7%
Primary	3	0.2%
Secondary school, high school, NVQ1-3	648	39.6%
University or equivalent, NVQ4	521	31.9%
Higher university, NVQ5	183	11.2%
Still in full time education	37	2.3%
Don't know	5	0.3%
Refused	18	1.1%

Note. In a regression, *Education* is a categorical variable with six levels. ('Don't know' and 'Refused' were excluded.)

A4.2 Phrases of the Questions in the Experiment

(a) The question about usual repayment behavior

“Which of the following statements best describes how you repay your credit card?”

Participants selected one answer from the following six descriptions.

1. I tend to pay the minimum payment amount
2. I tend to pay a set amount every month, more than the minimum but less than the full balance
3. I tend to repay an amount that varies between months, depending on how much I can afford that month
4. I tend to pay the full balance
5. I don’t use my credit card
6. Don’t know

(b) The estimation of the popularity of minimum repayments

“Out of 100 people like you, how many people do you think pay the minimum payment on their credit card bill?”

(c) The estimation of the popularity of full repayments

“Out of 100 people like you, how many people do you think pay their credit card bill in full?”

A4.3 Participants’ Credit Card Profile

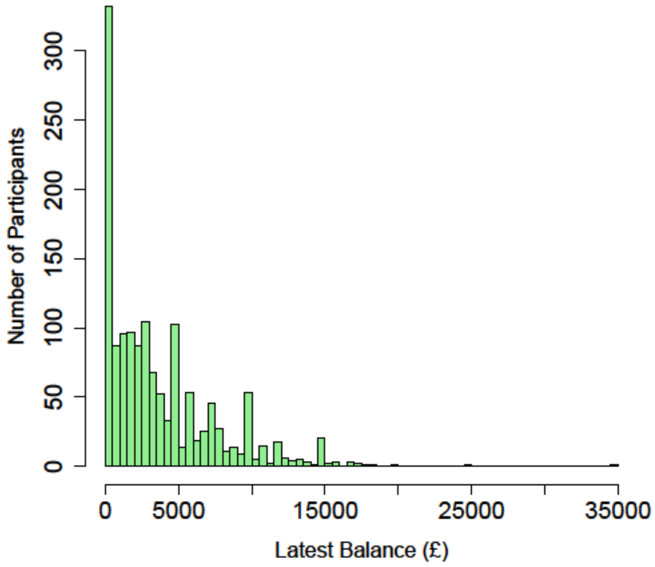

Figure A4.1.The distribution of participants’ latest credit card balance. The width of each bar is £500.

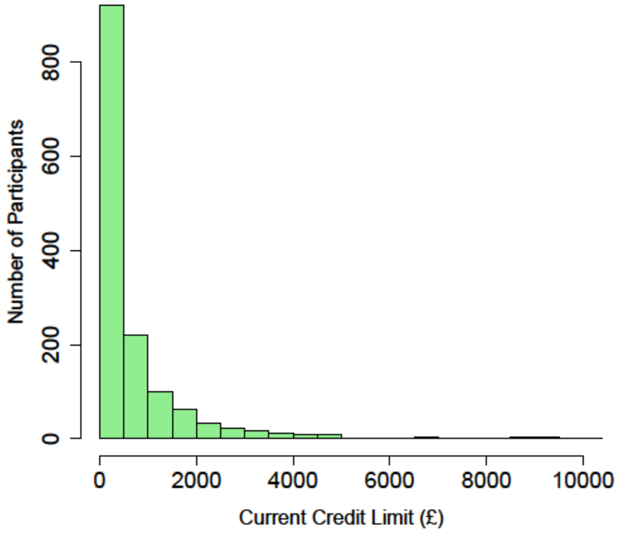

Figure A4.2. The distribution of participants’ current credit limit. The width of each bar is £500. Four participants have credit limit greater than £10,000 and are not included in this figure. The maximum value is £72,850.

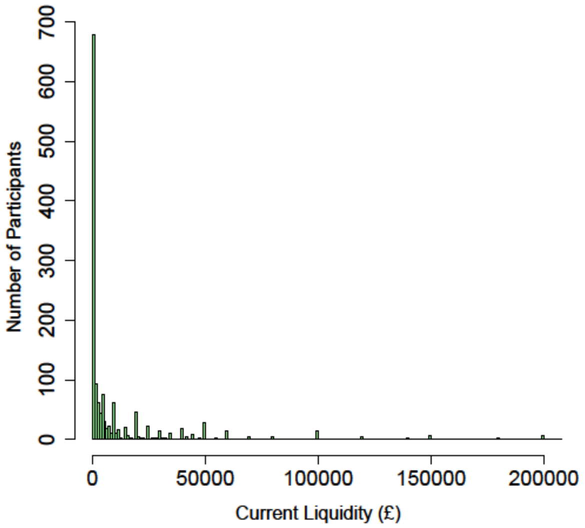

Figure A4.3. The distribution of participants' current liquidity. The width of each bar is £1,000. 10 participants have credit limit greater than £200,000 and are not included in this figure. The maximum value is £1,000,000.

A4.4 The Effect of Social Nudge on Participants' Belief about the Popularity of Minimum Repayments

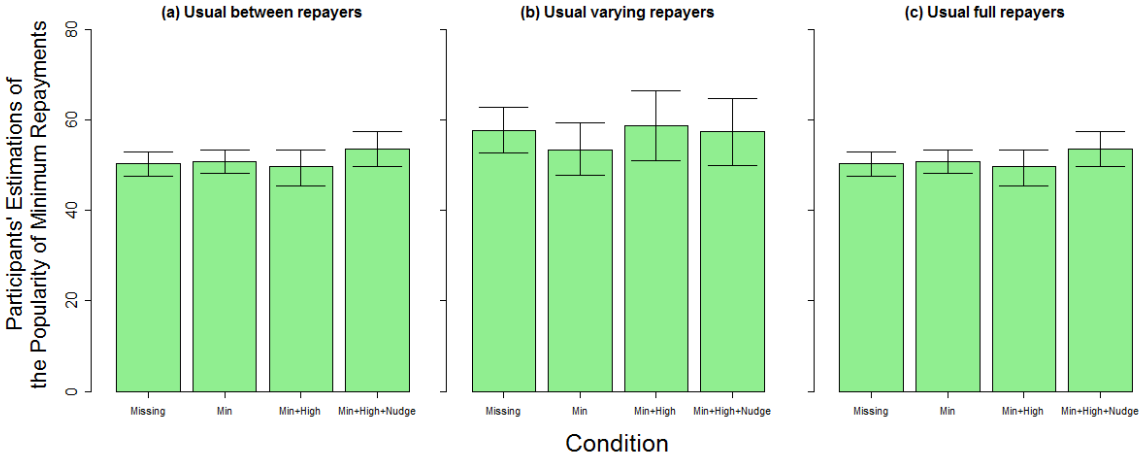

Figure A4.4. The mean estimation of the popularity of minimum repayments for Between, Varying, and Full repayers. Panel (a) shows the mean estimation of usual between repayers. Panel (b) shows the mean estimation of for usual varying repayers. Panel (c) shows the mean estimation of usual full repayers. On the x-axis, 'Missing' represents Missing-Minimum Condition, 'Min' represents Minimum Condition, 'Min+High' represents Minimum-and-High-Attractor-without-Social-Nudge Condition, and 'Min+High+Nudge' represents Minimum-and-High-Attractor-with-Social-Nudge Condition. The error bars are 95% confidence intervals computed by the bootstrap method with 1,000 resamples.

A4.5 Prediction of the Multinomial Regression with Equation 5.2

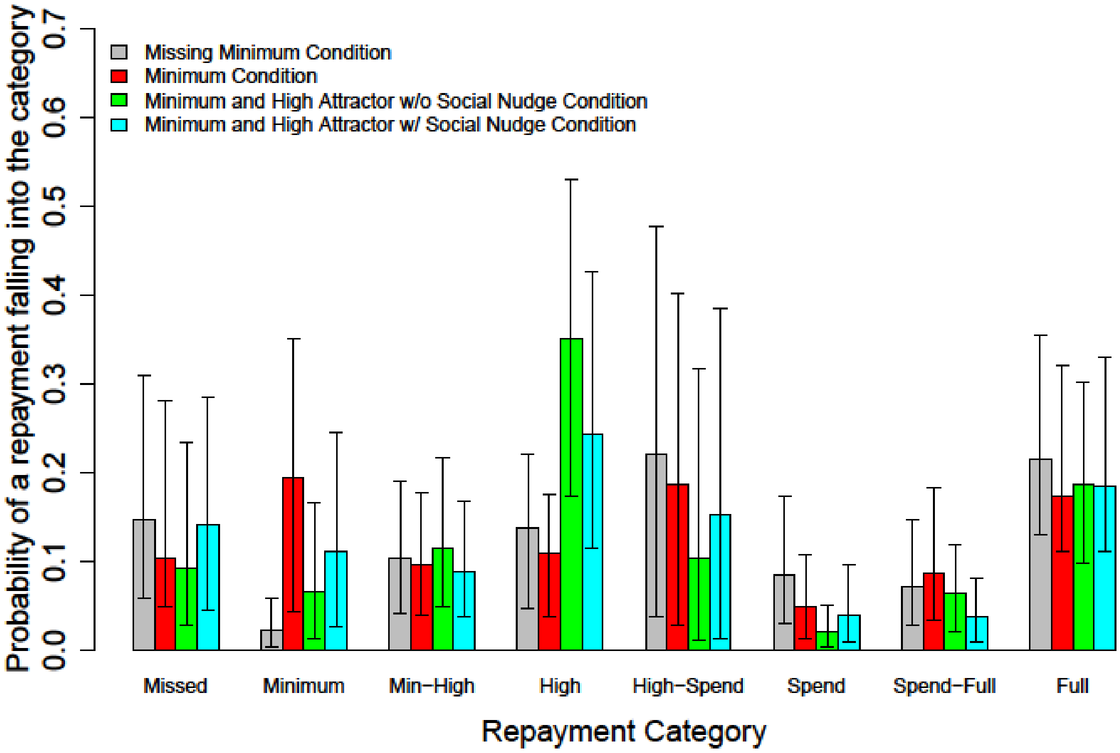

Figure A4.5. Model predictions (Equation 5.2) for the distribution of participants' repayments to a mock bill. Each panel represents an experimental condition which differ in information in the mock bill. The error bars are 95% confidence intervals computed by the bootstrap method with 1,000 resamples. In the predictions, Gender was set at male. House ownership status was set as 'Owned with mortgage or loan'. Educational level was set at NVQ1-3. Income was set as £21,001-38,000. Age was set 45-54. The median values were applied to Latest balance, Current credit limit, and Current liquidity.

A4.6 Regression Tables

Table A4.6. Coefficients from a Linear Regression with Equation 5.1

IV	Coefficient	LL	UL	S.E.	t value	Pr(>|t|)
Intercept	54.26	36.70	71.81	8.96	6.06	0.000000
Usual repayment behavior = Minimum	9.42	3.96	14.87	2.78	3.38	0.000719
Usual repayment behavior = Between	1.68	-3.22	6.58	2.50	0.67	0.501871
Usual repayment behavior = Full	-4.03	-7.94	-0.12	1.99	-2.02	0.043119
Minimum in the bill	-0.82	-3.90	2.26	1.57	-0.52	0.602183
High attractor in the bill	-0.55	-4.44	3.34	1.99	-0.28	0.782317
Social nudge in the bill	3.40	-1.00	7.80	2.24	1.52	0.129508
Female	3.69	1.14	6.25	1.31	2.83	0.004659
Age = 25-34	0.68	-5.96	7.33	3.39	0.20	0.840231
Age = 35-44	-2.95	-9.87	3.98	3.53	-0.83	0.404091
Age = 45-54	-0.90	-7.95	6.15	3.60	-0.25	0.802746
Age = 55-64	-7.31	-14.59	-0.03	3.71	-1.97	0.049011
Age = 65+	-7.24	-14.25	-0.24	3.58	-2.03	0.042772
Education = "Primary"	-14.58	-49.41	20.25	17.77	-0.82	0.411860
Education = "Secondary school, high school, NVQ1-3"	0.85	-14.95	16.66	8.06	0.11	0.915883
Education = "University or equivalent, NVQ4"	0.84	-15.03	16.70	8.09	0.10	0.917818
Education = "Higher university, NVQ5"	-1.25	-17.41	14.92	8.25	-0.15	0.879823
Education = "Still in full time education"	-8.30	-25.99	9.38	9.02	-0.92	0.357531
Income = £7,001-14,000	2.11	-5.83	10.06	4.05	0.52	0.601952
Income = £14,001-21,000	4.40	-3.14	11.94	3.85	1.14	0.252655
Income = £21,001-28,000	4.33	-3.22	11.88	3.85	1.12	0.261371
Income = £28,001-34,000	1.92	-5.74	9.57	3.91	0.49	0.623693
Income = £34,001-41,000	3.69	-4.25	11.64	4.05	0.91	0.362187
Income = £41,001-48,000	5.06	-3.45	13.57	4.34	1.17	0.243487
Income = £48,001-55,000	5.17	-4.57	14.91	4.97	1.04	0.298177
Income = £55,001-62,000	-2.67	-12.83	7.49	5.18	-0.52	0.606232
Income = £62,001-69,000	18.36	4.09	32.63	7.28	2.52	0.011687
Income = £69,001-76,000	7.20	-7.07	21.48	7.28	0.99	0.322547
Income = £76,001-83,000	6.50	-14.53	27.52	10.73	0.61	0.544733
Income = £83,001+	-13.28	-26.39	-0.17	6.69	-1.99	0.047078
House = "Owned with a mortgage or loan"	0.00	-3.33	3.33	1.70	0.00	0.998155
House = "Rented from the council"	5.14	-2.70	12.98	4.00	1.28	0.198912
House = "Rented from a housing association"	1.30	-4.89	7.49	3.16	0.41	0.680301
House = "Rented from a someone else"	0.72	-3.91	5.35	2.36	0.30	0.761062
House = "Rent free"	11.34	-0.21	22.89	5.89	1.93	0.054216
Latest Balance (× 10,000)	-1.66	-5.15	1.83	1.78	-0.93	0.352119
Current Credit Limit (× 10,000)	0.48	-4.93	5.88	2.76	0.17	0.863172
Current Liquidity (× 10,000)	-0.08	-0.32	0.17	0.12	-0.61	0.541930

N = 1231

R Square = .11

Table A4.7. Coefficients from a Multinomial Regression with Equation 5.2

IV	Repayment Category	Coefficient	LL	UL	S.E.	z value	Pr(>|z|)
Intercept	Missed	2.27	-0.61	5.15	1.47	1.54	0.122649
	Between Minimum and High Attractor	0.60	-2.38	3.59	1.52	0.40	0.691203
	Around High Attractor	0.08	-3.07	3.23	1.61	0.05	0.961376
	Between High Attractor and Spending	-31.28	-6963.04	6900.47	3536.61	-0.01	0.992942
	Around Spending	-16.52	-4835.45	4802.41	2458.64	-0.01	0.994640
	Between Spending and Full	-16.36	-5409.18	5376.47	2751.44	-0.01	0.995257
	Full	0.73	-2.50	3.96	1.65	0.44	0.656791
Minimum in the bill	Missed	-2.49	-3.49	-1.49	0.51	-4.87	0.000001
	Between Minimum and High Attractor	-2.23	-3.12	-1.34	0.45	-4.92	0.000001
	Around High Attractor	-2.38	-3.34	-1.42	0.49	-4.85	0.000001
	Between High Attractor and Spending	-2.32	-3.55	-1.08	0.63	-3.68	0.000234
	Around Spending	-2.70	-3.68	-1.71	0.50	-5.37	0.000000
	Between Spending and Full	-1.95	-2.90	-1.01	0.48	-4.05	0.000052
	Full	-2.36	-3.24	-1.49	0.45	-5.27	0.000000
High Attractor in the bill	Missed	0.95	-0.21	2.11	0.59	1.61	0.107362
	Between Minimum and High Attractor	1.25	0.35	2.16	0.46	2.71	0.006700
	Around High Attractor	2.22	1.28	3.17	0.48	4.62	0.000004
	Between High Attractor and Spending	0.47	-1.14	2.09	0.82	0.58	0.564478
	Around Spending	0.19	-1.08	1.47	0.65	0.30	0.766257
	Between Spending and Full	0.78	-0.23	1.78	0.51	1.51	0.129881
	Full	1.14	0.25	2.03	0.45	2.52	0.011791
Social Nudge in the bill	Missed	-0.08	-1.33	1.18	0.64	-0.12	0.901968
	Between Minimum and High Attractor	-0.76	-1.80	0.27	0.53	-1.44	0.149463
	Around High Attractor	-0.86	-1.89	0.17	0.52	-1.64	0.100115
	Between High Attractor and Spending	-0.11	-1.87	1.64	0.90	-0.13	0.899654
	Around Spending	0.14	-1.28	1.57	0.73	0.20	0.845156
	Between Spending and Full	-1.03	-2.24	0.19	0.62	-1.66	0.096962
	Full	-0.50	-1.51	0.50	0.51	-0.98	0.326356
House "Owned with a mortgage or loan"	Missed	-0.69	-1.67	0.29	0.50	-1.39	0.165257
	Between Minimum and High Attractor	-0.31	-1.16	0.55	0.43	-0.70	0.481730
	Around High Attractor	-0.20	-1.09	0.70	0.46	-0.43	0.665442
	Between High Attractor and Spending	0.43	-0.99	1.85	0.72	0.60	0.551793
	Around Spending	-1.08	-2.04	-0.12	0.49	-2.21	0.027070
	Between Spending and Full	-1.12	-2.02	-0.22	0.46	-2.44	0.014641
	Full	-1.33	-2.13	-0.53	0.41	-3.24	0.001178
House "Rented from the council"	Missed	-1.79	-3.45	-0.14	0.85	-2.12	0.033869
	Between Minimum and High Attractor	-0.08	-1.28	1.12	0.61	-0.13	0.896862
	Around High Attractor	-1.11	-2.62	0.41	0.77	-1.43	0.152608
	Between High Attractor and Spending	-16.73	-3184.99	3151.54	1616.46	-0.01	0.991743
	Around Spending	-18.42	-3041.14	3004.30	1542.21	-0.01	0.990470
	Between Spending and Full	-2.47	-4.27	-0.68	0.92	-2.70	0.006941
	Full	-3.09	-4.59	-1.59	0.77	-4.04	0.000054
House "Rented from a housing association"	Missed	-0.68	-2.03	0.66	0.68	-1.00	0.317483
	Between Minimum and High Attractor	-0.25	-1.45	0.94	0.61	-0.42	0.676082
	Around High Attractor	-0.55	-1.87	0.77	0.67	-0.82	0.412445
	Between High Attractor and Spending	0.41	-1.68	2.49	1.06	0.38	0.702403
	Around Spending	-0.96	-2.39	0.47	0.73	-1.32	0.186844
	Between Spending and Full	-1.39	-2.79	0.02	0.72	-1.94	0.052765
	Full	-1.87	-3.07	-0.68	0.61	-3.07	0.002124
House "Rented from a someone else"	Missed	-0.64	-1.78	0.50	0.58	-1.10	0.269529
	Between Minimum and High Attractor	-0.22	-1.21	0.77	0.51	-0.43	0.665443
	Around High Attractor	-0.58	-1.65	0.49	0.54	-1.06	0.287510
	Between High Attractor and Spending	0.04	-1.63	1.71	0.85	0.04	0.964250
	Around Spending	-1.66	-2.90	-0.41	0.64	-2.61	0.009100
	Between Spending and Full	-1.54	-2.67	-0.41	0.58	-2.67	0.007509
	Full	-1.89	-2.87	-0.91	0.50	-3.77	0.000165
House "Rent free"	Missed	-0.54	-3.56	2.47	1.54	-0.35	0.723560
	Between Minimum and High Attractor	0.40	-2.12	2.92	1.29	0.31	0.754479
	Around High Attractor	0.36	-2.14	2.86	1.28	0.28	0.780334
	Between High Attractor and Spending	-15.50	-3393.01	3362.01	1723.22	-0.01	0.992822
	Around Spending	0.08	-2.64	2.80	1.39	0.06	0.954491
	Between Spending and Full	-1.37	-4.41	1.68	1.55	-0.88	0.379468
	Full	-0.93	-3.39	1.53	1.26	-0.74	0.459106
Gender "Female"	Missed	-0.72	-1.43	-0.01	0.36	-1.99	0.046887
	Between Minimum and High Attractor	-0.28	-0.87	0.32	0.30	-0.92	0.358249
	Around High Attractor	-0.46	-1.09	0.17	0.32	-1.43	0.153502
	Between High Attractor and Spending	-0.87	-1.80	0.07	0.48	-1.82	0.068240
	Around Spending	-0.06	-0.77	0.65	0.36	-0.17	0.866434
	Between Spending and Full	-0.49	-1.15	0.17	0.34	-1.47	0.142472
	Full	-0.37	-0.95	0.21	0.29	-1.26	0.209284
Education "Primary"	Missed	-0.52	-25076.03	25074.99	12793.63	0.00	0.999967
	Between Minimum and High Attractor	19.72	-12663.86	12703.29	6471.21	0.00	0.997569
	Around High Attractor	-0.23	-26306.97	26306.52	13421.81	0.00	0.999987
	Between High Attractor and Spending	17.79	-27110.93	27146.52	13841.19	0.00	0.998974
	Around Spending	18.09	-25853.62	25889.80	13199.85	0.00	0.998906
	Between Spending and Full	16.82	-25728.63	25762.27	13135.43	0.00	0.998978
	Full	19.75	-12663.82	12703.33	6471.21	0.00	0.997564

Table A4.7. Coefficients from a multinomial regression with Equation 5.2 (Continue)

IV	Repayment Category	Coefficient	LL	UL	S.E.	z value	Pr(>|z|)
Education "Secondary school, high school, NVQ1-3"	Missed	0.99	-1.44	3.42	1.24	0.80	0.424274
	Between Minimum and High Attractor	2.12	-0.59	4.82	1.38	1.54	0.124619
	Around High Attractor	1.80	-0.83	4.43	1.34	1.34	0.180719
	Between High Attractor and Spending	17.13	-6228.95	6263.22	3186.78	0.01	0.995710
	Around Spending	17.69	-4801.23	4836.62	2458.64	0.01	0.994258
	Between Spending and Full	17.70	-5375.13	5410.52	2751.44	0.01	0.994868
	Full	1.90	-0.87	4.66	1.41	1.34	0.178916
Education "University or equivalent, NVQ4"	Missed	1.00	-1.47	3.48	1.26	0.79	0.427165
	Between Minimum and High Attractor	2.21	-0.52	4.94	1.39	1.59	0.112063
	Around High Attractor	2.02	-0.63	4.68	1.35	1.50	0.134674
	Between High Attractor and Spending	16.54	-6229.54	6262.63	3186.78	0.01	0.995858
	Around Spending	18.19	-4800.74	4837.12	2458.64	0.01	0.994096
	Between Spending and Full	18.31	-5374.51	5411.14	2751.44	0.01	0.994690
	Full	2.52	-0.27	5.30	1.42	1.77	0.076739
Education "Higher university, NVQ5"	Missed	1.01	-1.60	3.61	1.33	0.76	0.448189
	Between Minimum and High Attractor	1.94	-0.86	4.74	1.43	1.36	0.174751
	Around High Attractor	1.68	-1.05	4.42	1.39	1.21	0.227472
	Between High Attractor and Spending	16.85	-6229.23	6262.94	3186.78	0.01	0.995780
	Around Spending	18.10	-4800.83	4837.03	2458.64	0.01	0.994126
	Between Spending and Full	17.74	-5375.09	5410.56	2751.44	0.01	0.994857
	Full	2.26	-0.60	5.11	1.46	1.55	0.121273
Education "Still in full time education"	Missed	1.74	-1.58	5.05	1.69	1.03	0.303969
	Between Minimum and High Attractor	3.46	0.07	6.85	1.73	2.00	0.045549
	Around High Attractor	3.20	-0.20	6.60	1.73	1.85	0.064739
	Between High Attractor and Spending	18.10	-6227.99	6264.18	3186.78	0.01	0.995469
	Around Spending	18.82	-4800.11	4837.75	2458.64	0.01	0.993894
	Between Spending and Full	19.33	-5373.50	5412.15	2751.44	0.01	0.994396
	Full	3.76	0.25	7.27	1.79	2.10	0.035698
Age: 25-34	Missed	-0.77	-2.14	0.61	0.70	-1.10	0.273454
	Between Minimum and High Attractor	-0.24	-1.46	0.99	0.63	-0.38	0.706524
	Around High Attractor	-0.69	-1.93	0.55	0.63	-1.10	0.272562
	Between High Attractor and Spending	-0.88	-2.67	0.91	0.91	-0.97	0.334041
	Around Spending	-0.40	-1.93	1.13	0.78	-0.52	0.606415
	Between Spending and Full	-0.20	-1.68	1.28	0.76	-0.27	0.788415
	Full	0.41	-0.88	1.71	0.66	0.63	0.531284
Age: 35-44	Missed	-0.25	-1.73	1.23	0.75	-0.33	0.740878
	Between Minimum and High Attractor	0.48	-0.84	1.79	0.67	0.71	0.477444
	Around High Attractor	-0.37	-1.71	0.98	0.69	-0.54	0.591622
	Between High Attractor and Spending	-1.59	-3.65	0.48	1.05	-1.51	0.131411
	Around Spending	-0.45	-2.13	1.22	0.85	-0.53	0.596580
	Between Spending and Full	0.33	-1.23	1.89	0.80	0.41	0.682011
	Full	0.73	-0.66	2.11	0.71	1.03	0.304380
Age: 45-54	Missed	-0.60	-2.12	0.93	0.78	-0.77	0.443942
	Between Minimum and High Attractor	0.34	-0.99	1.67	0.68	0.50	0.616103
	Around High Attractor	-0.68	-2.08	0.71	0.71	-0.96	0.337211
	Between High Attractor and Spending	-1.50	-3.69	0.69	1.12	-1.34	0.179124
	Around Spending	-0.50	-2.23	1.22	0.88	-0.57	0.567002
	Between Spending and Full	0.45	-1.13	2.02	0.80	0.55	0.579140
	Full	1.24	-0.15	2.63	0.71	1.74	0.081386
Age: 55-64	Missed	0.16	-1.61	1.93	0.90	0.18	0.860187
	Between Minimum and High Attractor	0.90	-0.67	2.46	0.80	1.12	0.262937
	Around High Attractor	-0.24	-1.89	1.41	0.84	-0.29	0.774120
	Between High Attractor and Spending	-0.24	-2.53	2.04	1.17	-0.21	0.834553
	Around Spending	0.86	-0.99	2.71	0.94	0.91	0.363924
	Between Spending and Full	0.59	-1.23	2.40	0.93	0.64	0.525233
	Full	2.10	0.50	3.71	0.82	2.57	0.010091
Age: 65+	Missed	0.54	-1.02	2.10	0.79	0.68	0.496475
	Between Minimum and High Attractor	0.66	-0.77	2.09	0.73	0.91	0.363386
	Around High Attractor	-0.08	-1.56	1.40	0.75	-0.11	0.913917
	Between High Attractor and Spending	-0.94	-3.12	1.23	1.11	-0.85	0.396246
	Around Spending	0.95	-0.76	2.66	0.87	1.09	0.275290
	Between Spending and Full	0.70	-0.97	2.36	0.85	0.82	0.413508
	Full	1.93	0.45	3.41	0.75	2.56	0.010438
Income: £7,001-14,000	Missed	0.28	-1.59	2.16	0.96	0.30	0.767573
	Between Minimum and High Attractor	-0.62	-2.25	1.00	0.83	-0.75	0.451984
	Around High Attractor	0.24	-1.72	2.19	1.00	0.24	0.810990
	Between High Attractor and Spending	15.07	-2990.97	3021.11	1533.69	0.01	0.992161
	Around Spending	1.27	-1.28	3.82	1.30	0.98	0.327962
	Between Spending and Full	0.86	-1.25	2.98	1.08	0.80	0.424291
	Full	-0.41	-2.05	1.22	0.83	-0.50	0.620091
Income: £14,001-21,000	Missed	-0.24	-2.04	1.56	0.92	-0.26	0.792956
	Between Minimum and High Attractor	-0.86	-2.38	0.65	0.77	-1.11	0.265481
	Around High Attractor	0.10	-1.75	1.94	0.94	0.10	0.917086
	Between High Attractor and Spending	15.31	-2990.73	3021.35	1533.69	0.01	0.992034
	Around Spending	0.95	-1.53	3.43	1.26	0.75	0.453464
	Between Spending and Full	0.43	-1.61	2.46	1.04	0.41	0.679135
	Full	-0.16	-1.69	1.37	0.78	-0.21	0.835309
Income: £21,001-28,000	Missed	0.44	-1.37	2.25	0.92	0.47	0.636368
	Between Minimum and High Attractor	-0.89	-2.45	0.67	0.80	-1.12	0.261048
	Around High Attractor	0.49	-1.37	2.35	0.95	0.52	0.603801
	Between High Attractor and Spending	16.17	-2989.87	3022.21	1533.69	0.01	0.991589
	Around Spending	1.35	-1.14	3.85	1.27	1.06	0.288082
	Between Spending and Full	0.65	-1.41	2.72	1.05	0.62	0.535166
	Full	0.11	-1.45	1.67	0.80	0.14	0.890079

Table A4.7. Coefficients from a multinomial regression with Equation 5.2 (Continue)

IV	Repayment Category	Coefficient	LL	UL	S.E.	z value	Pr(>|z|)
Income: £28,001-34,000	Missed	-0.09	-1.98	1.79	0.96	-0.10	0.923899
	Between Minimum and High Attractor	-0.34	-1.91	1.23	0.80	-0.43	0.670422
	Around High Attractor	0.47	-1.43	2.36	0.97	0.48	0.627956
	Between High Attractor and Spending	15.41	-2990.64	3021.45	1533.69	0.01	0.991985
	Around Spending	0.96	-1.58	3.51	1.30	0.74	0.458793
	Between Spending and Full	0.78	-1.30	2.86	1.06	0.74	0.461892
	Full	0.10	-1.49	1.69	0.81	0.12	0.902863
Income: £34,001-41,000	Missed	0.04	-2.03	2.11	1.05	0.04	0.970613
	Between Minimum and High Attractor	-0.16	-1.85	1.53	0.86	-0.19	0.852115
	Around High Attractor	0.84	-1.15	2.83	1.01	0.83	0.406527
	Between High Attractor and Spending	15.44	-2990.60	3021.48	1533.69	0.01	0.991968
	Around Spending	1.60	-1.02	4.23	1.34	1.20	0.231511
	Between Spending and Full	1.34	-0.84	3.52	1.11	1.20	0.229642
	Full	0.70	-1.00	2.40	0.87	0.80	0.422363
Income: £41,001-48,000	Missed	-0.60	-2.79	1.60	1.12	-0.53	0.593495
	Between Minimum and High Attractor	-0.79	-2.53	0.95	0.89	-0.89	0.373401
	Around High Attractor	0.35	-1.67	2.36	1.03	0.34	0.736118
	Between High Attractor and Spending	14.52	-2991.52	3020.57	1533.69	0.01	0.992445
	Around Spending	0.72	-2.01	3.45	1.39	0.52	0.603774
	Between Spending and Full	0.88	-1.33	3.10	1.13	0.78	0.434632
	Full	0.11	-1.62	1.84	0.88	0.13	0.899856
Income: £48,001-55,000	Missed	0.10	-2.56	2.76	1.36	0.07	0.940601
	Between Minimum and High Attractor	0.10	-2.05	2.24	1.10	0.09	0.929054
	Around High Attractor	-0.14	-2.70	2.42	1.31	-0.11	0.913401
	Between High Attractor and Spending	16.31	-2989.73	3022.35	1533.69	0.01	0.991514
	Around Spending	1.36	-1.80	4.53	1.62	0.84	0.399567
	Between Spending and Full	1.46	-1.15	4.07	1.33	1.10	0.271748
	Full	0.69	-1.47	2.84	1.10	0.62	0.532181
Income: £55,001-62,000	Missed	0.94	-2.07	3.96	1.54	0.61	0.539604
	Between Minimum and High Attractor	0.59	-2.00	3.19	1.32	0.45	0.654233
	Around High Attractor	0.79	-2.13	3.72	1.49	0.53	0.594833
	Between High Attractor and Spending	17.32	-2988.73	3023.36	1533.70	0.01	0.990992
	Around Spending	2.81	-0.52	6.13	1.70	1.65	0.098709
	Between Spending and Full	1.96	-1.06	4.97	1.54	1.27	0.203160
	Full	1.25	-1.35	3.85	1.33	0.94	0.345773
Income: £62,001-69,000	Missed	-15.82	-4700.41	4668.77	2390.10	-0.01	0.994719
	Between Minimum and High Attractor	-0.84	-3.80	2.11	1.51	-0.56	0.575708
	Around High Attractor	0.32	-2.81	3.45	1.60	0.20	0.839535
	Between High Attractor and Spending	-0.05	-5884.49	5884.39	3002.26	0.00	0.999987
	Around Spending	-13.73	-2802.62	2775.17	1422.91	-0.01	0.992302
	Between Spending and Full	2.12	-1.02	5.25	1.60	1.32	0.186230
	Full	0.64	-2.14	3.42	1.42	0.45	0.649616
Income: £69,001-76,000	Missed	-16.03	-4513.28	4481.22	2294.52	-0.01	0.994426
	Between Minimum and High Attractor	-1.14	-4.35	2.08	1.64	-0.69	0.489166
	Around High Attractor	1.45	-1.50	4.40	1.51	0.96	0.335085
	Between High Attractor and Spending	17.24	-2988.80	3023.29	1533.70	0.01	0.991029
	Around Spending	1.62	-2.21	5.44	1.95	0.83	0.407925
	Between Spending and Full	-15.59	-4633.89	4602.71	2356.27	-0.01	0.994721
	Full	0.39	-2.44	3.22	1.44	0.27	0.785066
Income: £76,001-83,000	Missed	-2.06	-12553.93	12549.80	6404.01	0.00	0.999743
	Between Minimum and High Attractor	13.74	-6550.75	6578.22	3349.23	0.00	0.996728
	Around High Attractor	-3.42	-14405.62	14398.78	7348.06	0.00	0.999629
	Between High Attractor and Spending	13.25	-14862.43	14888.92	7589.63	0.00	0.998607
	Around Spending	-2.22	-12284.57	12280.12	6266.50	0.00	0.999717
	Between Spending and Full	15.66	-6548.83	6580.14	3349.23	0.00	0.996270
	Full	14.95	-6549.54	6579.43	3349.23	0.00	0.996439
Income: £83,001+	Missed	0.41	-2.95	3.76	1.71	0.24	0.812746
	Between Minimum and High Attractor	-17.26	-3960.84	3926.32	2012.03	-0.01	0.993155
	Around High Attractor	0.79	-2.33	3.91	1.59	0.50	0.619356
	Between High Attractor and Spending	-0.33	-5441.17	5440.51	2775.94	0.00	0.999905
	Around Spending	2.68	-0.80	6.16	1.78	1.51	0.131375
	Between Spending and Full	1.36	-1.92	4.65	1.68	0.81	0.416381
	Full	0.84	-1.97	3.66	1.43	0.59	0.556001
Latest balance (× 10,000)	Missed	-1.16	-2.66	0.33	0.76	-1.53	0.127075
	Between Minimum and High Attractor	-0.08	-1.10	0.95	0.52	-0.15	0.882583
	Around High Attractor	0.31	-0.71	1.33	0.52	0.60	0.551560
	Between High Attractor and Spending	1.89	0.60	3.19	0.66	2.87	0.004056
	Around Spending	0.51	-0.66	1.69	0.60	0.86	0.391475
	Between Spending and Full	1.22	0.16	2.28	0.54	2.26	0.023957
	Full	1.06	0.09	2.04	0.50	2.13	0.033138
Current credit limit (× 10,000)	Missed	-3.83	-7.27	-0.39	1.76	-2.18	0.029130
	Between Minimum and High Attractor	-0.41	-1.38	0.55	0.49	-0.84	0.399564
	Around High Attractor	-0.23	-0.84	0.37	0.31	-0.76	0.450192
	Between High Attractor and Spending	-2.63	-5.50	0.24	1.46	-1.80	0.071977
	Around Spending	-5.45	-8.71	-2.19	1.66	-3.28	0.001034
	Between Spending and Full	-4.38	-6.62	-2.14	1.14	-3.83	0.000127
	Full	-6.05	-7.87	-4.22	0.93	-6.50	0.000000
Current liquidity (× 10,000)	Missed	0.59	-0.64	1.81	0.62	0.94	0.347665
	Between Minimum and High Attractor	1.63	0.59	2.67	0.53	3.07	0.002147
	Around High Attractor	1.50	0.45	2.54	0.53	2.80	0.005159
	Between High Attractor and Spending	1.32	0.19	2.45	0.58	2.28	0.022446
	Around Spending	1.67	0.63	2.71	0.53	3.15	0.001644
	Between Spending and Full	1.48	0.43	2.52	0.53	2.76	0.005710
	Full	1.73	0.69	2.77	0.53	3.26	0.001130

Note. *N* = 1231. Log likelihood = -1768. LL and UL represent lower and upper bounds of 95% confidence intervals.

Appendix 5 Supplemental Materials for Chapter 6

A5.1 Summary Statistics for the Sell-Day Portfolios

Table A5.1. Descriptive Statistics

Statistic	Count
No. sell-day portfolios	35,761
No. stocks	181,896
No. accounts	10,675
No. unique sell-dates	1,467

Table A5.2. Summary of Control Variables

Variable	Mean	Std. Dev.	25th pctile	Median	75th pctile
Return since purchase	0.05	0.41	-0.11	0.01	0.15
Holding days	247	290	50	142	333

Table A5.3. Percentage of Sell-Day Portfolios by Composition

Proportion of Sell-Day		Number of Losses in a Portfolio										
		1	2	3	4	5	6	7	8	9	10	11+
Number of Gains in a Portfolio	1	22.5%	9.6%	4.3%	1.9%	0.9%	0.4%	0.2%	0.1%	0.1%	0.1%	0.1%
	2	11.0%	6.1%	3.3%	1.6%	0.9%	0.5%	0.2%	0.1%	0.1%	0.1%	0.1%
	3	5.1%	3.5%	2.1%	1.1%	0.7%	0.4%	0.3%	0.2%	0.1%	0.0%	0.1%
	4	2.4%	1.9%	1.2%	0.7%	0.5%	0.3%	0.2%	0.1%	0.1%	0.0%	0.1%
	5	1.4%	1.2%	0.8%	0.5%	0.3%	0.2%	0.1%	0.1%	0.1%	0.0%	0.1%
	6	0.8%	0.7%	0.5%	0.4%	0.2%	0.1%	0.1%	0.1%	0.0%	0.0%	0.1%
	7	0.4%	0.5%	0.3%	0.3%	0.2%	0.1%	0.1%	0.1%	0.0%	0.0%	0.1%
	8	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
	9	0.2%	0.2%	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%
	10	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	11+	0.2%	0.3%	0.3%	0.2%	0.2%	0.2%	0.1%	0.2%	0.1%	0.1%	0.2%

A5.2 A Multivariate Analysis of Composition Sensitivity in the Disposition Effect

In order to confirm the composition-sensitivity of the disposition effect in multivariate setting, a linear regression was conducted. The dependent variable is the dichotomous variable $Sell$ taking the value of 1 if a stock was sold, otherwise 0. The independent variables are $Gain \times Gain\ Loss\ Ratio\ Bin$, $Best$, $Worst$, $Gain \times Return$, $Loss \times Return$, $\sqrt{Holding\ Days}$, $Gain \times Return \times \sqrt{Holding\ Days}$, $Loss \times Return \times \sqrt{Holding\ Days}$, $Gain \times Return_{20}$, and, $Gain \times Volatility_{20}$. $Gain\ Loss\ Ratio\ Bin$ includes four bins: Mostly Losses ($N_G{:}\,N_L = 1{:}\,2{+}$), More Losses ($N_G{:}\,N_L = 1{:}\,2 - 1{:}\,1$), More Gains ($N_G{:}\,N_L = 1{+}{:}\,1 - 2{:}\,1$), and Mostly Gains ($N_G{:}\,N_L = 2{+}{:}\,1$). $Best$ and $Worst$ are dummies for the best and worst performing stocks in a sell-day portfolio. Hartzmark (2015) showed, the best and worst performing stocks in a portfolio are more likely to be sold than other middle performing stocks (the rank effect). Fixed effects of accounts and stock-by-dates were included. The standard errors were clustered by accounts and sell dates.

Table A5.4 reports the coefficients. The first four rows show the effect of $Gain$ (i.e., the disposition effect) interacting with $Gain\ Loss\ Ratio\ Bin$. Comparing the coefficients and corresponding confidence intervals among the four bins, it is clear that the disposition effect decreases from Mostly-Losses-Bin (the first row) to Mostly-Gains-Bin (the fourth row), showing that the larger the number of gains relative to the number of losses in a portfolio the smaller the disposition effect. The results are consistent with the composition-sensitivity of the disposition effect seen in Figure 6.4.

Table A5.4. A Linear Regression for Composition-Sensitivity of the Disposition Effect

IV	Coefficient	LL	UL	Clustered SE	t value	Pr(>|t|)
Gain × Mostly-Losses-Bin	0.154	0.063	0.245	0.046	3.310	0.001
Gain × More-Losses-Bin	0.107	0.040	0.174	0.034	3.114	0.002
Gain × More-Gains-Bin	0.042	-0.017	0.101	0.030	1.379	0.168
Gain × Mostly-Gains-Bin	0.017	-0.046	0.079	0.032	0.522	0.602
Best	0.148	0.087	0.208	0.031	4.752	0.000
Worst	0.037	-0.014	0.088	0.026	1.409	0.159
√Holding days	-0.002	-0.005	0.002	0.002	-0.795	0.426
Gain ×Return	0.041	-0.144	0.226	0.094	0.438	0.661
Loss ×Return	0.199	-0.152	0.550	0.179	1.111	0.267
Gain ×$Return_{20}$	0.066	-0.206	0.338	0.139	0.473	0.636
Gain ×$Volatility_{20}$	0.001	-0.006	0.007	0.003	0.167	0.867
Gain ×Return ×√Holding days	-0.003	-0.011	0.004	0.004	-0.834	0.404
Loss ×Return ×√Holding days	-0.011	-0.031	0.009	0.010	-1.040	0.298
R2 = .935						
Number of observations = 181,896						

Note. Fixed effects of accounts and stock-by-dates were included. The Standard errors were corrected for clustering by accounts and sell dates.

A5.3 Robustness Check on Tax-Exempt Accounts

Investors might have tax motivations to realize a gain or realize a loss, and thus, might evaluate only gains or only losses in their portfolio on the sell day. For checking whether our findings are robust without tax-motivated investors, we repeated the analysis with a sample of tax-exempt accounts (i.e., IRA and Keogh accounts). The results are shown in Figures A5.1 and A5.2.

Figure A5.1 shows that the composition sensitivity of the disposition effect seen in Figure 6.4 is observed in the sample consisting of tax-exempt accounts.

Figure A5.2 shows $P(Gain)$ and $P(Loss)$ as a function of N_G and N_L on the sample of tax-exempt accounts. While portfolios with an extreme composition (e.g., portfolios consisting of one gain and five losses) tend to deviate the pattern seen in Figure 6.5, the within-domain sensitivity is mostly confirmed. That is, $P(Gain)$ is inversely proportional to N_G but is not sensitive to N_L and $P(Loss)$ is inversely proportional to N_L but is not sensitive to N_G.

To recap, the findings of the main analysis are robust with the sample consisting of only tax-exempt accounts.

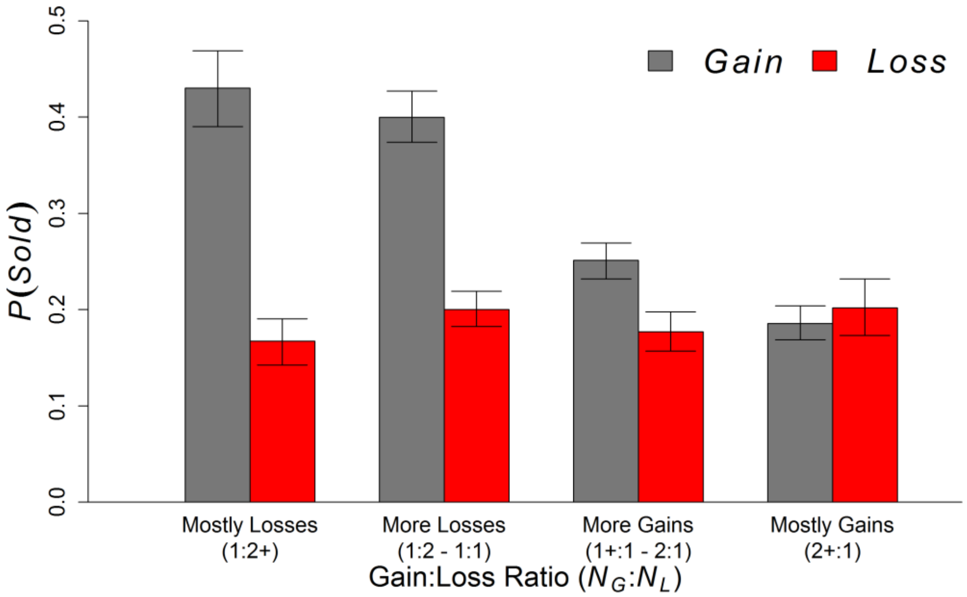

Figure A5.1. The disposition effect depends on the composition of the portfolio (tax-exempt accounts). This figure corresponds to Figure 6.4 reducing the sample to observations for IRA and Keogh accounts. The error bars are 95% confidence intervals computed with the bootstrap method with 1,000 resamples, corrected for clustering by accounts and sell dates.

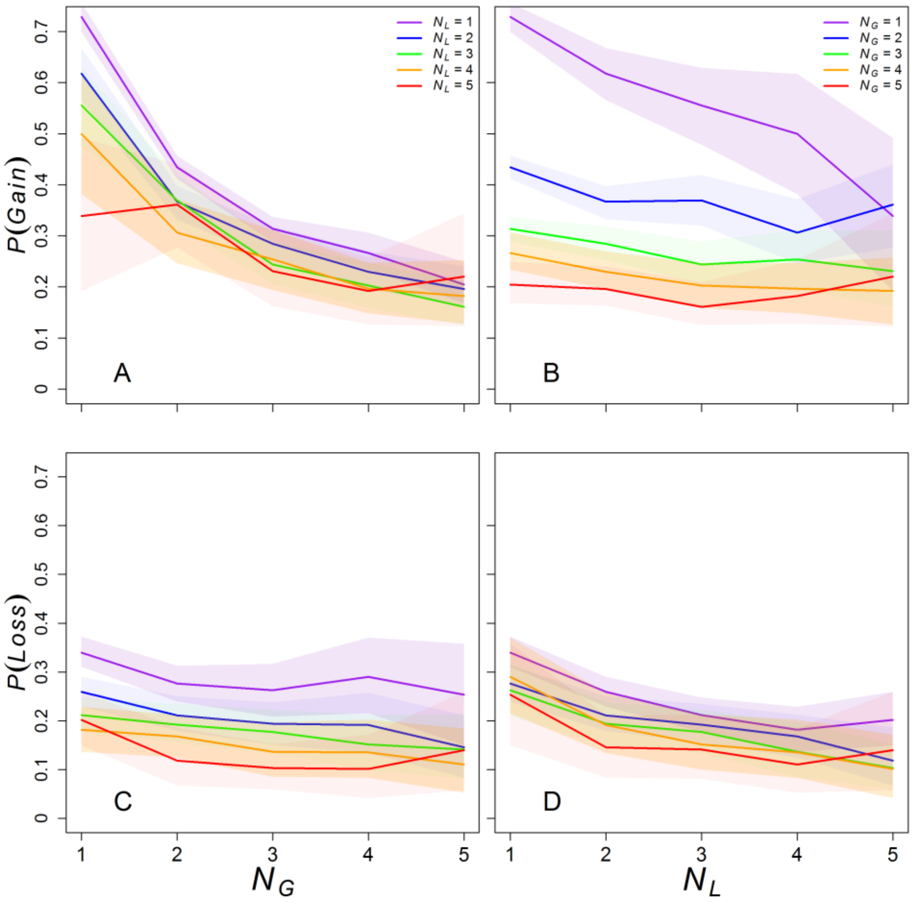

Figure A5.2. $P(Gain)$ and $P(Loss)$ as a function of N_G and N_L in the empirical data (tax-exempt accounts). This figure corresponds to Figure 6.5 reducing the sample to observations for IRA and Keogh accounts. The shaded areas are bootstrapped 95% confidence intervals, with clustering by accounts and sell dates. The right panels replot the data, swapping the roles of N_G and N_L.

A5.4 Estimating the Mixture of One- and Two-Stage Models

We estimate a mixture model, in which the probability that an individual stock is sold is a linear combination of the predictions of the one- and two-stage models. The one-stage model has free parameter β for the individual-stock-level disposition effect. The two-stage model has free parameter B for the domain-level disposition effect. We use free parameter w as the mixture parameter.

First, for each stock in sell-day portfolios, we calculated the probability of the stock being sold based on the one-stage model, $P_{one}(Gain)$ and $P_{one}(Loss)$, using Equations 6.1 and 6.2. We also calculated the probability of stocks being sold based on the two-stage model, $P_{two}(Gain)$ and $P_{two}(Loss)$, using Equations 6.3 and 6.4. We combined the predictions for $P(Gain)$ and $P(Loss)$ across the one- and two-stage models using the mixture parameter w.

$$P_{mix}(Gain) = (1 - w)P_{one}(Gain) + wP_{two}(Gain)$$

and

$$P_{mix}(Loss) = (1 - w)P_{one}(Loss) + wP_{two}(Loss)$$

We used the Nelder-Mead simplex algorithm to estimate values for β, B, and w by maximizing the likelihood of $P_{mix}(Gain)$ and $P_{mix}(Loss)$. To obtain 95% CIs for our parameter, estimates were bootstrapped using 1,000 samples, clustering our sampling by account and sell day. Our best-fitting estimates are $\hat{w}$ = 0.57, 95% CI [0.44, 0.65], $\hat{\beta}$ = 2.08, 95% CI [1.12, 4.12], and $\widehat{\mathrm{B}}$ = 2.09, 95% CI [1.12, 3.21].

We also separately estimated the one-stage model and the two-stage model. For the one-stage model alone, the best-fitting $\hat{\beta}$ = 2.16, 95% CI [2.04, 2.30]. For the two-stage model alone, the best-fitting $\widehat{\mathrm{B}}$ = 2.04, 95% CI [1.95, 2.14]. These models fit less well than the mixture model. Table A5.5 reports the log-likelihood, AIC, and BIC for the one- and two-stage models and the mixture model. Figure A5.3 compares the predictions of the one- and two-stage models and the mixture model with the empirical data.

Table A5.5. Model Selection Criteria for Three Optimized Models

Model	One-stage	Two-stage	Mixture
Log-likelihood	-78050	-77546	-77014
	[-81289, -75091]	[-80815, -74345]	[-79999, -74172]
AIC	156103	155094	154034
	[150185, 162580]	[148691, 161632]	[148351, 160005]
BIC	156113	155104	154065
	[150195, 162590]	[148702, 161642]	[148381, 160035]

This table reports model selection criteria for three optimized models. The numbers in parentheses are 95% confidence intervals, corrected for clustering by accounts and sell dates.

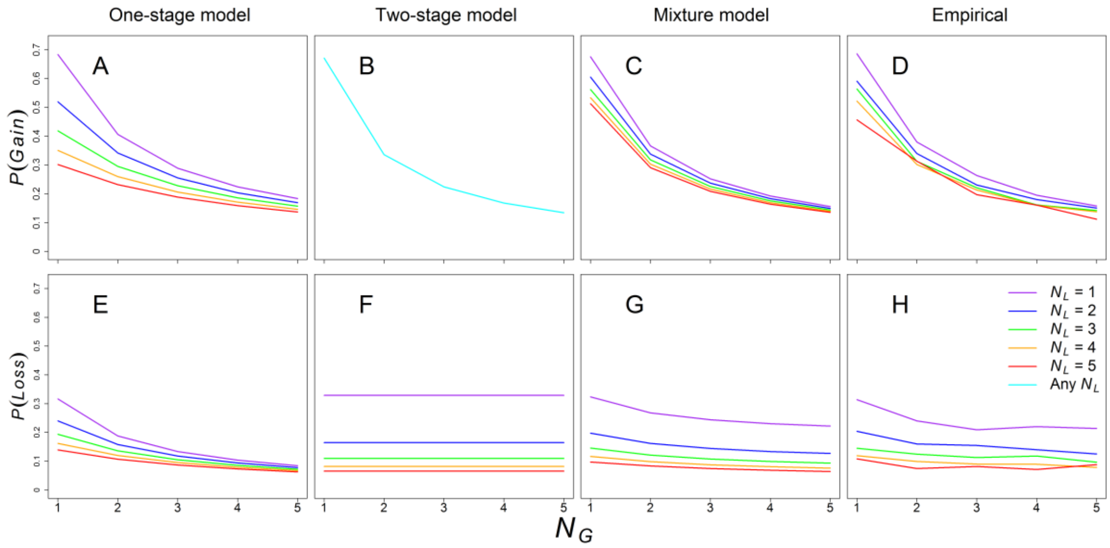

Figure A5.3. $P(Gain)$ and $P(Loss)$ as a function of portfolio composition for the one-stage, two-stage, and mixture models, and the empirical data. The one-stage, two-stage, and empirical columns repeat Figures 6.1, 6.2, and 6.5.

A5.5 Four Logistic Regression Models

Table A5.6. Regression Table for Four Logistic Models

IV	Models			
	1	2	3	4
Intercept	-1.776	-2.806	-0.825	-2.969
	[-1.847, -1.704]	[-2.889, -2.724]	[-0.909, -0.742]	[-3.058, -2.88]
$Gain$	0.593	0.042	1.041	0.134
	[0.522, 0.665]	[-0.079, 0.163]	[0.932, 1.15]	[0.011, 0.258]
$\sqrt{Holding\ days}$	-0.009	-0.006	-0.005	-0.005
	[-0.013, -0.005]	[-0.009, -0.003]	[-0.008, -0.003]	[-0.008, -0.002]
$Gain \times Return$	0.701	0.908	0.942	0.97
	[0.484, 0.918]	[0.685, 1.131]	[0.717, 1.167]	[0.739, 1.202]
$Loss \times Return$	-0.095	-0.268	-0.334	-0.317
	[-0.445, 0.254]	[-0.626, 0.091]	[-0.82, 0.153]	[-0.726, 0.091]
$Gain \times Return_{20}$	1.419	1.126	1.158	1.129
	[1.244, 1.594]	[0.964, 1.287]	[1.007, 1.309]	[0.969, 1.289]
$Loss \times Return_{20}$	-0.331	-0.428	-0.456	-0.451
	[-0.552, -0.111]	[-0.648, -0.208]	[-0.685, -0.228]	[-0.677, -0.225]
$Gain \times Volatility_{20}$ (× 1000)	0.056	0.110	0.106	0.120
	[-0.24, 0.352]	[-0.119, 0.339]	[-0.109, 0.322]	[-0.118, 0.357]
$Loss \times Volatility_{20}$ (× 1000)	0.001	0.001	0.001	0.001
	[0, 0.001]	[0, 0.001]	[0, 0.001]	[0, 0.001]
$Gain \times Return \times \sqrt{Holding\ days}$	-0.021	-0.031	-0.031	-0.032
	[-0.029, -0.013]	[-0.039, -0.022]	[-0.039, -0.022]	[-0.041, -0.023]
$Loss \times Return \times \sqrt{Holding\ days}$	-0.009	0.011	0.012	0.012
	[-0.025, 0.007]	[-0.006, 0.027]	[-0.008, 0.032]	[-0.006, 0.03]
$N_{G+L}^{-1} \times Gain$		7.27		
		[7.074, 7.467]		
$N_{G+L}^{-1} \times Loss$		4.441		
		[4.229, 4.653]		
$N_G \times Gain$			-0.339	
			[-0.357, -0.32]	
$N_L \times Loss$			-0.258	
			[-0.277, -0.238]	
$N_G \times Loss$			-0.041	
			[-0.056, -0.026]	
$N_L \times Gain$			-0.053	
			[-0.066, -0.039]	
$N_G^{-1} \times Gain$				2.991
				[2.916, 3.065]
$N_L^{-1} \times Loss$				1.664
				[1.581, 1.747]
$N_G^{-1} \times Loss$				0.622
				[0.548, 0.696]
$N_L^{-1} \times Gain$				0.571
				[0.515, 0.628]
LogLikelihood	-87423.83	-78074.19	-78282.05	-76923.32
R2	0.030	0.134	0.132	0.147
AIC	174869.67	156174.38	156594.10	153876.64
BIC	174980.89	156305.82	156745.77	154028.31
Number of observations	181896			

This table reports coefficients and model selection criteria for four logistic models. The numbers in parentheses are 95% confidence intervals, corrected for clustering by accounts and sell dates.