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The Impact of Wealth on Inattention: Evidence from Credit Card Repayments

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ABSTRACT

Inattentive decision makers do not make full use of information available to them. Existing, psychologically based, explanations for inattention include the impact of competing stimuli and the salience of the decision. These existing explanations, however, do not predict whether richer or poorer individuals are more likely to be inattentive, since either can face competing demands on their limited supplies of attention. We examine this issue using a confidential credit card database of more than one million data points. We document that a proportion of individuals who are delinquent have sufficient surplus funds on deposit, implying that these individuals could have avoided the costs of delinquency if they had been more attentive to their credit card repayments. Using various measures of income and wealth, we provide strong evidence that these inattentive individuals are more likely to be poorer.

1. INTRODUCTION

Inattention occurs when agents do not act on information available to them, and thus incur unnecessary costs. A large literature in finance has examined whether agents are inattentive (see DellaVigna, (2008) for a survey). Huberman and Regev (2003), for example, describe how equity investors can be more attentive to information reported on the front page of the New York Times compared to the same information on an inside page. DellaVigna and Pollet (2007) examine whether investors are inattentive to predictable factors about the distant future. Barber and Odean (2008) examine stocks in the news, and conclude that many purchases occur after they have "grabbed the attention" of the buyer. DellaVigna and Pollett (2008) examine whether equity traders are inattentive to announcements made on Fridays. Among papers that discuss the consequences of inattention, Abel, Eberly and Panageas (2007) model optimal attention to a stock market portfolio, Huang and Liu (2007), show that inattention leads to over- or under-investment in portfolio selection, Hirshleifer and Teoh (2003) model the impact that inattentive investors have on financial reporting, Peng and Xiong (2006), show that investors with limited attention make predictable errors and Almazan, Banerji and Motto (2008) model the conditions when managers will try to attract the market's attention. [1]

While the existing empirical literature has examined both the prevalence and consequences of inattention, it has not focussed on the characteristics of those who are inattentive. The aim of this paper is to examine empirically whether richer or poorer individuals are more inattentive after controlling for other factors possibly impacting inattention. This issue is important because the existing theoretical literature is unable to provide an unambiguous prediction regarding this question. It is not obvious, for example, whether richer or poorer individuals will have greater demands on their limited supplies of attention, and thus theoretically either could be more or less attentive.

In this paper we examine inattention across a sample of 75, 000 credit card holders[2]. In short, we provide strong evidence that poorer individuals are more inattentive

[1] Inattention has also been modelled in the macroeconomics literature (e.g. Reis (2006A), Reis (2006B) Ball, Mankiw and Reis (2005), Sims (2003) and Sims (2006)).

[2] Even though our research is the first in the literature to use credit card data to specifically examine the issue of inattention, it forms part of a growing empirical literature that has utilised credit card data. This

than richer individuals to credit card repayments, even after controlling for a variety of other factors such as age, education etc.

Specifically, we focus our tests on whether individuals incur the costs of being delinquent (i.e. not paying their minimum credit card balance due on time) while *at the same time* having sufficient funds on deposit to have avoided these costs. This situation is similar to the other cases of inattention described in the literature in that (1) individuals do not appear to act on information that is readily available to them (i.e. the amount and due date of their own minimum credit card payment due) and (2) incur an unnecessary cost as a result of such inattention (e.g. from resultant credit card penalty fees and reduced credit ratings).

While this is the first paper that examines inattention in the credit card repayment context, we can apply existing theories of inattention to this context. DellaVigna (2007), among others, argues that, based on psychological theory, two of the main determinants of inattention are: (1) the number of competing stimuli and (2) the salience of the decision[3]. We argue that these two psychologically based determinants are unable to provide *a priori* predictions as to how economic factors such as wealth impacts inattention. Specifically, in terms of the competing stimuli argument, it is unclear whether richer or poorer individuals are likely to face more demands on their attention (i.e. competing stimuli) relative to their limited supply of attention. Thus, in terms of the competing stimuli argument, it is possible for either richer or poorer individuals to make credit card repayment mistakes. In terms of the salience issue, an argument can also be made for either richer or poorer individuals being more inattentive. For example, richer individuals could be more inattentive because the immediate monetary costs of credit card penalty fees (usually around $30 to $50) are less salient to them than to poorer individuals. On the other hand, richer individuals may be more attentive so as to avoid the possibility of reduced credit ratings and increased borrowing costs in the future.

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literature includes Agarwal, Liu, and Souleles (forthcoming), Agarwal, Driscol Gabaix and Laibson (2007A), Agarwal, Driscol Gabaix and Laibson (2007B), Agarwal, Liu, Chomsisenphet and Souleles (2007), Knitel and Stango (2003), Gross and Souleles (2002A), Gross and Souleles (2002B), Stango (2000), Calem and Mester (1995) and Ausubel (1991).

[3] DellaVigna (2007) argues that a further determinant of inattention is opacity of information. In the context of credit card repayments, opacity of information is unlikely to be a significant factor in agents being able to determine the amount and date of their minimum payment due, from their monthly statement.

An alternative model, which also examines the link between wealth and attention in an economic development context, has been developed by Banerjee and Mullainathan (2008). Their model is based on the assumption that, because attention is a scarce resource, individuals face a choice between attention to problems at work and attention to problems at home. As in the psychological theory described above, there is no clear relationship in their model between wealth level and the use of attention to avoid problems at home[4].

In order to investigate the link between wealth and inattention, we build a large database of over one million data points by matching three original databases. Our first database consists of confidential individual monthly statement data on credit card and bank accounts for more than 75, 000 individual bank customers. This provides us with data on which individuals are delinquent while simultaneously having sufficient deposit funds available to avoid delinquency. These data are monthly and cover 19 months from December 2004 to June 2006. Our second data base is postal code level census data provided by Statistics Canada which provides a large amount of economic (e.g. income and wealth) and other (e.g. age, education etc.) data, which we link to each individuals postal code. Our third dataset is postal code level data on all residential property transactions, taken from the Land Titles Registry which enables us to derive post code level house price indices as wealth measures. Importantly, our database matching exploits a unique feature of the Canadian postal code system whereby the number of households in each Canadian postal code area averages 200 households, far smaller than what can be generated using US Census data[5]. This provides us with relatively fine grained data on economic, demographic and other control variables, which can be matched to our individual level bank credit card and deposit account data.

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[4] Both the rich and poor in this model, utilize attention based strategies to avoid problems at home. The rich avoid problems at home by purchasing "distraction-saving" goods and services, which can substitute for direct attention. On the other hand, the poor avoid problems at home by paying more attention at home, but at the expense of paying attention at work. As an example, Banerjee and Mullainathan (2008) note that poor individuals may choose to specialize in industries like agriculture because the amount of attention required in agriculture (i.e. work) is relatively low, which allows such individuals "to focus on problems of home life" (p. 492). While this model cannot predict whether the rich or the poor will be more attentive at *home*, it does predict that the rich will be more attentive at *work*. The home based (i.e. credit card) context of our study does not, however, allow us to study the impact of wealth on attention at work.

[5] US census data uses minimum geographic areas of 150000 inhabitants on average (see e.g. Luttmer, 2005).

Part 2 of the paper describes how we identify inattention, Part 3 describes our data and methodology and Part 4 provides our results. Part 5 concludes.

2. IDENTIFYING INATTENTION

In this paper our focus is on cases where individuals incur the costs of delinquency, while *at the same time* having sufficient deposits at the bank that issued the credit card[6]. To identify the subset of these cases which can specifically be ascribed to inattentiveness, we either remove from the data, or control for, other possible reasons for delinquency while holding sufficient deposits. This section also discusses the distinction between the concept of inattention and the concepts of financial literacy and rationality.

Our credit card issuing bank defines delinquency as occurring when a consumer fails to pay his/her minimum repayment balance due in any given month. A credit card delinquency involves a number of costs to the individual. Firstly, if a cardholder is delinquent for five months in a row, the data providing bank will declare him/her in default and withdraw the credit card. Secondly, when the cardholder is delinquent, there can often be a negative impact on his/her credit rating (e.g. Credit Bureau or FICO score), which can have a significant impact on the costs of future finance. Thirdly, all instances of delinquency involve the imposition of a penalty fee (in this case approximately $40). Fourthly, because the bank views credit card delinquency as a possible indicator of future default, it will communicate directly with consumers soon after the delinquency occurs instructing them to pay the minimum balance due. This might impose an "embarrassment" cost on the consumer.

At its simplest it could be argued that an individual is inattentive if he/she incurs these costs of delinquency, while simultaneously holding sufficient deposits to make the minimum card payment. In this simple case inattention would be defined to occur when:

$$\text{Minimum Payment Due} < \text{Deposits} \tag{1}$$

[6] At our data providing bank, 76% of credit card holders also hold deposit accounts at that bank. (See Appendix A1for more details).

However, the simple definition of inattention in (1) is not appropriate if the possibility exists that an individual may *deliberately* decide to incur the costs of delinquency while simultaneously holding sufficient deposit balances to make the minimum repayment. In such cases the behavior described in (1) cannot solely be ascribed to inattentiveness, because, by definition, inattentive behavior cannot be deliberate. Thus we modify our definition in equation (1) so as to isolate those events caused by inattention, from those events caused by deliberate action. We do this by identifying a variety of circumstances where an individual has an incentive to deliberately incur the costs of delinquency while simultaneously holding sufficient deposits. We either remove these deliberate events from the data, or control for them in our empirical tests.

Two key reasons for deliberately incurring the costs of credit card repayment delinquency while holding sufficient deposits to make the minimum card payment are: (1) agents fear being budget constrained in the *future* and/or (2) agents are *currently* budget constrained. Agents who fear being budget constrained in the future may deliberately choose to hold available deposits as precautionary balances rather than making minimum credit card payments on time. Agents who are currently budget constrained may also make the deliberate decision to incur the costs of delinquency, since available deposits may be required for more pressing immediate purposes. Below we list a variety of different empirical specifications for dealing with potential *future* budget constraints, and *current* budget constraints. Our empirical strategy is not to pre-select any one of these specifications but rather to formulate a variety of different tests controlling for all (or for subsets) of the different reasons listed here. In section 4 we show that our key findings are robust across all empirical specifications.

2.1. Precautionary Balances against Possible Future Budget Constraints.

We follow the existing literature by using two different empirical specifications of precautionary balances holdings against possible future budget constraints. Firstly, the literature on precautionary balances held by firms (e.g. Opler, Pinkowitz, Stultz and Williamson, (1999) and Bates, Kahle and Stultz (2007)) and individuals (Tsiang, 1969, Fusaro, 2008) suggests that the demand for precautionary balances will be larger the greater the volatility of cash flows. That is, agents with more volatile cash flows will tend to hold higher precautionary balances against possible liquidity constraints in the future. A significant advantage of our database is that it includes monthly deposit balances for each credit card user over a 19 month period, thus we can measure the volatility of deposit balances over time (the 19 months of our sample) as our first measure of precautionary balance holdings.

A second possible reason for holding precautionary balances (Telyukova (2008) and Telyukova and Wright (2008)) is because agents face upcoming pre-committed expenses such as rent which are viewed as being more important than minimum credit card payments. In our database we have postal code level census data from Statistics Canada on the average Rental Payment in each individual's postal code area (see Section 3 for a full description of how we match databases). We assume here that this rental payment measure can be used as a proxy for average pre-committed expenses in each individual's post code area.

Our empirical strategy is to control for precautionary balances by subtracting either, or both, of these measures (volatility of deposits and average rental payments) from deposit balances in our definition of inattention in (1), for all individuals in our sample. Our *adjusted* definition of inattention occurs when:

$$\text{Minimum Payment Due} < (\text{Deposits - Precautionary Balances}) \qquad (2)$$

where precautionary balances in equation (2) is defined as either or both of: one standard deviation of deposits over the sample period, and/or average rental payment in the postal code. Equation (2) can be interpreted as specifying that if an individual incurs the costs of delinquency when he/she has enough deposits available for *both* the minimum card payment *as well as* the amount of deposits required for precautionary reasons, then we can disregard the possibility that the agent is deliberately choosing credit card delinquency. That is, the non payment of the minimum credit card balance on time is likely to be due to inattention rather than deliberate choice.

2.2. Currently Budget Constrained Individuals

A second possible explanation for an individual choosing to hold deposits and incurring the costs of delinquency is that the individual is *currently* budget constrained and makes the deliberate choice to use his/her deposits for more immediate expenses, rather than to making a minimum credit card payment. While all individuals are likely to hold some precautionary balances against possible future budget constraints, only a subset of individuals is likely to be *currently* budget constrained. Below we discuss five alternative measures that could be used for identifying currently budget constrained individuals in our dataset. Our empirical strategy is to remove these individuals from our sample. By removing currently budget constrained individuals, our goal is to refine our database of individuals for whom any credit card delinquency, while having sufficient deposits available, can be ascribed to inattention. While it could be argued that budget constrained individuals are more likely to be poorer, and that by removing them from our database we create bias, this bias will be *against* our finding that poorer individuals are more inattentive. That is, by removing budget constrained individuals from our data we are creating a higher hurdle to find support for the hypothesis that the poor are more inattentive.

We measure currently budget constrained individuals in a number of ways.

(a) Income or Expense Shocks

If the individual is currently facing a large income shock (e.g. lost job) or expense shock (e.g. house fire) then the individual may deliberately decide to incur the costs of credit card delinquency because these deposits are required to mitigate the shock. We control for this effect by using the ratio of the individual's credit card balance to his/her credit card credit limit[7]. Specifically, an individual subject to such an unexpected negative income or expenditure shock is likely to increase credit card borrowings up to his/her credit card limit (i.e. a balance/limit ratio of 100%) before making the *deliberate* decision to incur the costs of credit card delinquency. We specify two alternative levels of the card balance/limit ratio to define an individual as being budget constrained – 75% and 90%. Specifically, we remove from our sample any individual whose card

[7] Agarwal, Lin and Souleles (2008) also utelise the credit limit and the credit balance as a measure of liquidity constraints.

balance/limit ratio is higher than 75% (or 90%) in any month. We argue that if individuals with a credit card balance/limit ratio of less than 75% (or alternatively 90%) are delinquent while holding sufficient deposits, this is indicative of inattention rather than being subject to a current budget constraint.

(b) Low Levels of Deposits

Another possible motivation to deliberately incur the costs of delinquency (even though deposits are available to make the card payment) is that the individual has a low level of deposit balances remaining and requires those balances for immediate expenses. We define "low" deposit balances as balances of those individuals whose average deposits are in the bottom quintile of all individuals in our sample (the cut off point is a monthly deposit balance of approximately $240). That is we drop those individuals from our sample (and do not define it as being due to inattention) when individuals with the lowest level of deposits are delinquent.

(c) Low FICO Score

A declining FICO score (external credit rating) may also be indicative of an individual facing an increased budget constraint. We control for this by alternatively removing from our sample any individual with a FICO score of either below 620 or a score below 560 for any month. Both of these scores are benchmarks used by the data providing bank; 620 or higher is required at the time of the credit card application for approval[8], and 560 or lower indicates that the individual has become a significantly less attractive card holder.

(d) Repeated Delinquency

In constructing our sample to reflect delinquencies plausibly caused by inattention, we also remove those individuals who are delinquent more than once over our sample period. It can be argued that individuals who are repeatedly delinquent, while holding sufficient deposits, are less likely to be doing so specifically due to inattention. One reason for such repeated behavior is that the individual is living close to his/her budget constraint over multiple time periods. On the other hand if there is only a single

[8] Even though a FICO score of 620 is required for approval of a new credit card account, and individuals score can fall below this level because of unsatisfactory behaviour after they became card holders.

episode of an agent being delinquent (while still having sufficient deposits available), then this is far more likely to be indicative of a cardholder making a mistake due to inattention.

(e) Bankruptcy

Our data also provides us with information on those individuals who became bankrupt or were declared in default during our sample period. We drop these individuals from our database as they are likely to be highly budget constrained. By removing such individuals from our sample we are also controlling for the possibility of strategic default where an individual decides to be deliberately delinquent (while holding sufficient balances in his/her deposit account) to take advantage of possible bankruptcy law protections.

2.3. Financial Literacy

In order to ensure that our definitions of credit card delinquency do indeed capture inattention, we need to distinguish between a cardholder's inattention and poor financial literacy and provide an argument as to why our events capture inattention rather than poor financial literacy. The existing literature on household finance[9] has documented that financial illiteracy is often a cause of financial mistakes relating to investment, pension or mortgage choices and that poor and less educated individuals are more likely to make such mistakes. Lusardi and Mitchell (2007) and others have measured financial literacy by specifically measuring whether an individual *understands* financial concepts such as net present value, rate of return and diversification etc.[10] However, the cognitive process involved in making mistakes related to incorrect mortgage/investment/pension choices usually involves the individual *not understanding* (as in Lusardi and Mitchell, 2007) the underlying finance or economics involved[11]. By comparison, the main

[9] See e.g. Vissing-Jorgensen (2003) Campbell (2006), Calvet, Campbell and Sodini (2007) Calvet, Campbell and Sodini (2008) and Lusardi and Mitchell (2007) etc.

[10] For example, Lusardi and Mitchel (2007) measure financial literacy based on an individual's response to survey questions such as "if you have $200 in a savings account and the account earns 10% interest per year, how much would you have in the account at the end of two years?"

[11] Stango and Zinman (2008) argue that decisions that are "abstract and made infrequently" (such as mortgage, pension and investment decisions) are subject to cognitive biases and heuristics. In comparison, we argue that the credit card repayment decisions we are examining are much less abstract and much more

cognitive process involved in not paying a minimum credit card balance on time involves the individual *not keeping track* of when credit card payments are due because of inattention.

This follows from the way that financial institutions typically respond to the different kinds of mistakes made by individuals. When an individual is delinquent on their credit card, the bank will usually communicate to the individual forcefully and rapidly to ensure that the minimum payment is made. This is because the bank needs to determine whether the delinquency is due to a mistake (because of inattention), or whether it is a signal of possible future default or bankruptcy. On the other hand, a financial institutions many not fully inform individuals that they are making inappropriate pension, investment or mortgage choices, because the financial institution stands to benefit financially from these types of mistake (e.g. by selling a financial product).

Furthermore, if we restrict our data (as described above) to only those individuals who make a single repayment mistake then it is even less evident that the cause of the mistake was financial illiteracy. Specifically, these individuals understood that timely repayment was important in all but one month in our sample period. Consequently, it does not seem plausible to argue that individuals who neglect paying their minimum credit card balances only once fail to *understand* that not paying the minimum credit card balance on time will be costly.

2.4 Rationality

In his review of the inattention literature, DellaVigna (2008) argues that in most empirical papers, it is not it possible to determine whether inattention is rational or irrational. For example, inattention can be modelled as rational behavior when the costs of acquiring information are high[12]. In this paper we follow DellaVigna (2008), by not seeking to draw conclusions about the rationality or irrationality of inattentive individuals.

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frequent (monthly). Thus credit card repayment decisions are less likely to be subject to the biases found in investment or pension or mortgage decisions, discussed by Stango and Zinman (2008) and others.

[12]For example, it is not clear whether an agent who is inattentive to their credit card repayment because of competing stimuli (e.g. a personal or work related crisis) is behaving rationally or irrationally.

3. DATA AND METHODOLOGY

3.1. Matching data across databases.

To test the relationship between wealth and inattention we combine three separate databases: (1) the individual account level database of a single bank's credit card and deposit accounts over 19 months, (2) Postal Code level Census data (from Statistics Canada) and (3) Postal Code level Land Titles Registry data. Appendix 1 describes in detail the procedures used to match these databases, while Table 1 provides detailed summary statistics of all variables used in our analysis[13].

An important definitional issue concerns the postal code based geographic area that we use in our data matching. As described in Appendix 1, each Canadian postal code area contains an average of 20 households. However, in order to match these with census data we are required to use a geographic measure called a Dissemination Area (or DA), which is an agglomeration of approximately 10 neighbouring postal codes with an average of approximately 200 households. Accordingly, in this paper we use the terms dissemination area (DA) or "postal code" interchangeably to refer to a DA area of 200 households. Table 2 summarizes the matching strategy used and Appendix 2 describes how the use of postal code based data can be used as an individual level proxy for cardholders who live in each postal code.

3.2. The Frequency of Inattention

Table 3 provides a summary of the frequency of each definition of credit card delinquency mistake defined in Section 2. These measures serve as dependent variables in our empirical analysis below. As can be seen, as the definition of what constitutes an inattentive mistake becomes more stringent, so the number and proportion of delinquency mistakes decline. The first row of Table 3 shows that 10.3 % of the total month/individual data points are delinquent, ignoring deposits. The simplest definition of

[13] Korniotis and Kumar (2008), and Kumar (2008) for example, also use US Zip code level data as a proxy for individual level demographic characteristics in examining investment behavior.

mistakes shows that 6.6% of the sample is delinquent, when deposits are larger than card payment balances due (ignoring any effects of precautionary balance and budget constraints.) Table 3 next lists six delinquency definitions controlling for various measures of precautionary balance demand and budget constraints. The frequency of these mistakes ranges from 4.1% (model 1 – which defines precautionary balances to be equal to one standard deviation of deposits) to 0.7% (model 6 – which defines precautionary balances as equal to one standard deviation of deposits plus rental payments in the post code area[14] plus dropping all currently budget constrained individuals as described above).

3.3. Independent Variables

We discuss here a large variety of independent variables that can be used to measure wealth, income as well as other individual characteristics that are used as control variables.

(a) Income Measure from Credit Card Data

We exploit an important institutional detail to generate an individual's income. The bank data provider utilizes a relatively simple rule to determine each individual's credit card credit limit, which is to set that limit equal to three times an individual's monthly income[15]. Because of this direct proportional relationship between income and the credit limit, we are able to generate a measure of an individual's income.

(b) Components of Income from Census Data

The Statistics Canada postal code (DA) level census database provides data on total income as well as its three components – employment income, income from government sources and business and investment income. Our credit limit data (described

[14] The Statistics Canada Census database only includes postcode level dollar rental amount paid data for approximately 53% of the individuals in our sample, thus estimations that include dollar rental amount paid data will have a significantly reduced sample size. There is however no systematic bias for which postal codes dollar rental amount paid data are included or excluded in the Census database. For example, when comparing the percentage who rent data (which are available in all post codes) an average of 24.5 % are renters where dollar rental amount data is available, while an average of 23.5 % are renters where dollar rental amount data is not available. Similarly, when comparing credit card credit limit (as a proxy for income), the average credit limit is $ 6736.47 where dollar rental amount data is available while the average credit limit is $6789.10 where dollar rental amount data is not available.

[15] The FICO score is used by the bank to determine whether a credit card is approved or not, while the "three times monthly income" rule usually determines the credit limit for those accounts that are approved.

above) provides a preferable measure of total income compared to the census total income data, because the bank's "three times total income" rule for setting the credit limit is measured at the individual rather than the postal code level. We are, however, able to include census measures of the different components of income. In order to avoid collinearity we don't include all components (i.e. employment income, government income[16] and investment income[17]) simultaneously, but examine various alternative combinations of the income components[18].

These components of income can also serve as proxies for different categories of wealth. We argue that the greater an individual's business and investment income, the greater his/her wealth. This is because wealthier individuals, with significant business and investment assets, are likely to generate higher income flows from those assets[19]. The second useful proxy for wealth from the Census data relates to the measure "Income from Government Sources". The main elements of this form of income are Old Age Security and Unemployment Insurance. In our empirical specifications we examine the *ratio* of government income to total income rather than the dollar level of government income. The main reason for this is that if government payments (rather than employment or investment income) make up a significant proportion of total income in any year, then this is a likely to be a proxy for low wealth.

(c) Rental Status from Census Data

Besides business and investment wealth described above, an individual's wealth can also include residential property wealth. One measure of household property wealth that can be derived from census data is the proportion of the population in each dissemination area (postal code) that rents its residence compared to the proportion that owns its residence. We argue that if individuals live in areas with higher proportion of

[16]Statistics Canada Census definition of 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.

[17] Statistics Canada Census definition of 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.

[18] In our data the average percentages of total income of its various components are: employment income 77%, government income 12% and business and investment income 10%.

[19] Our data captures annual income flows from business and investments. Our results would not change if we capitalized annual income flows by dividing business and investment income by the annual rate of return (i.e. wealth = income flows/rate of return).

renters than owners, then this serves as a proxy for those individuals having lower property wealth.

(d) Market Value of Residential Property from Land Titles Registry

Using the Land Titles Database, we are able to generate a further measure of residential property wealth based on the market values of properties in each postal code (DA). By measuring the average annual market value of residences sold, we can capture the cross sectional dispersion of residential property values among our sample of credit card holders.

(e) Other Demographic Characteristics from Census Data

In addition to wealth and income we control for a number of other individual characteristics that might impact credit card repayment decisions. Such factors are useful to analyse since they give a broader picture of the possible determinants of credit card repayment mistakes. Specifically, the Census data provides us with data on the average age, education and proportion of immigrants in the DA. For each postal code, we have data on the proportion of people in the postal code who have particular levels of education[20], and who fall within certain age brackets[21]. Moreover, in order to capture the impact of larger families on household behavior, we also include a variable for the average household size in each postal code.

(f) Type of Credit Card Choice

An additional card characteristic variable captures the type of credit card that each consumer has chosen. In the case of the bank that provided our data there are two main types of credit card – those that are "no frills" that do not have any *annual* fee, and those that provide a variety of features (e.g. air miles etc) in exchange for an annual fee. We include a dummy variable to capture no fee cards as an additional control variable. This

[20] In terms of education we have data on the percentage of people in each postal code who have (1) no high school, (2) high school only, (3) some post secondary and (4) bachelor or higher. Because these categories add up to 100% for each postal code, we drop one (no high school) category.

[21] In terms of age, Statistics Canada provides data on the percentage of each postal code 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 postal code, so we drop the category "over 65" and use this as our comparison categoryIt should be noted that in this database we do not have the individual birth year of each individual credit card consumer. Thus our results are not directly comparable to the results of Agarwal, Driscoll, Gabaix and Laibson (2007A) who use such individual level data in their work on the impact of age on financial mistakes.

allows us to test whether individuals who are concerned about avoiding regular *annual* fees on their credit cards are also more likely to be attentive so as to avoid penalty fees from unnecessary delinquency and card usage.

3.4. Econometric Methodology

Based on the above we test the following model (equation (3)):

$$\begin{aligned}\text{Inattention}_{it} = {} & \alpha + \beta_1 \text{ Credit Limit}_{it} + \beta_2 \text{ Government Income}_{it} + \beta_3 \text{ Business Investment Income}_{it} + \\ & \beta_4 \text{ Rent/Own}_{it} + \beta_5 \text{ Property Value}_{it} + \beta_6 \text{ Population Per House}_{it} + \beta_7 \text{ Credit Card Type}_{it} + \\ & \sum_{j=1}^{n} \beta_{j8} \text{ Education}_{jit} + \sum_{k=1}^{m} \beta_{k9} \text{ Age}_{jit} + \beta_{10} \text{ Immigrant}_{it} + \varepsilon, \end{aligned} \tag{3}$$

where i is the individual customer, and t is time from 1 to 19 months, n is the number of education indexes and k is the number of age categories. We use the 6 different measures of the inattention variable (as listed in Table 3) as alternative dependent variables in our tests. In equation (3) Credit Limit is the FICO score measure of income, Government Income measures the DA level of government income as a percentage of total income, Business and Investment Income is measured at the DA level as a dollar value, Rent/Own is the percentage of a DA that rents its home, Property Value is the average property value in each DA, Credit Card Type is a dummy variable for card characteristics, Education and Age are DA level percentages for different categories, and immigrant is the percentage of a DA that are immigrants. The error term captures idiosyncratic shocks (e.g. health shocks, family issues, work crises etc.) that may cause inattention in a particular individual in a particular month, but which are not systematically related to our dependent variables.

This section describes a variety of methodological and econometric issues that are relevant to testing the model in equation (3). Since we use panel data a significant concern is that both the independent variables as well as the equation residuals can be correlated across clusters (i.e. individuals) resulting in biased estimates. Accordingly, following Petersen (2008) we conduct our econometric tests using logit models where the standard errors are robust and clustered by individual[22]. As a robustness check we also reran all our tests with the data clustered by the Dissemination Area (DA) rather than by individual. Finally, following Petersen (2008) we also reran our tests using random effect logit models for all our specifications. As discussed below, our results are very robust across these alternative specifications.

An additional issue in estimating (3) is the potential for selection bias if the individuals who tend to be inattentive to their credit card payments select to live in poorer neighborhoods because being inattentive to their credit card payments makes them poorer. We argue however, that such selection bias is unlikely. In particular, our empirical tests already exclude all individuals who are budget constrained and include only those who make a single mistake in the 19 months of our sample. Because we isolate inattentive mistakes as being rare occurrences by individuals who are not budget constrained over time, it is unlikely that those individuals who remain in our sample will become so much poorer, because of their inattentiveness to their credit card repayments, that they will be forced to move to a poorer neighborhood [23].

This selection bias concern can also be couched in terms of reverse causality. In our tests causality runs from individual characteristics (e.g. wealth, income) to inattention (as measured by delinquency while holding sufficient deposits). Reverse causality could occur if delinquency (while having sufficient deposits) lowers an individual's income or wealth levels in the future. In addition to the argument already made above, that individuals in our sample make such mistakes rarely, and that these mistakes have small financial consequences, we argue that using postal code level census data as a proxy for individual wealth has significant advantages in terms of specifying the direction of causality. In particular, it seems highly unlikely that a specific individual's financial mistake will impact the average wealth of a whole postal code area. Indeed it seems more than plausible to argue that the average wealth of a postal code (which serves as a proxy for individual wealth) is a characteristic of those individuals who are more likely to make a card repayment mistake.

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[22] The main finding of Petersen (2008) is that "the standard errors clustered by firm, (in our case individual), are unbiased and produce correctly sized confidence intervals." (p. 40).

[23] The issue may be different if the mistakes we were examining involved issues such as choosing inappropriate pensions or mortgages etc, which could have a significant impact on income or wealth, and thus could cause a possible selection bias.

Similar arguments regarding selection bias can be made in terms of our credit card credit limit variable. As described above, the bank determines the credit limit at approximately three times the total monthly income of the individual (thus we consider credit limit to be a measure of total income). Discussions with the bank indicated that it is unlikely that a single credit card delinquency could impact the credit limit. Indeed, the bank informed us that only frequent or repeated delinquencies would impact the individuals FICO score, but not the credit limit. Moreover, changes to credit card credit limits usually occur, with a significant lag, following changes in income. For these reasons, we argue that we are also unlikely to face selection issues with our credit limit variable[24].

4. RESULTS

4.1 Main Results

As we described above, our empirical strategy in this paper is not to impose any particular definition of precautionary balances and credit constrained individuals, but rather to examine six different specifications and examine the robustness of our results across these specifications. Our results are presented in Table 4.

(a) The impact of Wealth and Income on Inattention

Our wealth and income variables, across all specifications, show that lower wealth and income individuals are more likely to be inattentive (as measured by being delinquent with sufficient deposits available). In all of the models the credit card credit limit coefficient (which we use as a measure of total income because of the "three times total monthly income" rule used by the bank to set credit limits) is highly significant and negative. Our results strongly indicate that individuals with a lower credit limit (i.e. lower income) are more likely to be inattentive. The magnitudes of these estimates are significant. The estimated elasticities indicate that a 1% increase in a credit limit results

[24] Our measures of property values from the land titles registry data, are calculated annually. These data enter our main specification concurrently. Even though it is very unlikely that causality could run from credit card mistakes to postal code area averages of property prices, we test for possible reverse causality by lagging property values by one year. This had no impact on any of our findings. These results are not reported to save space.

in a percentage decline in the delinquency variables ranging from -1.6% (model 1) to -0.4% (model 4).

Furthermore, in all six models in Table 4, the census based variable measuring government income as a percentage of total income is positive and significant. Taking this variable as a proxy for wealth (because lower wealth individuals will have a greater percentage of income from government sources) the results indicate that lower wealth individuals are more inattentive to their credit cards. The estimated elasticities, indicate that a 1% increase in government income (as a ratio of total income) will result in an increase in the delinquency variables, ranging from 0.14% (model 6) to 0.06% (model 1)[25].

Our measures of residential characteristics also support our main finding that lower wealth individuals are more inattentive. Models 4, 5, and 6 all show that the lower the residential property values of the postal code where the individual lives, the greater will be his/her inattention to credit card repayments (with elasticities ranging from -0.04 to -0.02). Moreover, model 1 finds that the greater the proportion of a postal code area that rents, the greater will be the degree of inattention.

Overall, our results strongly indicate that lower wealth and income individuals are more inattentive to their credit card repayments. These results are robust across many alternative measures of income and wealth, as well as many alternative measures of precautionary balances and budget constraints.

Our results can also be linked to theoretical discussions on the causes of inattention. Standard psychological theory (DellaVinga (2008) etc.) states that inattention is a result of (1) competing stimuli and/or (2) salience. One possible way to interpret our results therefore is that lower wealth individuals are, on average, (1) more likely to face greater levels of competing stimuli relative to the attention required for credit card

[25] As described above the census provides data on three components of total income (employment, government income and business & investment income). In all of our specifications the only significant component is the ratio of government to total income, which is significant in all our models. In all cases the dollar value of business and investment income is insignificant in our main results. Furthermore, as a robustness check, we replace business and investment income by employment income in all our models. In all cases, the employment income coefficients are also insignificant and out main results are unchanged.

repayment and/or (2) view credit card delinquency as less salient than higher wealth individuals[26].

It is also of interest to discuss the effects of our control variables on inattention.

(b) The Impact of Education on Inattention

Across each of our six specifications we include variables for high school, some post secondary and bachelor or higher degree (each measured relative to no high school). The vast majority of these education variables are insignificant[27]. One possible interpretation of these findings is that if our education measures are correlated with the financial literacy measures used by Lusardi and Mitchell (2007) and others, then our results would indicate that financial literacy was not a key determinant of inattention in the context of credit card repayments.

(c) The Impact of Age on Inattention

We also examine the impact of age on inattention (where all our results are relative to individuals older than 65). Our results across all six specifications show that no discernable pattern emerges, as to which age groups are more likely to be inattentive. As such, our findings using credit card data differ from the of Agarwal, Driscoll, Gabaix and Laibson (2007A) who find evidence of a "U" shaped relationship, with younger or older individuals making more mistakes than middle aged individuals, in contexts such as mortgage and investment choices[28].

4.2. Alternative Econometric Specifications

Finally, as robustness checks we also replicate the results in Table 4 using standard error clustering by postal code (DA) rather than clustering by individual card-holders. Theses results (which are not displayed to save space) are very similar to those when we cluster by individual. Furthermore, following Petersen (2008) we also reran

[26] As described in the introduction, higher wealth individuals may view credit card delinquency as a salient event because they believe that the possible reduction in credit ratings following delinquency could increase the costs of future borrowing.

[27] The two significant exceptions are the negative "bachelor or higher" coefficient in model 1 and the negative "some post secondary" coefficient in model 2.

[28] It should be noted however that our data only measures average age at the postal code (DA) level, while Agarwal, Driscoll, Gabaix and Laibson (2007A) utilize data on age based on each individual's date of birth.

these models using random effects instead of the robust clustered standard error models (not reported). Overall the robust clustered standard errors models and the random effects models are very similar.

5. CONCLUSIONS

Inattention occurs when agents fail to utilize the information available to them and thus incur a financial cost. A large and growing literature in economics and finance has examined the prevalence and consequences of inattention, but little research has been conducted on the characteristics of those individuals who are inattentive. In this paper we empirically examine the impact of wealth and income on inattention. This is an important issue because existing, psychologically based, theories are unable to make a clear prediction about the impact of wealth on inattention. Indeed it is theoretically possible that either richer or poorer individuals are more inattentive because each could be facing competing demands on their limited supplies of attention.

This paper investigates this issue in the context of credit card repayments. We define inattention as occurring when individuals are delinquent on their credit cards *even though* they simultaneously held sufficient deposit balances to have been able to avoid delinquency (after controlling for precautionary balances). Using a variety of alternative econometric methodologies and specifications, we provide strong evidence that poorer individuals are more likely to make credit card repayment mistakes due to inattentiveness than richer individuals. Thus the costs of inattentiveness in the credit card context are more likely to fall on the poor.

APPENDIX 1: DATA ISSUES

This appendix describes some of the data issues involved with building our database.

A1. 1. Data Requirements

Campbell (2006) 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. He argues that the challenge is to build databases that approximate as closely as possible these characteristics.

In the existing literature on household financial mistakes, two different kinds of databases have been used; (1) survey data such as the survey of consumer finance (SCF) and (2) large databases of individual consumer accounts taken from financial institutions. Both approaches have both advantages however neither by itself fulfills the requirements of Campbell's list of an "ideal" database.

The use of surveys, (e.g. the SCF), include detailed measures of wealth, but they require the voluntary participation of selected households, and is thus vulnerable to systematic non participation by some households. For example, 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.

The advantage of using large database taken from an individual financial institution 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 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).Thus even if demographic data such as wealth, income and education are collected by financial institutions, they may become very outdated over time[29].

Clearly, neither of these two data approaches accords with the ideal data characteristics required for this kind of research. 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[30].

A1.2. Database Matching (Dissemination Area (DA) vs. Postal Code)

This paper attempts to address the data concerns outlined above by using a unique combination of three very large databases. Our first database is the confidential data on individual credit card and deposit accounts. An important advantage of this database is that it includes the Canadian postal code for each individual. We use the postal code to

[29] The one obvious exception to demographic data becoming stale is date of birth data. This data is used by Aggarwal et al (2007A) in their study of the impact of age on financial mistakes.

[30] Recent work by Calvet, Campbell and Sodini (2007) and (2008) uses a very rich database that includes disaggregate measures of wealth and income from the entire population of Sweden.

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 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. For ease of understanding, in other sections of this paper we refer to both "postal code" as well as "DA" interchangeably to refer to the Dissemination Area (with 200 households on average). 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).

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) 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)[31].

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 below.

While access to 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

[31] 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).

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 these 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 property 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 4, below, provides a summary of the three different databases that we match together in our analysis.

A1. 3 The Individual Bank Account Data.

The Bank that provided us with their credit card data is a full service retail bank that provides a full set of financial services to its clients. For confidentiality reasons we are not able to provide any more information about the characteristics of the bank. In the Canadian context it is usual for consumers to hold both credit card as well as deposit accounts at the same bank. From Table 3 it can be seen that in our database the bank provided us with 1.4 million individual/month data points from their credit card accounts. Of these, 1.1 million (or 76 % of the total) also had deposit accounts with the same bank at the same time. These 1.1 million data points (where an individual has both a credit card as well as a deposit account) form the basis of our research. Our sample size is also reduced slightly to 0.97 million data points because we exclude individuals who had less than 5 monthly data points in light of our need to calculate the standard deviation of monthly income flows to control for precautionary balances. The period of our data runs from December 2004 to June 2006. This was a period of rapid economic growth in Canada, as can be seen, for example, in the increasing nominal values of land titles registry properties over time displayed in Table 3.

APPENDIX 2: POSTAL CODE DATA AS A PROXY FOR INDIVIDUAL DATA

This appendix examines the issue of using postal code level data as independent variables when the dependent variables are individual level data on mistakes. The discussion below examines whether the use of postal code data (from 200 households) as a proxy for individual data is appropriate.

A2.1. Do Post Codes 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.

A2.2. 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.

Table 1: Summary Statistics					
	Observations	**Mean**	**Std. Dev.**	**Min**	**Max**
Bank Account Data (Monthly Statement)					
Credit Card Minimum Payment Due ($)	1 496 451	79.75	195.05	0	21097.51
Credit Card Total Balance ($)	1 496 451	2054.73	3454.02	-4962.6	90723.45
Credit Card Amount Paid ($)	1 496 451	654.13	2074.02	0	612000
Deposit Balance ($)	1 133 378	9339.23	35145.22	0	6451989
Credit rating – (FICO Score)	1 387 456	730.23	73.5	369	880
Credit Limit on Credit Card ($)	1 493922	157.535	6271.716	500	150000
Type of Credit Card (No Fee Dummy)	1 496 452	0.66	0.47	0	1
Matched Census Data					
Government Income (% of total)	1 460 288	11.83	7.47	0	78.9
Business and Investment Income ($)	1 399 227	2689.39	2338.82	0	64983.6
Residence Rent/Own Status (% Rent)	1 460 288	24.6	21.38	0	100
Average Rent ($ in DA)	793 009	625.73	184.16	0	2157
No High School (% in DA)	1 460 288	22.7	9.4	0	72.7
High School (% in DA)	1 460 288	11.8	4.7	0	46.1
Trades (% in DA)	1 460 288	15.3	5.5	0	75
College (% in DA)	1 460 288	23.3	6.6	0	60
University (% in DA)	1 460 288	19.2	12.9	0	93.8
Age 0 to 19 (% in DA)	1 462 827	28.2	7.4	0	58.6
Age20 to 34 (% in DA)	1 462 827	20.6	8.2	0	76.5
Age 35 to 54 (% in DA)	1 462 827	30.1	5.5	0	77.7
Age 55 to 64 (% in DA)	1 462 827	8.3	3.2	0	44.4
Age Over 65 (% in DA)	1 462 827	12.6	9	0	100
Population per Household	1 460 288	2.6	0.5	1	5.3
Immigrant (% in DA)	1 457 435	11	8.4	0	95.3
Matched Land Title Registry Data					
Average Property Value 2004 ($ in DA)	1 436 594	203 521.8	483772.4	16000	4.85E+07
Average Property Value 2005 ($ in DA)	1 444 021	207 194.3	433374.6	10000	4.29E+07
Average Property Value 2006 ($ in DA)	1 445 000	262 779.4	567530.8	10000	3.63E+07
Average Property Value 2007 ($ in DA)	1 415 057	296 253.9	557222.5	13700	3.60E+07
DA Stands for Dissemination Area, the minimum geographic area (approx 200 households) which can link all three of the databases that we use. All $ values are logged in our empirical specifications.					

Table 2: Database Matching and Minimum Geographic Size.

This Table summarizes our empirical strategy for matching three separate databases (1) account level credit card data (2) Statistics Canada Census data and (3) Land Titles Registry data. A full description of our database building procedure is in Appendices 1 and 2.

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

Table 3: Percentage Occurrences of Delinquencies under Various Specifications of Precautionary Balances and Budget Constraints.
These variables are the dependent variables in Logit models 1-6 in Table 4.

Logit Model Number	Definition	% Delinq
-	**Total Delinquencies in Database** (Ignoring Deposits)	10.3%
-	**Delinquency when Deposits > Balance Due** (Ignoring Precautionary Deposits and Budget Constraints)	6.6%
Delinquency when (Deposits > Balance Due). Alternative specifications for controlling for Precautionary Balances and Budget Constraints		
1	(1)Definition of Precautionary Balances Standard Deviation of Deposits (2) Drop Budget Constrained Individuals None	4.1%
2	(1)Definition of Precautionary Balances Standard Deviation of Deposits and Average Rent in DA (2) Drop Budget Constrained Individuals None	2.6%
3	(1)Definition of Precautionary Balances Standard Deviation of Deposits (2) Drop Budget Constrained Individuals Low Deposits, Multiple Mistakes, FICO<620, Card balance/limit<75%	1.1%
4	(1)Definition of Precautionary Balances Standard Deviation of Deposits and Average Rent in DA (2) Drop Budget Constrained Individuals Low Deposits, Multiple Mistakes, FICO<620, Card balance/limit<75%	0.7%
5	(1)Definition of Precautionary Balances Standard Deviation of Deposits and Average Rent in DA (2) Drop Budget Constrained Individuals Low Deposits, Multiple Mistakes, FICO<620, Card balance/limit<90%	0.7%
6	(1)Definition of Precautionary Balances Standard Deviation of Deposits and Average Rent in DA (2) Drop Budget Constrained Individuals Low Deposits, Multiple Mistakes, FICO<560, Card balance/limit<90%	0.7%

Table 4: Inattentive Delinquency (Part 1)

Dependent Variable is delinquency with sufficient deposits after controlling for precautionary balances and budget constrained individuals (defined in Table 3). Data is panel data and dependent variable is binary (1 = delinquent and 0 = not delinquent). Methodology is panel logit methodology with clustered robust standard errors (as in Petersen, 2008), clustered by individual. For each model both logit coefficients as well as elasticity is reported.

$$\text{Inattention}_{it} = \alpha + \beta_1 \text{Credit Limit}_{it} + \beta_2 \text{ Government Income}_{it} + \beta_3 \text{ Business Investment Income}_{it} + \beta_4 \text{ Rent/Own}_{it} + \beta_5 \text{Property Value}_{it} + \beta_6 \text{ Population Per House}_{it} + \beta_7 \text{ Credit Card Type}_{it} + \sum_{j=1}^{n} \beta_{j8} \text{Education}_{jit} + \sum_{k=1}^{m} \beta_{k9} \text{Age}_{jit} + \beta_{10} \text{ Immigrant}_{it} + \varepsilon,$$

Logit Model Number	1			2		
Precautionary Balances	Standard Deviation of Deposits			Standard Deviation of Deposits Plus Avg Rental Payment in Area		
Drop Budget Constrained	None			None		
	Coefficient	**Std Error**	**Elasticity**	**Coefficient**	**Std Error**	**Elasticity**
Credit Limit on Credit Card ($)	-0.2052***	0.00782	-1.62148	-0.1372***	0.012063	-1.099882
Government Income (% of Total)	0.005767**	0.00264	0.068682	0.007**	0.003444	0.10147
Business & Investment Income ($)	-0.01701	0.01771	-0.12516	0.013361	0.024019	0.099622
Rent/Own Status (% Rent)	0.002105***	0.00072	0.049268	-0.001245	0.001063	-0.030691
Residential Property Value ($)	-0.01808	0.02298	0.002987	-0.0583*	0.032023	0.011402
Population per Household	-0.02073	0.05167	-0.05304	-0.1144*	0.066691	-0.290033
Type of Credit Card (No Fee Dummy)	-0.07966***	0.02007	-0.05086	-0.02292	0.031164	-0.015072
High School (% in DA)	0.001568	0.00206	0.017814	-0.00235	0.002878	-0.026259
Some Post Secondary (% in DA)	0.001063	0.00123	0.059194	-0.00302*	0.001676	-0.164803
Bachelor or Higher Degree (% in DA)	-0.00333**	0.00149	-0.04164	0.000208	0.001984	0.002555
Age 0 to 19 (% in DA)	0.006543**	0.00322	0.178332	0.0162***	0.004136	0.427572
Age 20 to 34 (% in DA)	0.000863	0.00229	0.017001	0.000609	0.003251	0.011842
Age 35 to 54 (% in DA)	0.003522	0.00257	0.101595	0.0085**	0.003433	0.248541
Age 55 to 64 (% in DA)	0.005943	0.00413	0.047161	0.00941*	0.005471	0.081433
Immigrant	-0.00082	0.00137	-0.00857	-0.0012	0.00189	-0.014387
Constant	-1.76867***	0.29991		-3.0098***	0.398526	
Number of Observations Wald Chi2 Psuedo R2	1036776 825.03 0.0059			707250 235.42 0.0038		

Table 4: Inattentive Delinquency (Part 2)

Dependent Variable is delinquency with sufficient deposits after controlling for precautionary balances and budget constrained individuals (defined in Table 3). Data is panel data and dependent variable is binary (1 = delinquent and 0 = not delinquent). Methodology is panel logit methodology with clustered robust standard errors (as in Petersen, 2008), clustered by individual. For each model both logit coefficients as well as elasticity is reported.

$$\begin{aligned}\text{Inattention}_{it} &= \alpha + \beta_1 \text{Credit Limit}_{it} + \beta_2 \text{ Government Income}_{it} + \beta_3 \text{ Business Investment Income}_{it} + \\ &\beta_4 \text{ Rent/Own}_{it} + \beta_5 \text{Property Value}_{it} + \beta_6 \text{ Population Per House}_{it} + \beta_7 \text{ Credit Card Type}_{it} + \\ &\sum_{j=1}^{n} \beta_{j8} \text{Education}_{jit} + \sum_{k=1}^{m} \beta_{k9} \text{Age}_{jit} + \beta_{10} \text{ Immigrant}_{it} + \varepsilon,\end{aligned}$$

Logit Model Number	3			4		
Precautionary Balances	Standard Deviation of Deposits			Standard Deviation of Deposits Plus Avg Rental Payment in Area		
Drop Budget Constrained	Low Deposits, Multiple Mistakes, FICO<620, Card balance/limit<75%			Low Deposits, Multiple Mistakes, FICO<620, Card balance/limit<75%		
	Coefficient	**Std Error**	**Elasticity**	**Coefficient**	**Std Error**	**Elasticity**
Credit Limit on Credit Card ($)	-0.0902***	0.010985	-0.74557	-0.05425***	0.017008	-0.44938
Government Income (% of Total)	0.0082***	0.003386	0.101585	0.008102*	0.004464	0.112811
Business & Investment Income ($)	0.01761	0.022832	0.133919	0.039875	0.029936	0.303754
Rent/Own Status (% Rent)	0.001156	0.000934	0.027231	-0.00031	0.001368	-0.00766
Residential Property Value ($)	0.000608	0.030048	-0.0001	-0.08676**	0.042655	0.017042
Population per Household	0.070989	0.066858	0.187089	0.050526	0.085488	0.130365
Type of Credit Card (No Fee Dummy)	-0.1266***	0.026184	-0.08504	-0.04776	0.040514	-0.03255
High School (% in DA)	0.00145	0.00268	0.016927	0.001138	0.003631	0.012864
Some Post Secondary (% in DA)	0.000472	0.001586	0.027079	-0.00092	0.002116	-0.05085
Bachelor or Higher Degree (% in DA)	-0.00219	0.001905	-0.02859	0.00039	0.0025	0.004978
Age 0 to 19 (% in DA)	0.005687	0.004121	0.159419	0.010298*	0.005293	0.276381
Age 20 to 34 (% in DA)	0.0114***	0.00292	0.230352	0.009074*	0.004106	0.177044
Age 35 to 54 (% in DA)	0.0048	0.003343	0.144623	0.00181	0.004439	0.053637
Age 55 to 64 (% in DA)	0.0167***	0.005146	0.138289	0.019512***	0.006767	0.173118
Immigrant	-0.005***	0.001798	-0.05392	-0.00591**	0.00255	-0.06826
Constant	-4.758***	0.386784		-5.58355***	0.513176	
Number of Observations Wald Chi2 Psuedo R2	685701 119.35 0.0012			466700 60.58 0.0015		

Table 4: Inattentive Delinquency (Part 3)

Dependent Variable is delinquency with sufficient deposits after controlling for precautionary balances and budget constrained individuals (defined in Table 3). Data is panel data and dependent variable is binary (1 = delinquent and 0 = not delinquent). Methodology is panel logit methodology with clustered robust standard errors (as in Petersen, 2008), clustered by individual. For each model both logit coefficients as well as elasticity is reported.

$$\begin{aligned}\text{Inattention}_{it} &= \alpha + \beta_1 \text{Credit Limit}_{it} + \beta_2 \text{ Government Income}_{it} + \beta_3 \text{ Business Investment Income}_{it} + \\ &\beta_4 \text{ Rent/Own}_{it} + \beta_5 \text{Property Value}_{it} + \beta_6 \text{ Population Per House}_{it} + \beta_7 \text{ Credit Card Type}_{it} + \\ &\sum_{j=1}^{n} \beta_{j8} \text{Education}_{jit} + \sum_{k=1}^{m} \beta_{k9} \text{Age}_{jit} + \beta_{10} \text{ Immigrant}_{it} + \varepsilon,\end{aligned}$$

Logit Model Number	5			6		
Precautionary Balances	Standard Deviation of Deposits Plus Avg Rental Payment in Area			Standard Deviation of Deposits Plus Avg Rental Payment in Area		
Drop Budget Constrained	Low Deposits, Multiple Mistakes, FICO<620, Card balance/limit<90%			Low Deposits, Multiple Mistakes, FICO>560, Card balance/limit<90%		
	Coefficient	**Std Error**	**Elasticity**	**Coefficient**	**Std Error**	**Elasticity**
Credit Limit on Credit Card ($)	-0.0652***	0.01618	-0.5396	-0.06714***	0.015868	-0.55401
Government Income (% of Total)	0.00977**	0.004247	0.135863	0.010142***	0.004171	0.140849
Business & Investment Income ($)	0.029069	0.028591	0.221212	0.039118	0.028153	0.297555
Rent/Own Status (% Rent)	-0.00057	0.001306	-0.01394	-0.00053	0.001285	-0.01301
Residential Property Value ($)	-0.0795**	0.040108	0.015725	-0.07128*	0.039206	0.014088
Population per Household	0.07057	0.081829	0.182123	0.063381	0.080037	0.163595
Type of Credit Card (No Fee Dummy)	-0.01508	0.038676	-0.01009	-0.03456	0.037986	-0.02314
High School (% in DA)	0.000826	0.003475	0.009346	0.000547	0.003426	0.006189
Some Post Secondary (% in DA)	0.00031	0.002019	0.017163	-0.0003	0.001978	-0.01684
Bachelor or Higher Degree (% in DA)	0.000102	0.002392	0.001302	6.38E-05	0.002351	0.00081
Age 0 to 19 (% in DA)	0.008624*	0.005087	0.231571	0.009407*	0.004991	0.252673
Age 20 to 34 (% in DA)	0.007381*	0.003921	0.144558	0.007005*	0.003863	0.137404
Age 35 to 54 (% in DA)	0.001711	0.004235	0.050717	0.002698	0.004168	0.079989
Age 55 to 64 (% in DA)	0.0169***	0.006455	0.150065	0.016669***	0.006395	0.147438
Immigrant	-0.0058**	0.002413	-0.0675	-0.00556**	0.002364	-0.06424
Constant	-5.4559***	0.489104		-5.49433	0.47983	
Number of Observations Wald Chi2 Psuedo R2	512518 66.5 0.0014			527491 69.56 0.0015		

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