Who Makes Credit Card Mistakes?

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ABSTRACT

We document that not all individuals who pay penalty fees on their credit cards (e.g. for not paying the minimum monthly payment, or for exceeding their credit limit) do so because they don't have enough money. In fact, a sizable proportion of those who incur credit card penalty fees do have enough money in their deposit accounts, and so could have avoided those penalties. In other words these penalties are incurred by mistake, caused by the inattention of individuals to their credit card payments and expenditures. Individuals who make such mistakes can be very attractive to the banks, because while they pay the penalty fees, mistakes caused by inattention do not necessarily signal an increased risk of future credit card default. Using a unique database of more than one million data points we show that individuals who make these kinds of unnecessary credit card mistakes are poorer. In particular individuals who make these mistakes (1) live in areas with more renters than owners, (2) receive a greater proportion of income from government sources such as unemployment insurance and government pensions and (3) receive smaller amounts from the ownership of businesses and other investments.

INTRODUCTION

In his American Finance Association 2006 Presidential Address, Campbell (2006) argues that "mistakes are central to the field of household finance" (p. 1554). He defines mistakes as the differences between positive consumer finance (i.e. what consumers actually do) and normative consumer finance (i.e. what consumers should do). The issue of financial mistakes is important and controversial because it falls at the center of debates on the rationality or otherwise of individual financial decision making. Besides theoretical issues concerning rationality, Campbell (2006) also argues that there is a very strong public policy interest in whether certain types of individuals – for example poorer individuals - make more financial mistakes.

In this paper we study whether poorer individuals make a specific kind of financial mistake - unnecessarily incurring penalty fees and other costs on their credit cards *even though* they had sufficient money in their deposit accounts so that they could have avoided those costs. Examples of such mistakes include unnecessarily being delinquent (failing to pay the minimum monthly balance due) in spite of having sufficient deposits available, and unnecessarily being overlimit (charging more than the authorized credit limit) in spite of having sufficient deposits available.

The main story we are telling is that individuals who are don't pay their minimum balance due or go over their limits *in spite of* having sufficient deposits available (i.e. by mistake) are very different from individuals who don't pay or are overlimit *because* they don't have sufficient deposits (i.e. are facing financial difficulties). Possible reasons for such mistakes include people who forget to mail their payment check to the credit card company on time, or who miscalculate their outstanding balances relative to their pre-approved credit limits and go over their limit. These individuals have the deposit balances available in order to avoid being delinquent or overlimit, but because of inattention or carelessness, they have unnecessarily incurred the penalty fees associated with being delinquent or overlimit.

It can be argued that an individual, who is delinquent or overlimit *because* he does not have enough money to make the required payments (i.e. is facing financial difficulties), is clearly signalling an increased risk of default to the bank. However, it seems likely that an individual who is delinquent or overlimit *in spite* of having sufficient funds available is signalling inattention with respect to personal financial management, rather than indicating an increased future risk of default or bankruptcy. Indeed, it can be argued that individuals who make these kinds of mistakes because of inattention[1] may be particularly profitable to the banks because while the banks earn the penalty fees, the individual does not necessarily become a higher default risk for the bank[2].

While the issue of who makes these specific kinds of credit card mistakes and why is clearly of importance in the context of recent research on household finance by Campbell (2006) and others, this issue is also of public policy importance. Recently, regulators in a variety of countries, including the US, Canada and the UK, have expressed dissatisfaction with the ways that banks have been using rapidly increasing penalty fees (e.g. delinquent fees or overlimit fees) as revenue generators (see Massoud, Saunders and Scholnick, (2007) for a detailed discussion). For example, as part of his 2004 Presidential campaign, Senator John Kerry argued that the way credit card penalty fees were implemented were unfair to consumers, and threatened to increase regulation in this area if he were elected President. The main public policy response of the representatives of the credit card industry has been that recent credit card penalty fee increases are a compensation for risk. The credit card industry argues that an individual being delinquent or overlimit is a signal that that individual has a higher risk of eventual default or bankruptcy, and thus rapidly increasing credit card penalty fees can be justified as a compensation for this increased risk.

It can be argued, however, that this public policy position of the credit card industry presupposes that all individuals who are delinquent or overlimit are in fact signalling that they have an increased risk of eventual default or bankruptcy. Their

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[1] A variety of recent papers e.g. Abel, Eberly and Panageas (2007), Reis (2006) Ball, Mankiw and Reis (2005) examine the issue of inattention in a theoretical framework where individuals are not attentive because the costs of attention (e.g. information processing costs) exceed the benefits. For example, Abel et al (2007), show that, under certain assumptions, it is optimal to check on a stock market portfolio every eight months.

[2] In a 2007 Harvard Business Review article, McGovern and Moon argue that these kinds of consumer mistakes are very profitable for firms. They examine why "so many companies infuriate their customers by binding them with contracts, bleeding them with fees, confounding them with fine print and otherwise penalizing them for their business. Because, unfortunately, it pays" McGovern and Moon (2007).

argument that penalty fees compensate for increased future risk of default will, however, be weakened the greater the extent to which those who pay penalty fees do so by mistake through inattention to personal financial management (i.e. *in spite of* having enough deposits) compared to those who pay penalty fees because they are facing financial difficulties (i.e. *because of* not having enough deposits). In this public policy context, therefore, empirical research is clearly needed to determine the proportion of individuals who are delinquent and overlimit by mistake through inattention, rather than because they don't have the money to pay their minimum balances due and avoid being overlimit.

Furthermore, in the public policy debate on credit card fees, critics of the credit card industry (including Senator Kerry and many others) have argued that credit card fees are particularly harmful to poorer individuals. Thus, empirical research is also required on the characteristics of those individuals who make such mistakes, and in particular whether poorer individuals make more of these credit card mistakes.

As described in detail by Campbell (2006), however, empirical research on financial mistakes and also on the relationship between financial mistakes and wealth has been severely impeded by the lack of useful data. Campbell (2006) outlines the significant difficulties involved in collecting data for research on household finance – primarily because households guard their financial privacy very jealously. In order to conduct research into household financial mistakes, Campbell emphasises that financial mistakes data should be representative across all demographics (especially wealth). He argues, however, that such data has been particularly scarce, and overcoming these data limitations is a primary goal of research into individual or household finances.

In this paper we study the relationship between these credit card mistakes and wealth, by building a new database which provides important advantages over existing data used in this literature. We build this database by exploiting a unique element of the Canadian postal code system where the average number of households in each Canadian postal code is orders of magnitude smaller than in each US zip code. There are, on average, only 200 households in each postal code[3] we use in our analysis. Using this, we match (1) confidential individual account level data on credit card and other transactions

[3] Technically, the specific 200 household geographic area we use in our analysis is called a Dissemination Area (or DA) which is very closely related to a Canadian postal code. A full description of these geographic technicalities is given in Section 2.2 below.

provided to us by a Canadian bank, with (2), postal code level census data on a variety of measures of wealth provided by Statistics Canada, and with (3) postal code level data on all residential property transactions, taken from the Land Titles Registry. Our combined new database has more than a million data points.

This new database allows us to examine two separate questions; (1) how many credit card mistakes are made and (2) what are the characteristics of those individuals who make these mistakes. For the first part of the paper we use the confidential monthly account level database provided to us by a Canadian bank to calculate the proportion of their customers who make credit card mistakes. This database includes data for almost 90 000 individuals over 19 months. Because we have data on both credit card as well as deposit accounts we are able to measure when an individual was delinquent or overlimit by mistake (i.e. when sufficient deposits were available in their deposit accounts to have avoided these unnecessary costs).

An important issue when defining mistakes is to define exactly what having "sufficient funds" on hand in a deposit account entails. A possible argument may be that individuals don't use their funds in a deposit account to pay their minimum credit card balance because they are holding those funds as precautionary balances. We control for precautionary balances by using a variety of proxies from the precautionary balance literature (e.g. Opler, Pinkowitz, Stultz and Williamson, (1999),) and Bates, Kahle and Stultz (2007)) which argue that individuals will hold more precautionary balances if their income flows are very volatile or if the level of income flows is low. We thus define a mistake as occurring when an individual is delinquent or overlimit, even though (1) he has sufficient funds in his deposit account and (2) after accounting for holding those deposits as possible precautionary balances.

The second part of the paper examines the characteristics of those individuals who make mistakes, in particular whether they are predominantly poorer individuals. Using the fact that each Canadian Postal Code only consists of 200 households on average, we are able to match each individual's bank account data with postal code level data on different components of wealth taken from Census and Land Titles Registry data. These include the market value of residential property, annual income from business and investment sources, residence rental/ownership status, income from government sources etc. This data allows us to study in detail how different components and measures of wealth at the postal code level impact a large variety of different credit card mistakes made by individuals.

Our new database is rich enough to allow us not only to examine the issue of credit card mistakes in the public policy context described above (i.e. examining the credit card industry's position that penalty fees are compensation for the increased default risk that they face), but also to provide new evidence on three additional issues that have been raised in the literature.

The first additional motivation for our study is that we can examine the impact of wealth on financial mistakes, as those mistakes vary from being smaller "frictional" mistakes (involving a perhaps a few dollars) to larger "consequential" mistakes (which can have severe consequences for the individual). We argue that financial mistakes should be considered as lying on a spectrum from frictional to consequential. One important reason for examining mistakes in the context of this spectrum lies in empirically examining hypotheses developed by Ellison (2005). He provides a theoretical model of how wealth could impact small frictional mistakes (in his model of who pays for add-on pricing). He describes two competing theories – one of which predicts that richer individuals will make more small frictional mistakes, while the other which predicts that poorer individuals will make frictional mistakes. His first "traditional" theory is that the rich have a low marginal utility of income and thus don't particularly care about the few dollars of unnecessary costs, and will thus make more small frictional mistakes than the poor. His alternative "behavioural" hypothesis is that the poor will make more small frictional mistakes because the poor are more financially unsophisticated compared to the rich.

It remains an empirical question however as to which of Ellison's (2005) competing hypotheses (i.e. whether richer or poorer individuals make more frictional mistakes) is supported by the data. Furthermore, evidence is required for examining which of Ellison's competing models are supported as the actual mistakes involved become more consequential and less frictional. Theoretically it can be predicted that as mistakes become more consequential, so even the rich should become concerned about avoiding making them, thus Ellison's "traditional" prediction that the rich should make more mistakes should in theory become less relevant.

In this paper we consider being delinquent or overlimit by mistake as being a moderately consequential mistakes for the individual, because not only is the individual subject to a fee, but also such actions can negatively impact the individuals credit rating (or FICO score). In order to examine whether these relatively consequential mistakes are different from frictional mistakes we also examine as an example of frictional mistakes, the case of individuals unnecessarily utilising expensive cash advance facilities on their credit cards, when sufficient deposits were available that could be withdrawn instead at no cost.

The issue of mistakes falling at various points of the frictional-consequential spectrum is also important for comparing our empirical results with results found by Campbell (2006), Calvet, Campbell and Sodini (2007 A and B) and Lusardi and Mitchell (2007) etc. These authors examine financial mistakes which are substantially more consequential than the mistakes we analyse here. They include choosing inappropriate mortgages and pension arrangements and failure to invest in the stock market. A common empirical finding in this stream of research (e.g. Vissing-Jorgensen (2003) Campbell (2006) and Calvet, Campbell and Sodini (2007A)) is that richer individuals make fewer of these consequential mistakes in the context of stock market participation, mortgage choice etc.

The central argument of these authors is that these kinds of mistakes are a result of the complexity of the financial decisions involved and are caused by the relative financial illiteracy of the individual making the decision (e.g. the need to make long term economic predictions when choosing a mortgage or pension arrangements)[4]. We argue that the kinds of mistakes we are examining here (i.e. not paying the credit card minimum balance or exceeding the credit card credit limit) do not require the solving of complex long term financial problems, but rather require the individual to keep track of monthly credit card payments and expenditures. It is for this reason that we ascribe the cause of these mistakes to inattention rather than financial illiteracy. The new empirical evidence

[4] Ameriks, Caplic and Leahy (2003) provide evidence that long term planning has significant impacts on retirement wealth.

in this paper thus allows us to examine whether wealth does impact mistakes specifically caused by inattention, or whether such wealth effects are limited to the more consequential mistakes caused by financial illiteracy as described in the existing literature.

The second additional motivation for our study is that our data allows us to examine whether the location that an individual chooses to live in (as represented by a postal code) can provide predictive information on the kinds of financial mistakes that the individual will make. While financial mistakes are costly to an individual, they can also be very profitable to a financial institution. The question that our data allows us to ask is whether banks can use available data, based on the location that an individual lives in, to maximise its profits by focussing on providing cards to individuals who have a higher probability of making mistakes. The issue of banks using geographic criteria to make financial decisions can be very controversial, as highlighted by “redlining” procedures used in the past by some US banks. Redlining refers to the banks making mortgage decisions based on the racial composition of various neighbourhoods. Nevertheless, Finkelstein and Poterba (2006) provide evidence that the geographic location an individual lives in (using the UK postal code system) does indeed provide information on the behaviour of individuals in the context of their financial transactions with insurance companies and in particular the issue adverse selection. We examine a similar yet different question in this paper – i.e. can postal code level geographic location assist in predicting credit card mistakes.

The third additional motivation for this study is that it allows us to examine whether the different *components* of wealth impact the making of financial mistakes, as emphasised by Campbell (2006). Distinguishing between the wealth effects from different components of wealth (rather than simply total wealth or even total income) has recently become important, for example, in research on consumption. Campbell and Cocco (2007) and Sinai and Souleles (2007) examine if the wealth effect from residential property could be different from the wealth effect from non-residential financial wealth. They argue that if individuals believe that if they sell their current house they will simply have to purchase another house that has also increased (or decreased) in price by a similar amount, then the wealth effect on consumption from residential property may be less than the wealth effect from non residential financial wealth. It is an outstanding empirical issue, however, as to whether such differences in the size of wealth effects across the different components of wealth (e.g. residential property compared to non-residential property wealth) are evident in the determinants of financial mistakes.

The final part of our paper examines the issue of strategic default. It is possible to argue that what we have defined as a mistake can also be defined as strategic default if an individual deliberately decides to default on their credit card debt (in spite of having sufficient deposits) because of the advantages that bankruptcy or default can confer. Our data however allows us to specifically examine whether "mistakes" should be defined as strategic default by examining whether the individual does indeed default or declare bankruptcy in the months following a mistake. We find that strategic default is an exceptionally rare occurrence.

The outline of the paper is as follows. Part 1 defines a large variety of different credit card mistakes and examines how often they occur. Part 2 describes the data we use to examine the characteristics of those who make financial mistakes, while part 3 examines the issue of using postal code level data as a proxy for individual level data. Part 4 provides our results.

1. HOW OFTEN ARE CREDIT CARD MISTAKES MADE?

This section first defines a variety of credit card mistakes including both relatively consequential as well as frictional mistakes under a variety of different definitions relating to precautionary balances etc. It then provides evidence on the prevalence of these mistakes using data from our confidential consumer level database provided to us by a Canadian Bank.

1.1 Defining Credit Card Mistakes

In this paper all mistakes we examine occur when an in individual unnecessarily incurs costs on their credit card in spite of having sufficient deposits available to have avoided those costs. We examine four events (1) delinquency, (2) overlimit, (3) cash advance and (4) simultaneous delinquency and overlimit in a single month, as the basis of our definitions of mistakes. We first describe each of the four mistakes and then we describe how we define "sufficient deposits" in detail below.

The first type of mistake that we examine is when a consumer is delinquent on their credit card repayment, even though the consumer has "sufficient deposits" in their deposit account. The bank that supplied us with our individual credit card data defines delinquency as occurring when a consumer fails to repay at least the minimum repayment due on any given month. This is a very serious act that has some potentially severe consequences for the consumer. According to the Bank involved, if a consumer is delinquent for five months is a row, the bank will declare the consumer in default, and withdraw the credit card. Furthermore, every time the consumer is delinquent, there is a significant negative impact on the consumer's credit rating (e.g. Credit Bureau or FICO score). For this reason we define this as a "consequential" mistake that has significant negative impacts on an individual.

The second mistake we examine is when a consumer is overlimit on their credit card but still has sufficient balances in their deposit account that could have been used to avoid being overlimit. Being overlimit is defined by the bank who provided us with the credit card data as occurring when a consumer uses credit that exceeds the pre-approved credit limit set by the bank. When the consumer is overlimit the consequences are still consequential, but are somewhat less sever than when the consumer is delinquent. An overlimit consumer faces a decline in both their internal as well as external credit rating (which can increase future borrowing costs and access to credit) as well as a fee for each overlimit episode. However, the consumer does not face the situation of a card being withdrawn (unlike the case of being delinquent).

The third mistake we examine is a combination of the delinquent and overlimit mistakes described above occurring within the same month. This is clearly more consequential for the individual than for either of the two mistakes occurring separately.

The final mistake we examine is when a consumer pays a cash advance fee, even though the consumer has sufficient deposits available. The cost structure of the bank from which our data is derived is such that a consumer is able to use their credit card to withdraw cash from an ATM machine or a branch, but there is a cost to the consumer of a fee of $x as well as the (very high) credit card interest rate. Consumers are essentially faced with a choice when withdrawing cash directly from an ATM or a branch as to whether they withdraw directly from their deposit account, or alternatively whether they withdraw cash using the cash advance facility on their credit card. We argue that if the consumer has sufficient funds (which we define below) in their deposit account, then it is a mistake for the consumer to make use of the credit card cash advance facility rather than withdrawing funds directly from their deposit account. The additional costs incurred when using a credit card to withdraw funds at an ATM or branch are higher than when the funds are drawn directly out of a deposit account. However, this mistake is essentially frictional and not very consequential for the consumer and results in a few dollars loss. It is representative of the kinds of frictional mistakes discussed by Ellison (2005) and by Gabaix and Laibson (2006) in their model of shrouding.

The second part of our definition of mistakes is defining what we mean by "sufficient deposit balances". An important issue to consider is that individuals may be holding some of their balances in their deposit accounts as precautionary balances – i.e. as a precaution against unforeseen future shocks. If deposit balances are being held for precautionary reasons, then it may be inappropriate to consider it a "mistake" when the individual does not use these balances to avoid the credit card costs described above. Because of this we provide various alternative definitions of mistakes which control for the holding of deposits under a variety of assumptions about holding precautionary balances.

The literature on precautionary balances (e.g. Opler, Pinkowitz, Stultz and Williamson, (1999), Alan (2006) and Bates, Kahle and Stultz (2007)) has provided two main conditions under which precautionary balances are held. These are (1) when cash flows are very volatile and (2) when cash flows are low. The argument is that individuals whose deposit balances are volatile over time or are relatively low, will likely hold a much larger amount of precautionary balances compared to individuals whose monthly deposit balances are less volatile or are at a higher level. In this paper we are able to control for either or both of these factors when providing our various definitions of mistakes.

A significant advantage of our data is it is panel data that includes monthly deposit balances for each individual for 19 months. Having access to 19 months worth of deposit balances for each individual provides us with a natural way to calculate our first measure for the precautionary holding of deposits – i.e. the volatility or standard deviation of deposit balances over the 19 months. The second motive for holding precautionary balances is that cash flows are "low". In this paper we define "relatively low" cash flows as those individuals whose average deposit balances is in the bottom quintile of all individuals in our sample (the cut off point is a monthly deposit balance of approximately $240).

As an additional measure of mistakes we also examine the proportion of individuals who make the various mistakes in *consecutive* months. By examining how many individuals make repeated mistakes in consecutive months, we can examine whether individuals learn from their mistakes and don't repeat them. This part of our study is similar to the work of Agarwal, Driscoll, Gabaix and Laibson (2006) who show that once an individual has paid a credit card fee (e.g. late, overlimit or cash advance) the individual pays fewer fees in subsequent months, (but will pay fees again at some longer term point in the future). The key distinction between our research and the work of Agarwal et al (2006) is that we focus on *mistakes* (i.e. paying a fee in spite of having sufficient deposit balances), while they examine all fee payments. By examining whether individuals make mistakes in consecutive months, we can ask a similar but different question to that of Agarwal et al (2006), that is whether individuals learn from their mistakes and don't repeat them.

Using these alternative measures of mistakes we can thus provide a variety of different definitions of mistakes in Table 1.

1.2 Evidence on the prevalence of credit card mistakes

Table 1 provides a summary of the prevalence of each kind of mistake ((1) delinquent, (2) overlimit, (3) cash advance and (4) delinquent & overlimit) under the various definitions for mistakes that can be used. Each cell in Table 1 is reported as a percentage of the total individual/month datapoints in the database (approx 1 million data points).

The first row provides data on the raw total, which is simply the number of individual/month datapoints where an event such as delinquency, overlimit etc. occurred, without any adjustment for deposit balances. Our first definition of mistakes (row 2) shows the percentage of individuals who incur the costs in row 1 *and* the individual has sufficient deposits available to avoid those costs. This first definition of mistakes ignores the issue of precautionary balances. Our second and third definitions of mistakes (rows 3 and 4), control for various definitions of precautionary balances. In row 3 we define "sufficient deposits" available to be total deposits minus one standard deviation of deposits over 19 months. This accounts for precautionary balances being a function of the volatility of cash flows. Our definition in row 4 is the same definition in row 3 with the additional constraint that those individuals with average deposit balances that are in the bottom quintile of our sample (i.e. less than $240 per month) are defined not to have made a credit card mistake. This reflects the fact that individuals with low cash flows, may hold additional deposits as precautionary balances. Our fourth definition of mistakes (row 5) is the same as in row 4, except that it examines the proportion of individuals who make such mistakes in two consecutive months.

There are a number of important conclusions we can draw from Table 1. Firstly, comparing the various definitions of mistakes with the raw totals in row 1, provides evidence on what proportion of the raw total of events can be classified as mistakes. The data shows that across all four kinds of mistake (columns), as we strengthen the definition of what constitutes a mistake so the number of mistakes declines. However the data for mistakes definition 1, 2 and 3 indicate that a significant proportion of individuals who pay a fee or cost in a single month, do so by mistake (i.e. in spite of having sufficient deposits). Even by our most stringent definition of mistakes in a single month (Definition 3) we find that 4% of the sample is mistakenly delinquent, 1.7% is mistakenly overlimit and 1.5% mistakenly uses a cash advance facility.

Table 1 also shows the relatively small number of individuals who make mistakes in consecutive months (definition 4) compared to the number making mistakes is a single month. Additional evidence (not shown) is that the number of individuals making mistakes for three consecutive months is even smaller. This evidence is consistent with the argument that individuals learn from their mistakes and do not continue to make mistakes systematically.

Table 1: Percentage Occurrences of Credit Card Mistakes

This Table provides the percentage occurrences of various mistakes. All percentages are a proportion of almost 1 million month/consumer data points.

	Delinquent	**Overlimit**	**Cash Advance**	**Delinquent and Overlimit in Single Month**
Raw Total Ignoring Deposits	10.3%	5.8%	4.6%	2.5%
Mistakes- Definition 1 Unnecessary Cost when Sufficient Deposits Available	6.6%	3.2%	2.7%	1%
Mistakes – Definition 2 Precautionary Balances function of standard deviation of deposits.	4.1%	1.8%	1.5%	0.5%
Mistakes – Definition 3 Precautionary Balances function of standard deviation of deposits *and* bottom quintile of deposits	4.0%	1.7%	1.5%	0.5%
Mistakes – Definition 4 *Consecutive* Months of Definition 3 Mistakes	0.6%	0.4%	0.3%	0.09%

The second important implication from Table 1 can be seen by comparing (across the columns) the number of individuals who make delinquent or overlimit mistakes (which can have significant negative consequences) with the number of individuals who make cash advance mistakes (which we described as a frictional mistake involving only a few dollars of additional costs). Building on of Ellison's (2005) "traditional" model that small frictional mistakes occur because there is a relatively low cost that the individual has to be concerned about, it can be hypothesised that small frictional mistakes should be more common than more consequential and costly mistakes. Our data in Table 1 shows that the reverse is true, with the greatest number of mistakes being delinquent mistakes – which are potentially the most costly to an individual because such mistakes incur a fee, impact credit ratings and can lead to the loss of a credit card.

This finding that our data is not consistent with the frictional hypothesis (that mistakes are made because the costs of making them are not significant for the individual) implies that other explanations need to be examined, including the "behavioural" model of Ellison (2005) that certain types of individuals make mistakes because of the characteristics of the individual. We examine this issue in the following section.

2. WHO MAKES CREDIT CARD MISTAKES?

Once we have defined a variety of credit card mistakes (Part 1 above), we are then able to examine the characteristics of those individuals who make those credit card mistakes. This section describes the task of building our new database so that we can match our dependent variables (credit card mistakes) with a large variety of independent variables, including measures of the different components of wealth etc. The following section (Part 3) examines the issue of using postal code level data for our independent variables data while using individual level data for our dependent variables (mistakes).

2.1 Data Requirements

In his 2006 AFA Presidential Address, Campbell emphasises the severe challenges in building databases that are suitable for research into household financial mistakes. He lists five characteristics of an “ideal” database for such research. These characteristics are data that (1) are representative over the whole population (especially wealth), (2) measures both total wealth as well as the different components of wealth, (3) distinguishes between different assets, (4) are reported with a high level of accuracy and (5) is panel data that covers individuals over time. Campbell (2006) argues that a dataset with all of these characteristics does not yet exist, but the challenge of researchers in this area are to build databases that approximate as closely as possible these characteristics.

In the existing literature on financial mistakes, two different kinds of databases have been used; (1) survey data such as the survey of consumer finance (SCF) (used by Campbell, 2006) and (2) large databases of individual consumer accounts taken from financial institutions (used by Aggarwal et al, (2006), Aggarwal et al (2007), Gross and Souleles (2002) and others. Both approaches have both advantages as well as disadvantages.

Campbell (2006) in his study of mortgage and stock market participation mistakes uses the Survey of Consumer Finance (SCF). Although this survey includes measures of wealth, is also subject to some significant drawbacks as a database. As described by Campbell (2006) possibly the most important concern with all surveys is data accuracy, and the lack of control over how survey participants record the relevant data. Furthermore, like all surveys, the SCF requires the voluntary participation of selected households, and is thus vulnerable to systematic non participation by some households. For example, Campbell (2006) notes that 87% of very wealthy households refused to participate in the SCF and that 56% of moderate wealth households refuse to participate. Another concern with the SCF is that it is not a panel that follows the same households through time. Finally, while the SCF and other surveys have been used in a variety of research contexts in this literature, no survey type instrument exists that specifically examines credit card penalty fees which are the focus of this paper.

The second approach to empirically examining who makes financial mistakes has been used by Aggarwal et al, (2006), Aggarwal et al (2007), Gross and Souleles (2002). These authors make use of very large databases of individual consumer accounts taken from a single financial institution. The advantage of such an approach is that the researchers have detailed data on financial transactions and which of these may constitute financial mistakes. The disadvantage of such an approach is that researchers are limited to using the wealth and demographic data that can be provided by the financial institution. Most financial institutions only collect wealth and demographic type data very rarely, if at all. If data such as total wealth, income and education is ever collected, it is only done at the onset of a new financial contract (e.g. when a new mortgage is applied for[5]).Thus even if demographic data such as wealth, income and education are collected by financial institutions, they may become very outdated over time[6].

Clearly, neither of these two data approaches accords with the ideal data characteristics required for this kind of research as listed by Campbell (2006). What seems to be required is a combination of the richness of the wealth and demographic data provided in surveys such as the SCF survey, combined with the representative, accurate, large scale and panel nature of the data taken from individual account data at financial institutions[7].

2.2 Database Matching

This paper attempts to address the data concerns outlined by Campbell (2006) by using a unique combination of three very large databases. Our first database is the confidential data on individual credit card and deposit accounts described in detail above in our discussion of mistakes. An important advantage of this database is that it includes the Canadian postal code for each individual. We use the postal code to match our data on credit card mistakes with two additional databases, (1) postal code level census data provided by Statistics Canada and (2) postal code level data on the actual market values

[5] One of the issues at the center of the financial market volatility of August 2007 is that many banks in the US issued sub-prime mortgages *without* any information on income or wealth from the borrower.
[6] The one obvious exception to demographic data becoming stale is date of birth data. This data is used by Aggarwal et al (2007) in their study of the impact of age on financial mistakes.
[7] Recent work by Calvet, Campbell and Sodini (2007A) and (2007B) uses a very rich database that includes disaggregate measures of wealth and income from the entire population of Sweden.

of residential properties taken from the Provincial Land Titles Registry. The Statistics Canada Census data provides us with various proxies for different components of wealth including Business and Investment Income and Rent/Own status of residential property. The Land Titles Registry data provides us with market values of residential properties.

In order to match the three databases based on postal codes we follow the procedures adopted by Statistics Canada and Canada Post by using a concept known as the Dissemination Area (DA) as the minimum geographic area into which we can place all of our various data. A DA consists of a number of neighbouring postal codes. In terms of size, the average Canadian Postal Code has approximately 20 households, while the average Dissemination Areas (DAs) has 200 households. We are able to uniquely convert each postal code into each DA using the Postal Code Conversion File (PCCF) published by Statistics Canada and Canada Post (Statistics Canada, March 2006). (For ease of understanding we have used the term “Postal Code” up to this point in the paper rather than the more technical but more correct term “Dissemination Area”).

Even though each Canadian DA has more households (200 households) than an individual Canadian postal code (20 households), it is still orders of magnitude smaller than each US Zip Code (approx 10 000 people SOURCE) or the size of UK geographic region used by Finkelstein and Poterba (2007) (each UK “ward” having 9 000 individuals). A full description of the geographic concept of the Dissemination Area is provided by Puderer, (2001)[8].

The main reason for our use of the DA geographical area is that we can match the postal code of an individual bank customer with DA level data from both the Canadian Census (e.g. data on business and investment income, government income and rent/own status etc.) as well as data from Provincial Land Titles Registries (e.g. data on the market value of residential property prices). Full details of these and other variables are provided

[8] In brief; the geographic concept of the DA has been designed by Statistics Canada as a relatively stable geographic unit composed of one or more neighbouring blocks, with a population of 400 to 700 persons (or on average 200 households). A DA can be formed within another DA when the population of an apartment or townhouse complexes meets or exceeds 300 persons (or as little as 125 households). DAs are defined by Statistics Canada to have intuitive (or visible) boundaries, such as roads or selected geographic features (such as rivers etc). (Statistics Canada 2001). A key issue concerns the homogeneity of individual households within a DA (i.e. same type of people). According to Statistics Canada, the homogeneity of each DA follows from the fact that “dwelling type often tends to be consistent from block to block without sudden transitions” (Statistics Canada, Mechanda and Puderer, 2001, p. 7).

below. While access Canadian Census level data at the DA level is relatively straightforward, sorting Land Titles Registry House Price data into DAs is more complex.

The Provincial Government Land Titles database lists the purchase/sale of every residential property in a Canadian Province. Unfortunately the raw data in the Provincial Government Land Title Database does not list the postal code of the property, but rather lists the so called Legal Address of each property (e.g. Map Number, Unit Number, Plot Number etc) that appears on Land Title documents. What we require is a conversion of this Legal Address into a Postal Address that includes a postal code. We are able to undertake this conversion because every legal address has a unique longitude and latitude marker. Using Geocoding (i.e. Geographic Information Systems) techniques (conducted for us by Wayto Consultants Inc. who specialize in GIS and Geocoding) we are able to convert the legal address of every property into a postal address – including the postal code. Then, using the Statistics Canada – Canada Post Corporation conversion file between postal code and DA we are thus able to match the transaction price of every residential property sold in the province to a Dissemination Area. Using this data we are able to derive average market values of residences in each DA (i.e. about 200 households on average) in each year. We made the choice not to disaggregate down to the postal code level (i.e. about 20 households on average) for two reasons. First, postal code areas (20 households) would often be too small to ensure that we have enough residential sale transactions in each year to calculate a meaningful average. Secondly, using the DA as a measure of market values of properties fits with Statistics Canada using the DA as the unit to measure Census data reported above.

Table 2, below, provides a summary of the three different databases that we match together in our analysis.

Table 2:

Database Matching and Minimum Geographic Size.

Database	**Variables**	**Minimum Geographic Size**	**Match By**
1. Individual Credit Card Accounts (from Bank)	• Credit Card Mistakes • FICO • Credit Limit • Card Type	Individual with known Postal Code (20 households)	Postal Code to Dissemination Area Conversion File
2. Statistics Canada Census Data	• Income from Business and Investments • Income from Government Sources • Rent/Own	Dissemination Area (DA) (Approx 200 Households)	Dissemination Area
3. Land Title Registry (Provincial Government)	• Prices of Residential Properties Sold and Date of Sale	Postal Code, but aggregate up to DA to ensure enough transactions.	Postal Code to Dissemination Area Conversion File

2.3. Wealth Proxies from Census Data

The Statistics Canada DA level census data provides us with a very useful set of variables – particularly variables that can serve as useful proxies for different components of wealth. Firstly, the Census variable “Business and Investment Income” provides us with a good proxy for the business and investment wealth of individuals in each DA.

Note that all of the elements of this variable (see definition in footnote[9]) refer to the annual income from assets, rather than the assets themselves. Thus if we theoretically multiplied business and investment wealth by the rate of return, this would result in our business and investment income variable. We argue therefore, that the higher the level of the business and investment income, the higher the wealth of these individuals. In our empirical specifications we measure business and investment income as a total dollar value.

The second useful proxy for wealth from the Census data is Income from Government Sources[10]. The main elements of this form of income are Old Age Security and Unemployment Insurance (see footnote for complete Statistics Canada definition). We argue that if these payments make up a significant proportion of total income in any year, then this is a good proxy for low wealth.

Another useful proxy for income that we derive from census data is the proportion of the population in each dissemination area (DA) that rents its residence compared to the proportion that owns its residence. We argue that if individuals rent rather than own their residence then this is a very useful proxy for those individuals having lower wealth.

2.4. Wealth Proxy from Land Titles Registry

Using this Land Titles Database, we are able to generate a variety of alternative measures of market values of house prices in each DA. Our first approach is simply to measure the average market value of residences in any specific year, thus capturing the cross sectional dispersion of residential property values across our sample of credit card holders. As an alternative approach we can examine the average market value of residential property over time, by averaging the "real" market value of property prices in multiple years. In this case we deflate the property price in each DA/Year by the average property price in all DAs for that year, and then average across multiple years.

[9] **Business and Investment Income:** Dividends, interest on bonds, deposits and savings certificates, and other investment income, income from unincorporated business and/or professional practice and farms, retirement pensions, superannuation and annuities, including those from RRSPs and RRIFs.

[10] **Income from Government Sources:** Canada Child Tax benefits, Old Age Security pension and Guaranteed Income Supplement, Benefits from Canada or Quebec Pension Plan, Benefits from Employment Insurance.

2.5. Other Demographic Characteristics from Census Data

In addition to providing us with proxies for wealth, the Census data also provides us with other demographic data – in particular age and education. For each DA, we have data on the proportion of people in the DA who have particular levels of education, and who fall within certain age brackets. For example, in terms of education we have data on the percentage of people in each DA who have (1) no high school, (2) high school only, (3) some post secondary and (4) bachelor or higher. Because these four categories add up to 100% for each DA, we have to drop one category to serve as the relative variable in our regressions. In the case of education, we drop no high school – thus all our education coefficients estimate the impact of the other education category relative to the no high school category.

In terms of age, Statistics Canada provides data on the percentage of each DA that falls within the following categories: 0-19, 20-34, 35-54, 55-64, and 65 and over. Once again these categories will add up to 100% for each DA, so we drop the category "over 65" and use this as our comparison category. It should be noted that in this database we do not have the individual birth year of each individual credit card consumer in the Credit Card database. Thus our results are not directly comparable to the results of Agarwal, Driscoll, Gabaix and Laibson (2007) who use such individual level data in their work on the impact of age on financial mistakes.

In order to capture the impact of larger families on household behaviour, we also include a variable for the average household size in each DA.

2.6. Individual Credit Characteristics

When examining consumer behaviour (e.g. mistakes) with respect to credit cards, a key issue that we need to control for is individual consumer risk. In order to control for consumer risk, we use two variables taken from the Individual level credit card database provided by the Canadian bank. These measures are an externally determined risk score as captured by the consumers FICO score, and an internally determined risk score as captured by the consumer credit card credit limit.

The FICO score (or the "Beacon Score" as it is referred to in Canada) is a score provided by the credit bureaux for each consumer that is updated quarterly. This score captures past credit history, including past delinquency/defaults, past overlimit behaviour, multiple applications etc. It is important to note that the FICO score does *not* include data on variables such as income and wealth etc. Rather its components are essentially data that an individual financial institution can easily and rapidly observe on a quarterly basis (such as delinquency, multiple new applications etc.) Note also that the FICO score is different from our “mistakes” variable as we define above – which are all subject to the condition that the consumer has “sufficient funds in their deposit account”. Furthermore, the FICO score measures a weighted average of past behaviour only, whereas our dependent variables only measure current behaviour as it applies to a particular mistake.

Our second score of individual consumer risk is the credit card credit limit that each consumer is allowed by the bank on their credit card. The credit limit captures the banks own internal assessment on how much credit each consumer can be allowed. The credit card credit limit can thus be thought of as an internal credit evaluation by the bank itself, while the FICO score can be thought of as an external credit score by the credit bureaux.

Our final variable captures the kind of credit card that each consumer has chosen. In the case of the bank that has provided us with the data there are two main types of credit card – those that are “no frills” and do not have any fees, and those that provide a variety of features in exchange for a fee. We include a dummy variable to capture no fee cards. This reflects the choice of consumers who are concerned about paying additional fees for features. It can hypothesised that such consumers who choose a “no fees” card may be expected to be more careful – and thus less likely to make credit card mistakes.

3. POSTAL CODE (or DA) DATA AS A PROXY FOR INDIVIDUAL DATA

Before we present our results (section 4 below) this section examines the issue of using postal code (or DA) level data as independent variables (describing the components of wealth etc) when the dependent variables are individual level data on mistakes. In the introduction to this paper we note (among others) two different motivations for our research using postal code level data. The first is to examine the issue of whether banks can use information available to them about where an individual lives (i.e. postal code) as a way to predict whether the individual will make more profitable mistakes. This is similar to the question asked by Finkelstein and Poterba (2006) who examine whether postal codes provide predictive information regarding individual financial decision making in insurance markets. In this context, it can be argued that the postal code level data that we use is appropriate.

The second motivation that we discuss in the introduction concerns using postal code level data as a *proxy* for individual data – particularly in the context of examining whether different components of wealth have different impacts on financial mistakes. The discussion below examines whether the use of postal code data (from 200 households) as a proxy for individual data is appropriate.

3.1 Do Post Codes (or DAs) Reflect Individuals?

In the context of their study using postal code level data from Britain as a proxy measure for individual data in the insurance market Finkelstein and Poterba (2006) provide a useful mechanism for examining the extent to which post code level data is reflective of individual data for residents of that post code. They do this by examining the ratio of the standard deviation of a characteristic (e.g. income, wealth etc) across postal codes compared with the standard deviation of this same characteristic across individuals. If this ratio of standard deviations is zero, then this implies that information about the postal code an individual lives in provides no information about the individual. As an extreme example, consider if the *average* (but not individual) wealth in each postal code was exactly the same, then the standard deviation of postal code level average measures of wealth would be zero. In such an example, knowing the postal code an individual lived in would not provide any information about that individual. At the other extreme, if the postal code level measure of the characteristic is perfectly predictive of the individual's characteristic, then these two standard deviations should be equal (i.e. their ratio equals 1). Finkelstein and Poterba (2006) thus use this ratio, which can fall between 0 and 1, as a measure of the extent to which post code level data can act as a proxy for individual level data.

In order to implement this procedure, data is the same data is needed at both the individual and post code level. In this paper, we can implement the Finkelstein and Poterba (2006) procedure by examining individual level data taken from the bank credit card database and sorting every individual into a specific DA. In particular, we have individual level data on line of credit allowed by the bank for each individual's credit card as well as each individual's credit rating (FICO Score). Both the credit rating as well as FICO score reflect to some extent the wealth of an individual. We find for Credit Card Credit Limits that the ratio of the standard deviation of DA averages to the standard deviation of all individuals is 0.44. Similarly the ratio for FICO Scores is 0.42. Clearly, these results show that while the DA may not be a perfect proxy for individual credit limits and credit ratings (which implies a ratio of 1), knowing the DA of an individual does provide significant information on the credit limit and credit rating of that individual. We are not able to repeat this exercise for data about which we don't have individual information (e.g. census data on income from investments etc), but these results indicate that postal codes are of some use in acting as a proxy for individual data.

3.2 Post Code Data as Exogenous Variables.

One possible advantage of using DA level proxies for individual levels of wealth in our empirical specifications, concerns issues of endogeneity and causality. The key question that we ask in this paper is weather the different components of wealth impacts financial mistakes. However it is possible the causality can run in the other direction – i.e. that an individual who makes a financial mistake can cause lower wealth in the future. We argue that by using post code level census data as a proxy for individual wealth has significant advantages in terms of specifying the direction of causality. Post code level census data represents the average level measured in 2001, while our data on financial mistakes is measured in 2004 to 2006. Thus in terms of timing measured wealth occurs significantly before the measured mistakes. Furthermore, in terms of specifying endogenous and exogenous variables in our regressions, it seems very unlikely that that a specific individuals financial mistake will impact the average wealth of a postal code. Rather it can be argued that the average wealth of a postal code (which serves as a proxy for individual wealth) impacts which individuals are more likely to make a financial mistake.

3.3 Use of Post Codes in other Disciplines

While we believe that this is the first paper to exploit the smaller size advantages of the Canadian Postal Code system over the US Zip Code system in the context of research on financial mistakes, these advantages have been commonly used by researchers in other disciplines. One common example is medical research where questions of the links between socio-economic status and various diseases (e.g. infant mortality, lung cancer) or access to different types of medical care is very important. Subramanian , Chen , Rehkopf, Waterman and Krieger (2006) provide a detailed review of different geographic measures that can be used for Socio-Economic measures in the US and conclude that the US Census Tract (which includes on average 4 000 individuals) is the most appropriate for medical research. These authors recommend against the use of US Zip Codes because of the poor links between Zip Codes and US Census data.

In contrast to this, the fact that Canadian postal codes can be very well matched to census data using the Dissemination Area procedure (described above) at a very fine grained level, has resulted in a large variety of studies in the medical literature using Canadian Post Code level census data for socio economic variables. Examples of this include Shortt and Shaw (2003), Deondan et al (2000), Demissie et al (2000) and Mustard and Frohlich (1995).

In the case of research into financial mistakes, the fact that we are able to utelise Canadian post code level data is especially valuable, given the fact that for confidentiality reasons banks will not usually provide researchers with confidential street address information (which can facilitate the identification of individual account holders), but will only provide post code information. Such post code information is clearly much more valuable in the Canadian compared to the US context. Not only are US Zip codes much larger, but as described by Subramanian et al (2006) in the medical context, matching US Zip Codes to US Census tracts can be problematic.

4. RESULTS

Our results are reported in Tables 3, 4 and 5. Each of these Tables has as a dependent variable one of the alternative definitions of credit card mistakes reported in Table 1 above (where the dependent variable equals 1 for a mistake and 0 for no mistake). Table 3 examines credit card mistakes where precautionary balances are measured by one standard deviation of monthly deposits. Table 4 extends this definition to in addition define as precautionary balances those monthly deposits that are in the bottom quintile of deposits (i.e. only individuals whose monthly deposit balances is more than $240 will be defined to have made a mistake based on the definition in Table 3). Table 5 uses the same definition as Table 4, but examines cases where these mistakes happen in *consecutive* months. Each of these Tables reports on four different kinds of mistakes (delinquent, overlimit, cash advance and delinquent & overlimit in a single month). We thus report on 12 different models.

In all of these tables we report results using panel logit models with random effects. The panels consist of individual customer level data over 19 months. Our usable data consists of almost 75 000 individual bank customers and almost 1 million total individual/month datapoints. Because some of our independent variables (e.g. post code level census and land titles registry data) remains constant over the 19 months for each individual, the use of fixed effects panel models is not appropriate.

In terms of our various components of wealth variables, the proportion who rent variable is significant in 11 of the 12 different models we report. In all cases the sign is positive indicating that renters make significantly more of these credit card mistakes than owners. Based on the argument that renters will tend to be lower wealth on average than owners, this finding very strongly supports the proposition that poorer individuals make more mistakes.

The second component of wealth variable of interest is the dollar amount received from business and investment income. This variable is significantly negative in six out of the eight models examining single months (Tables 3 and 4) and one out of four models examining mistakes in consecutive months (Table 5.) In other words, these results show that the greater an individual's wealth that is held in the form of investments or ownership of businesses, the fewer of these credit card mistakes will be made. Once again this finding strongly supports the proposition that poorer individuals make more mistakes.

The third measure of wealth we can examine is the percentage of total income that is derived from government sources such as unemployment insurance or government pensions. These variables are significantly positive in all three of Tables 3, 4 and 5 in the specific case of mistakes involving unnecessary delinquency. We can thus conclude that the greater proportion of income received from government sources, the more delinquency mistakes are made. These results again strongly support the hypothesis that poorer individuals make more credit card mistakes.

Another finding of interest concerns the significance of the residential property value variable taken from the land title registry database. This variable is insignificant in all models with the exception of the cash advance mistake specification in consecutive months model (Table 5). In the case of all of the models where the residential property value is insignificant, this implies that there is no wealth effect of residential property values on mistakes. This finding is similar to the recent arguments by Campbell and Cocco (2007), and Sinai and Souleles (2007) that the wealth effects from housing can be small if individuals believe that rising house values does not increase wealth. This happens if individuals believe that if they sold their current house they would have to replace it with an equally expensive new house.

Of particular interest however is the finding that residential property value is *positive* and significant in the model examining cash advance mistakes in consecutive months (Table 5). In other words individuals who live in residential properties with higher market values are more likely to unnecessarily pay cash in advance costs in consecutive months. This finding is consistent with the "traditional" theoretical model of Ellison (2005) that richer individuals may make more frictional mistakes because they have a lower marginal utility of income and thus are less concerned about losing a few extra dollars than poorer individuals. In this paper we have highlighted that cash advance mistakes are different than delinquent or overlimit or delinquent because they are more frictional rather than consequential.

It is also noteworthy that in all of our models (with one exception at 10% significance) our measure of annual income is not significant. This highlights Campbell's (2006) argument concerning the importance of using measures of wealth (and also measures of the different components of wealth) rather than income in these kinds of behavioural models.

In our models we include two individual level measures of risk taken from the bank credit card database - the consumers FICO score which represents an external risk measure, as well as the pre-approved credit card line of credit, which represents the banks own internal assessment of the risk of an individual borrower. In all of our models these variables are significantly negative. This implies that the greater the assessed risk of the individual, the more mistakes the individual makes. (Note that our measures of FICO and credit limit are taken from the beginning of the sample period, so a mistake during the sample period will not impact those variables). These risk variables are important control variables because they allow us to interpret our preceding results on the impact of wealth on mistakes as having controlled for individual risk.

As an example of the importance for controlling for risk (i.e. including FICO and credit limit in our regressions) consider our finding (described above) that individuals who rent are more likely to make mistakes. It could be argued that the fact that an individual has a bad credit history can imply both that the individual will (1) be unable to get a mortgage and thus be forced to rent and (2) make more credit card mistakes. In other words, both propensity to rent as well as propensity of making mistakes could be the result of a third variable – past poor credit history. However because we are able to include the exact measures that the bank uses to measure and reflect individual risk (FICO and Credit Limit) in our regressions implies that our finding reported above can be interpreted that renters make more mistakes, even after controlling for past credit history.

A second important reason for including the risk variables (FICO and credit limit) in our regressions is in the context of the work on the information content of postal codes of Finkelstein and Poterba (2007). Finkelstein and Poterba (2007) provide evidence that the postal code an individual lives in provides information on consumer behaviour in insurance markets, thus potentially allowing a bank to use postal code data to make financial decisions. Our results can be interpreted in a similar light if we assume that information available to the bank is captured by the FICO score and the credit card credit limit. The fact that a variety of post code level wealth variables (described above) are significant even after controlling for FICO and credit limit implies that the bank could capture additional information on who makes (profitable) credit card mistakes by examining post code level data. One possible reason, noted by Finkelstein and Poterba (2007) why banks don't typically make credit decisions based on postal code data are past controversies when banks have attempted to use geographic location in credit decisions such as "redlining" of mortgages.

In all our regressions we have included a dummy variable to reflect the type of credit card chosen by the individual. Individuals typically have a choice between two broad classes of credit cards – a "no frills" card that does not include any fees etc, or a card that charges fees for a variety of "extras". Our results across 10 of our 12 regressions show that individuals who have chosen a card without the possibility to pay fees make significantly fewer credit card mistakes. This is consistent with the explanation that individuals who chose cards without fees are concerned with paying additional costs and thus are more careful about making unnecessary credit card mistakes.

Our findings on education level are interesting because they are not monotonic. We find that bachelor or higher make significantly fewer mistakes than no high school and that there is no significant difference between high school and no high school. However we also find that some post secondary make more mistakes than no high school. One possible explanation for this non-monotonic finding in education is the distinction we drew in our introduction above between mistakes that are caused because of *inattention* (i.e. the credit card mistakes discussed here) and mistakes cased by *financial illiteracy (*e.g. mistakes involving complex long term financial decisions) such as the choice of mortgage or pension plan as discussed by Campbell (2006) and Lusardi and Mitchell (2007).

We argue however that the kind of mistakes examined in this paper (i.e. remembering to pay the minimum credit card payment, and keeping track so as not to exceed the card credit limit) are not necessarily the result of financial illiteracy (i.e. failure to understand complex long term financial problems). In other words, our results for education may be non-monotonic because the kinds of mistakes we are examining are not typically caused by a lack of individual *understanding* or financial literacy (which could be strongly proxied by education level) but rather caused by a lack of personal ability to keep track of payments etc because of inattention. While education level could have some impact on financial organization (e.g. the ability to keep track of credit card payments), we argue that this impact will be less than the impact of education on financial understanding or literacy.

Our main finding with respect to our age variables is that no discernable pattern emerges. Thus our findings differ from the of Agarwal et al (2007) who find evidence of a “U” shaped curve, with younger or older individuals making more mistakes than middle aged individuals. It should be noted however that our data only measures average age at the postal code (DA) level, while Agarwal et al (2007) have data on age from each individual’s date of birth.

5. STRATEGIC DEFAULT

An individual can decide to strategically default on their credit card debt because of the advantages that default and bankruptcy can sometimes provide (protection from creditors etc.). An individual who is attempting to strategically default can therefore decide to be delinquent or overlimit, even if the individual has sufficient balances in their deposit account. In other words strategic default can look like the mistakes we have been examining in this paper. Recall that the bank that provided us with our data will withdraw a credit card from an individual and declare the individual charged off after five successive months of being delinquent (not paying the minimum balance due).

One very important advantage of the panel nature of our data (i.e. examining individual accounts over 19 months) is that we can examine how the individual behaves with respect to delinquency in the months after a “mistake” has been made to determine if the individual is attempting to strategically default. We can further distinguish between bankruptcy (which can be declared by the individual) and chargeoff (which is declared by the bank of the individual has failed to pay the minimum balance due for five months).

We examine how many individuals who have made a mistake for three months in a row have gone on to be charged off by the bank (we select mistakes for three months in a row because this is a very severe measure of mistakes). Out of a total sample of more than 90 000 individuals, only 3502 have made a delinquency mistake for three months in a row. Of those only 49 have gone on to be charged off and only 3 have declared bankruptcy. In other words, we can show that while strategic default may be a possible reason for individuals making mistakes, this is a very rare occurrence.

6. CONCLUSIONS

This paper documents that a significant proportion of individuals who pay credit card penalty fees do so in spite of having sufficient deposits available which would have allowed them to avoid these fees. In other words, these individuals are paying the penalty fees by mistake through inattention, rather than because they are facing financial difficulties.

The paper also finds that the individuals who pay credit card penalty fees by mistake are poorer. In particular individuals who make these mistakes (1) live in areas with more renters than owners, (2) receive a greater proportion of income from government sources such as unemployment insurance and government pensions and (3) receive smaller amounts from the ownership of businesses and other investments. We base these results on an innovative new database, that combines confidential individual level credit card account data with postal code level data from the Canadian Census as well as from Provincial Land Titles Registry data. Our ability to match these databases is based on the very small size of Canadian postal codes, which are orders of magnitude smaller than US Zip Codes.

Our findings contribute to the existing literature on household finance in a number of ways. First, the new database that we build goes some way towards meeting the requirements of the "ideal" database for research in household finance outlines by Campbell (2006). We argue that our combined new database has important advantages over databases used in the existing literature (e.g. survey data such as SCF, or bank account data that is not matched with a variety of measures for wealth and other demographics).

Second, our research allows us to empirically tests models such as Ellison (2005) as to whether richer or poorer individuals make more frictional mistakes. He argues that richer individuals can be predicted to make more small frictional mistakes because they have a lower marginal utility of income, and thus are less concerned by such small mistakes. Our findings, however, that poorer individuals make more frictional mistakes, imply that our evidence is consistent with Ellison's behavioural hypothesis that the poor are more financially unsophisticated.

Third, our research can also examine the impact of wealth on mistakes as the mistakes change from being small frictional mistakes to larger more consequential mistakes. Our finding that poorer individuals make more mistakes is consistent with other recent evidence in the literature (e.g. Vissing-Jorgensen (2003) Campbell (2006) and Calvet, Campbell and Sodini (2007A)) who all examine significantly more consequential mistakes than we do. However, the importance of our new results is that our evidence refers to mistakes that are caused by inattention (i.e. forgetting to pay the credit card account on time) rather than because of financial illiteracy (i.e. being unable to understand the long term financial calculations involved in choosing a mortgage or retirement plan) as described in the existing literature.

Fourth, our research allows us to examine if the location an individual lives in (i.e. a postal code) can provide information on the propensity of that individual to make a credit card mistake (which is profitable to the bank). Our results show that postal code level data does indeed provide such additional information to the bank, and is thus similar to the finding of Finkelstein and Poterba (2006) who examine post code level data in the context of the insurance market.

Fifth, our data allows us to examine the impact of not only total wealth, but also the components of wealth on mistakes. This follows recent work by Campbell and Cocco (2007) and Sinai and Souleles (2007) who emphasise that wealth effects from residential property values can be less than wealth effects from other components of wealth because if a house is sold it needs to be replaced. Our evidence shows that this is also the case for the impact of wealth on mistakes. While we find evidence that as business and investment wealth increases so mistakes decline, we do not find strong evidence that as residential property wealth increases, mistakes decline.

Finally, our findings have important public policy implications. We argue that an individual who pays a credit card penalty fee by mistake because of inattention (e.g. not paying the minimum balance due *in spite* of having sufficient deposits available to do so) has a lower risk of future default compared to an individual who pays a penalty fee because of financial difficulties (i.e. not paying the minimum balance due *because* of not having sufficient deposits). Because we can document that a significant proportion of those who pay credit card penalty fees do so by mistake because of inattention, this weakens the argument often proposed by the credit card industry that that rapidly rising credit card penalty fees are compensation for increasing default risk.

Table 3. DETERMINANTS OF CREDIT CARD MISTAKES

SINGLE MONTHS

PRECAUTIONARY BALANCES PROXIED BY 1 STANDARD DEVIATION OF DEPOSITS

Data is panel data and dependent variable is binary (1 = mistake and 0 = no mistake). Use Panel (Random Effects) Logit Methodology. Dependent Variables are (1) Unnecessary Delinquency (2) Unnecessary Over-Limit and (3) Unnecessary Cash Advance (4) Unnecessary Delinquency and Cash Advance in the same month if have sufficient deposits. Sufficient Deposits defined as total deposits minus one standard deviation of deposits to proxy for precautionary balances due to deposit volatility. Independent Variables include different components of wealth including (1) Business and Investment Income and (2) Residential Property Value. Other variables are proxies for low wealth, i.e. income from government sources and proportion of dissemination area that rents rather than owns residences. Also included is Annual Total Income. Control variables include individual specific risk variables (FICO Score, Credit Limit) as well as other demographic variables such as age and education. All $ values are logged.

	Delinquent	**Over-Limit**	**Cash Advance**	**Delinquent & Over-limit in Single Month**
Residential Property Value ($)	-0.0121	-0.0010	0.0075	0.0390
Government Income (% of Total)	0.0074**	0.0026	0.0061	0.0024
Business & Investment Income ($)	-0.0147	-0.0747***	-0.0656**	-0.0700*
Residence Rent/Own Status (% Rent)	0.0021***	0.0039***	0.0065***	0.0035**
Annual Income Total ($)	0.0066	-0.0204	0.0648	-0.0651
Credit Rating –FICO Score	-0.0018***	-0.0038***	-0.0021***	-0.0038***
Credit Limit on Credit Card ($)	-0.1692***	-0.5542***	-0.2247***	-0.5897***
Type of Credit Card (No Fee Dummy)	-0.0374*	-0.4252***	-0.4545***	-0.1266***
High School (% in DA)	0.0021	-0.0019	-0.0001	-0.0010
Some Post Secondary (% in DA)	0.0005	0.0066***	0.00941***	0.0056**
Bachelor or Higher Degree (% in DA)	-0.0028*	-0.0110***	-0.0169***	-0.0104***
Age 0 to 19 (% in DA)	0.0087**	0.0028	0.0001	-0.0010
Age 20 to 34 (% in DA)	0.0025	0.0078**	0.0143***	-0.0013
Age 35 to 54 (% in DA)	0.0035	0.0084**	0.0034	-0.0012
Age 55 to 64 (% in DA)	0.0096**	0.0113*	0.0122*	0.0017
Population per Household	-0.0350	0.0429	0.1511*	0.0445
Immigrant (% in DA)	-0.0023	0.0032	0.0037	-0.0014
Constant	-1.8922***	1.6286***	-4.1208***	1.8050**
Number of Observations	970774	970774	970774	970774
Number of Groups	74769	74769	74769	74769
Observations Per Group				
Average	13	13	13	13
Maximum	19	19	19	19
Waldo Chi	1697.66	6187.97	1315.5	3691.04
Prob > Chi-Square	0	0	0	0
Log Likelihood	-147336.2	-68281.782	-57532.347	-26914.783

Table 4. DETERMINANTS OF CREDIT CARD MISTAKES

SINGLE MONTHS

PRECAUTIONARY BALANCES PROXIED BY 1 STANDARD DEVIATION OF DEPOSITS AND LOWEST QUINTILE OF DEPOSITS

Data is panel data and dependent variable is binary (1 = mistake and 0 = no mistake). Use Panel (Random Effects) Logit Methodology. Dependent Variables are (1) Unnecessary Delinquency (2) Unnecessary Over-Limit and (3) Unnecessary Cash Advance (4) Unnecessary Delinquency and Cash Advance in a the same month if have sufficient deposits. Sufficient Deposits defined as total deposits minus one standard deviation of deposits to proxy for precautionary balances due to deposit volatility. Also, to proxy for the holding of precautionary balances due to low deposits a "mistake" is not defined as a mistake if deposits fall below $240 (i.e. lowest quintile of deposits). Independent Variables include different components of wealth including (1) Business and Investment Income and (2) Residential Property Value. Other variables are proxies for low wealth, i.e. income from government sources and proportion of dissemination area that rents rather than owns residences. Also included is Annual Total Income. Control variables include individual specific risk variables (FICO Score, Credit Limit) as well as other demographic variables such as age and education. All $ values are logged.

	Delinquent	**Over-Limit**	**Cash Advance**	**Delinquent & Over-limit in Single Month**
Residential Property Value ($)	-0.0104	-0.0030	0.0037	0.0369
Government Income (% of Total)	0.0079***	0.0040	0.0066	0.0016
Business & Investment Income ($)	-0.0152	-0.0827***	-0.0763***	-0.0731*
Residence Rent/Own Status (% Rent)	0.00180**	0.00393***	0.0063***	0.0035**
Annual Income Total ($)	0.0033	-0.0212	0.0786	-0.0674*
Credit Rating –FICO Score	-0.0019***	-0.0037***	-0.0021***	-0.0038***
Credit Limit on Credit Card ($)	-0.15181***	-0.5321***	-0.2158***	-0.5689***
Type of Credit Card (No Fee Dummy)	-0.0376*	-0.4292***	-0.4499***	-0.1266***
High School (% in DA)	0.0019	-0.0026	0.0017	-0.0013
Some Post Secondary (% in DA)	0.0005	0.0063***	0.0091***	0.0057**
Bachelor or Higher Degree (% in DA)	-0.0025	-0.010***	-0.0163***	-0.0102***
Age 0 to 19 (% in DA)	0.0081**	0.0019546	-0.0005	-0.0031
Age 20 to 34 (% in DA)	0.0028	0.0090**	0.0143***	-0.0018
Age 35 to 54 (% in DA)	0.0030	0.0087**	0.0024	-0.0020
Age 55 to 64 (% in DA)	0.0096*	0.0143**	0.0127***	0.00134
Population per Household	-0.0338	0.0749	0.1425	0.06447
Immigrant (% in DA)	-0.0026*	0.0026	0.0035	-0.0016
Constant	-2.0176***	1.3002***	-4.2584***	1.7183**
Number of Observations	970774	970774	970774	970774
Number of Groups	74769	74769	74769	74769
Observations Per Group				
Average	13	13	13	13
Maximum	19	19	19	19
Waldo Chi	1539.85	5702.09	1260.82	3535.67
Prob > Chi-Square	0	0	0	0
Log Likelihood	-143642.3	-65125.96	-56711.85	-26261.76

Table 4. DETERMINANTS OF CREDIT CARD MISTAKES

TWO CONSECUTIVE MONTHS

PRECAUTIONARY BALANCES PROXIED BY 1 STANDARD DEVIATION OF DEPOSITS AND LOWEST QUINTILE OF DEPOSITS

Data is panel data and dependent variable is binary (1 = mistake and 0 = no mistake). Use Panel (Random Effects) Logit Methodology. Dependent Variables are (1) Unnecessary Delinquency (2) Unnecessary Over-Limit and (3) Unnecessary Cash Advance (4) Unnecessary Delinquency and Cash Advance in the same month if have sufficient deposits. Sufficient Deposits defined as total deposits minus one standard deviation of deposits to proxy for precautionary balances due to deposit volatility. Also, to proxy for the holding of precautionary balances due to low deposits a "mistake" is not defined as a mistake if deposits fall below $240 (i.e. lowest quintile of deposits). Dependent Variables are only defined as a mistake if the event occurs in two consecutive months. Independent Variables include different components of wealth including (1) Business and Investment Income and (2) Residential Property Value. Other variables are proxies for low wealth, i.e. income from government sources and proportion of dissemination area that rents rather than owns residences. Also included is Annual Total Income. Control variables include individual specific risk variables (FICO Score, Credit Limit) as well as other demographic variables such as age and education. All $ values are logged.

	Delinquent	**Over-Limit**	**Cash Advance**	**Delinquent & Over-limit in Single Month**
Residential Property Value ($)	-0.0420	0.0098	0.1673***	0.0157
Government Income (% of Total)	0.0102*	0.0053	0.0098	0.0097
Business & Investment Income ($)	0.0193	-0.0858**	-0.0659	-0.045
Residence Rent/Own Status (% Rent)	0.0015	0.0056***	0.0060***	0.0078***
Annual Income Total ($)	0.0234	-0.0539	0.0833	-0.068
Credit Rating –FICO Score	-0.0033***	-0.0039***	-0.0017***	-0.0038***
Credit Limit on Credit Card ($)	-0.1125***	-0.3469***	-0.1413***	-0.45***
Type of Credit Card (No Fee Dummy)	-0.0679	-0.1718***	-0.3321***	-0.020
High School (% in DA)	0.00377	0.0008	-0.0011	0.0061
Some Post Secondary (% in DA)	0.00367	0.0100***	0.0060*	0.011**
Bachelor or Higher Degree (% in DA)	-0.0061*	-0.011***	-0.0158***	-0.015**
Age 0 to 19 (% in DA)	0.01890***	0.0081	0.0034	0.023
Age 20 to 34 (% in DA)	0.0041	0.0017	0.01140*	-0.001
Age 35 to 54 (% in DA)	0.0055	0.0055	0.0005	0.0083
Age 55 to 64 (% in DA)	0.0109	0.0187*	0.0129	0.016
Population per Household	-0.2189**	-0.0542	0.1311	-0.31
Immigrant (% in DA)	0.0053*	0.0031	-0.0029	0.003
Constant	-4.1995***	-1.1584	-6.3234***	-1.76
Number of Observations	970774	970774	970774	979774
Number of Groups	74769	74769	74769	74769
Observations Per Group				
Average	13	13	13	13
Maximum	19	19	19	19
Waldo Chi	1356.51	2252.52	303.43	1050.63
Prob > Chi-Square	0	0	0	0
Log Likelihood	-30328.4	-22175.4	-20038.3	-5690.0

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