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 sizable proportion of individuals who incur credit card penalty fees for being delinquent or overlimit have sufficient surplus funds on deposit, implying that these individuals could have avoided penalty fees if they had been more attentive to their credit card repayments. Using various measures of wealth, we provide strong evidence that these inattentive individuals are more likely to be poorer.

1. INTRODUCTION

A large literature in economics and finance has examined whether agents are sometimes inattentive to valuable information. (see DellaVigna, (2007) for a survey). Among recent empirical papers, Huberman and Regev (2003) describe how equity investors can be more attentive to information reported on the front page of the New York Times compared to essentially the same information on an inside page. DellaVigna and Pollet (2007) examine whether investors are inattentive to predictable factors about the distant future (e.g. demographic changes) that can impact stock returns. Barber and Odean (2008) examine "attention grabbing stocks" for example stocks in the news, and conclude that many purchases of stocks occur after they have "grabbed the attention" of the buyer. Finally, DellaVigna and Pollett (2008) examine whether market traders are inattentive to announcements made on Fridays[1].

In this paper we examine inattention in a different context - whether individuals are attentive to their own credit card repayments. In particular, we study whether individuals incur the costs of being delinquent (not paying their minimum credit card balance due on time) or overlimit (exceeding their pre-approved credit limit) *when at the same time* they had sufficient funds on deposit so that they could have avoided these costs. This situation is similar to the various cases of inattention described above in that (1) individuals do not appear to act on information that is available to them (i.e. their own minimum payment due or their own preauthorised credit limit) and (2) incur a cost as a result of such inattention (from the resultant credit card penalty fees or the reduced credit rating (FICO score)).

The principal reason for studying inattention in the credit card context is that it allows us to study exactly *who* is inattentive across the wide spectrum of individual credit

[1] In addition to these empirical papers, there has also been recent theoretical interest in inattention in financial markets. Abel Eberly and Panageas (2007) develop a model of the optimal attention to a stock market portfolio, based on the costs and benefits of inattention. 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. 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)). These authors examine whether inattention can explain the relatively slow transmission of information through the economy and whether this can explain macroeconomic dynamics.

card holders. In particular, we examine the impact of wealth on inattention – i.e. whether richer or poorer credit card holders are more or less likely to be inattentive to their credit card repayments[2].

This issue is important because the existing literature is unable to provide an unambiguous prediction as to whether richer or poorer individuals are more inattentive. DellavVigna (2007), for example, 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. We argue however that these psychologically based constructs (competing stimuli and salience) are unable to provide a priori predictions as to how economic factors such as wealth impact inattention in the credit card context. Specifically, in terms of the number of competing stimuli – it is unclear a priori whether richer or poorer individuals are more likely to face more competing stimuli relative to their limited supply of attention. Thus it is theoretically possible for either richer or poorer individuals to make credit card repayment mistakes caused by competing stimuli. In terms of the salience issue, arguments can also be made for either richer or poorer individuals being more inattentive. For example, richer individuals could be more inattentive because the 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 a reduced credit rating, thus increasing the costs of future borrowing which may be larger for richer individuals.

A further motivation for our study is that we are able to isolate inattention as one of the causes of financial mistakes. Much of the recent research on household finance has focussed on whether poorer individuals make more financial mistakes due to lower financial literacy[3] (rather than inattention). Low financial literacy impacts the solving of complex intertemporal financial problems as would be needed for making investment,

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

mortgage and/or pension choices. We argue that the kinds of mistakes examined here (i.e. not paying the credit card minimum balance even though sufficient funds are available) does not require the solving of complex financial problems, but much more simply, 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.

In order to conduct our research we build a large new database of over one million data points by matching three databases. Our first database consists of confidential individual monthly statement data on credit card and other bank accounts for more than 75 000 bank customers. This provides us with data on which individuals pay delinquent or overlimit fees while simultaneously having sufficient deposits available to avoid such fees. 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. 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. These latter two databases provide a large amount of data on different forms of wealth. 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, a far smaller number than in each US zip code. This provides us with very fine grained data on wealth that we can match to our confidential individual level bank credit card and deposit account data.

In short, our paper finds strong evidence that poorer individuals are more inattentive than richer individuals to their credit card repayments. We conclude therefore that not only (as shown in the existing literature) are poorer individuals more likely to make financial mistakes because of financial illiteracy, but in addition they are also more likely to make financial mistakes because of inattention.

The outline of the paper is as follows. Part 2 defines credit card mistakes and Part 3 describes the wealth characteristics of those who make these mistakes. Part 4 describes our methodology and results and Part 5 concludes.

2. CREDIT CARD REPAYMENT MISTAKES

2.1. Defining Credit Card Mistakes

In this paper the mistakes we examine occur when an individual unnecessarily incurs credit card penalty fees, while at the same time having sufficient deposits available in the bank that issued the credit card[4]. These deposits imply that the penalty fees could have been avoided if the individuals were more attentive. We examine two particular events leading to penalty fees (1) delinquency and (2) going over the credit card limit. As extensions we also examine (3) the case when an individual incurs a simultaneous delinquency and overlimit fee in a single month and (4) when an individual uses a cash advance facility of the credit card, when cheaper forms of liquidity (i.e. deposits) are available. We first describe these four events and then discuss how we define "sufficient deposits".

The first type of mistake we examine is when a consumer is delinquent on credit card repayments, even though sufficient funds are available on deposit with the bank. The credit card issuing bank defines delinquency as occurring when a consumer fails to repay at least the minimum repayment due on any given month. According to the bank data provider, if a consumer is delinquent for five months in a row, the bank will declare the consumer in default and withdraw the credit card. Furthermore, when the consumer is delinquent, there is the potential of a negative impact on his/her credit rating (e.g. Credit Bureau or FICO score).

The second mistake we examine is when a consumer is overlimit on his/her credit card but still has sufficient balances on deposit that could have been used to avoid being overlimit. Being overlimit is defined as occurring when a consumer has a credit card balance that exceeds the pre-approved credit limit set by the bank. An overlimit consumer faces a possible decline in both their internal as well as external credit rating 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

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

is a combination of the delinquent and overlimit mistakes described above occurring within the same month.

For comparison purposes, the fourth and final mistake we examine is when a consumer pays a cash advance fee on their credit card, even though the consumer has deposits available. It can be argued that if the consumer has sufficient funds on deposit and ATMs are readily available, then it is a mistake to make use of the credit card cash advance facility. Unlike the mistakes above, such a mistake will not result in a reduction of a credit score or withdrawal of a card.

In defining credit card mistakes, we need to define what we mean by "sufficient deposit balances". At its simplest we can examine whether an individual is making a mistake by comparing the amount of the delinquency (or overlimit amount) with the amount of deposits in the individual's deposit account. However, individuals may hold some proportion of funds on deposit as precautionary balances – i.e. as "liquidity insurance" against unforeseen future income or wealth shocks. If deposit balances are being held for precautionary reasons, it would be inappropriate to consider it a "mistake" when the individual does not use these balances in full to avoid the credit card costs described above. Consequently, we provide alternative definitions of mistakes which control for the holding of deposits under a variety of assumptions about consumer precautionary balance demand.

The literature on precautionary balances (e.g. Opler, Pinkowitz, Stultz and Williamson, (1999) 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. A significant advantage of our data is that it includes monthly deposit balances for each credit card user over a 19 month period. Having access to 19 months of deposit balances data for each individual provides us with our first measure for the precautionary holding of deposits which is based on the standard deviation of the card holder's deposit balances over the 19 months. Our second measure is linked to the motive for holding precautionary balances when cash flows are "low". We define "low" cash flows as those individuals whose average deposit balances are in the bottom quintile of all individuals in our sample (the cut off point is a monthly deposit balance of approximately $240).

Our time series on individual credit card and deposit balances also allows us to examine individuals who make mistakes in *consecutive* months. By observing how many individuals make repeated mistakes we can assess whether individuals learn from their mistakes[5].

2.2. Measuring credit card mistakes

Table 1 provides a summary of the prevalence of each kind of credit card mistake in our database ((1) delinquent, (2) overlimit, (3) delinquent & overlimit and (4) cash advance) under the various definitions for mistakes. Each cell in Table 1 is reported as a percentage of the total individual/month observations in the database.

The first row provides data on the raw total, which is simply the number of individual/month datapoints where an event such as delinquent payment or overlimit charge 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 while at the same time holding sufficient deposits available to avoid these costs. This (row 2) definition of mistakes, however, ignores the demand for precautionary balances. Our next two definitions of mistakes (rows 3 and 4), control for various definitions of precautionary balances. In row 3 we define "sufficient deposits" to be equal to total deposits minus one standard deviation of deposits over our 19 month sample period, thereby capturing the demand for precautionary balances by individuals with volatile cash flows. Our definition in row 4 uses the same definition as row 3, but *in addition* defines any individual with an average monthly deposit balance of $240 or less not to have made a mistake. Our definition in row 4 thus captures both the "volatile cash flow" as well as the "low cash flow" motivations for precautionary balances. Our final definition of mistakes (row 5) is the same as in row 4, except that it examines the proportion of individuals who make mistakes in two consecutive months.

[5] This part of our study is similar to the work of Agarwal, Driscoll, Gabaix and Laibson (2007B) 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). While Agarwal et al (2007B) examine all penalty fee payments, our study only examines penalty fees when individuals have sufficient deposit balances.

A number of observations can be drawn from Table 1. Specifically, across all four kinds of mistake (columns), as we strengthen the definition of what constitutes a mistake the number of mistakes declines. Nevertheless, the data for mistakes definitions in rows 2, 3 and 4 indicate that a significant proportion of individuals who make a mistake in a single month, do so in spite of having sufficient deposit balances. Even by our most stringent definition of mistakes in a single month (row 4) 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 (row 5) compared to the number making mistakes in a single month[6]. Another important element of our data is the correlation across the various mistakes; that is the relationship between delinquent, overlimit and cash advance mistakes. Table 2 reports on the correlations between these mistakes based on precautionary balances equal to one standard deviation of deposits (alternative definitions of precautionary balances produce similar results). The results show that there is little correlation among the different kinds of mistakes.

3. MATCHING DATA AND MEASURING WEALTH

3.1. Matching data

In order to measure the effects of wealth on inattention we need to match our credit card account level data base (dependent variables) with two post code level databases we use for our independent variables (Statistics Canada Census data and Land Titles Registry data). Appendix 1 describes the procedures we use to match these databases, while Table 3 provides detailed summary statistics of all variables used in our analysis.

An important definitional issue concerns the postal code based geographic area that we use in our data matching. As Appendix 1 describes, each Canadian postal code area contains an average of 20 households. However, in order to match with census data

[6] 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.

we are required to use a geographic measure called the Dissemination Area (or DA), which is an agglomeration of approximately 10 neighbouring postal codes with on average approximately 200 households. Accordingly, in this paper we use the terms dissemination area (DA) or "postal code" interchangeably to refer to the DA area of 200 households[7]. Table 4 summarizes the matching strategy used. Appendix 2 describes how the use of postal code based data can be used as a proxy for individual level data of individuals who live in each postal code.

3.2. Wealth Proxies from Census Data

Statistics Canada postal code (dissemination area) level census data provides us with a very useful set of wealth proxies. First, the Census variable "Business and Investment Income" provides us with a good proxy for the business and investment wealth of individuals in each postal code. Note that all of the elements of this variable refer to the annual income from assets, rather than the assets themselves[8]. We argue that the higher the level of the business and investment income, the greater the wealth of these individuals.

The second useful proxy for wealth from the Census data is "Income from Government Sources"[9]. The main elements of this form of income are Old Age Security and Unemployment Insurance. We argue that if these payments make up a significant proportion of total income in any year, then this is a proxy for low wealth.

A third proxy for 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 rent rather than own their residence then this is a very useful proxy for those individuals having lower wealth.

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[7] US census data uses minimum geographic areas of 150000 inhabitants on average (see e.g. Luttmer, 2005), an indication of the very fine grained nature of our Canadian data .

[8] 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.

[9] 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.

3.3. Wealth Proxy from Land Titles Registry

Using the Land Titles Database, we are able to generate a variety of other measures of wealth based on the market values of houses in each postal code (DA). By measuring the average market value of residences in any specific year, we can capture the cross sectional dispersion of residential property values across our sample of credit card holders. We also examine a variety of alternative specifications for the land titles registry property variables including percentage growth rates of property values as well as the clustering of property values by region rather than by postal code (DA).

3.4. 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 postal code, we have data on the proportion of people in the postal code 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 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.

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 category[10]. 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.

3.5. Individual Credit Characteristics

When examining credit card mistakes, a key issue that needs to be controlled for is individual credit payment history or credit risk. In order to control for credit history (or

[10] It 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.

risk), we use two variables taken from the individual level credit card database provided by the data supplying bank. These 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 credit bureaux for each consumer and is updated quarterly. This score captures past credit history, including past delinquency/defaults, past overlimit behaviour, multiple credit applications etc[11]. 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 bank's own internal assessment on how much credit each consumer can be allowed.

Our final individual characteristic 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 annual fees, 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.

4. TEST METHODOLOGY AND RESULTS

4.1. Test Methodology

This paper used panel data of more than 75 000 individual credit card holders over 19 months (December 2004 to June 2006). A significant concern in using panel data of this type is that both independent variables as well as residuals can be correlated across clusters (i.e. individuals) resulting in biased estimates. Using Monte Carlo based tests Petersen (2008) evaluates a large variety of panel data techniques in order to determine

[11] Note that in our tests below the (independent variable) FICO score is very different from the (dependent variable) "mistakes". The dependent "mistakes" variable captures current delinquency or overlimit *only* when the consumer has "sufficient funds in their deposit account". The FICO score on the other hand measures a weighted average of *past* behaviour only, which includes delinquency and default, as well as a large number of other risk factors in a weighted average. It is also important to note that the FICO score does *not* include data on variables such as income and wealth etc thus it should not be correlated with the wealth variables. 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.)

how best to account for such high within cluster correlation. Following Petersen (2008) we conduct our econometric tests using logit models where the standard errors are robust and clustered by individual[12].

As a robustness check we also reran all our tests with the data clustered by the Dissemination Area (DA) measure of postal codes, rather than by individual. Also, following Petersen (2008) we re-estimate our test using random effects logit models for all our specifications.

4. 2 Results

Our results are reported in Tables 5 to 13. Our main results are presented in Tables 5 and 6. We then present a number of robustness tests in Tables 7 to 13.

4.3. Delinquent and Overlimit Results – Tables 5 and 6

Our main results for our alternative definitions of delinquent or overlimit mistakes are reported in Tables 5 and 6. Table 5 has as dependent variables delinquent and overlimit mistakes where precautionary balances are measured by one standard deviation of monthly deposits. Table 6 extends the definition of precautionary balances to include individuals whose average monthly deposits are also in the bottom quintile of deposit holding (i.e. only individuals whose monthly deposit balances is more than $240 will be defined to have made a mistake). For each of the delinquent and overlimit models in Tables 5 and 6 we report both the estimated coefficient as well as the elasticity of the dependent variable with respect to the independent variable to indicate the economic magnitude of the coefficients.

In terms of our alternative wealth proxies, the proportion who rent variable is highly significant in all of the different models we report. In all cases the sign is positive indicating that property renters (a proxy for lower wealth individuals) make significantly more card mistakes than property owners.

[12] 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 whether the firm (individual) effect is permanent or temporary." (p. 40).

In the case of the delinquent payment models the government income coefficient is significant and positive indicating that the greater proportion of income an individual receives from government sources (a proxy for low wealth), the greater the number of mistaken delinquencies. Furthermore, in the case of the overlimit models, the business and investment income coefficients are significant and negative. This implies that individuals with lower amounts of business and investment income (a proxy for low wealth) are more likely to be mistakenly overlimit.

The residential property value variable taken from the land title registry database is insignificant in all models. This finding is consistent with 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 do 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.

In our tests we include, as control variables, two measures of individual card holder credit history (risk) taken from the bank credit card database - the FICO score, and the pre-approved credit card line of credit, which represents the banks internal assessment of the default risk of an individual borrower. In all models these variables are significantly negative, implying that the worse the credit history (greater the assessed risk) of the individual, the more mistakes the individual makes[13].

As an additional control we 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 for the overlimit regressions show that individuals who have chosen a “no frills” card without annual fees make significantly fewer credit card mistakes.

[13] As an example of the importance for controlling for credit history 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 history (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.

With respect to education level, we find the relationship between education and mistakes to be non-monotonic. Specifically, we find that bachelor or higher degree holders make significantly fewer mistakes than those with no high school and that there is no significant difference between high school and no high school. However we also find that individuals with some post secondary education (but less than a bachelor's degree) make more mistakes than individuals with no high school. One possible explanation for this non-monotonic finding in education is that the inattentive mistakes examined in this paper could theoretically be made by either educated or less-educated individuals since either or both could have excess demands (from competing stimuli) on their limited supplies of attention. In other words, while it can be predicted, a priori, that education should have an impact on financial mistakes caused by financial illiteracy, the impact of education on mistakes caused by inattention remains theoretically ambiguous.

Finally, with respect to age, no discernable pattern emerges. As such, our findings 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. 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.

4.4. Robustness Checks – Tables 7 to 13

4.4.1. Alternative Variables

Table 7 uses as a dependent variable individuals being unnecessarily overlimit or delinquent for two consecutive months after accounting for precautionary balances. The dependent variable in this case is the most restrictive definition of mistakes reported in Table 1. The results from Table 7 indicate that many of the wealth variables that are significant in Tables 5 and 6 are no longer significant (with the exception of the rental variable in the overlimit model). The implication of this finding is that wealth appears to be less of a factor in determining repeated mistakes.

Table 8 reports the determinants of overlimit and delinquent mistakes in the same month for a variety of definitions of precautionary balances. It also reports on incidences

of both mistakes in consecutive months. The main finding of Table 8 is that the wealth variables (e.g. business and investment income) and rent are significant with all signs indicating poorer individuals make such joint mistakes. We also find that the annual income variable is significant and negative.

Table 9 examines individuals mistakenly using the expensive cash advance facility available on the credit card. As discussed above, this mistake differs from the delinquency/overlimit mistakes that are the main focus of this paper. Cash advance mistakes can be considered less costly because they typically involve a fee only, rather than the possible reduction in credit rating that can follow an individual being overlimit or delinquent. The main result of interest in Table 9 is that while the rental coefficient is significant and negative across all specifications, the other elements of wealth are not significant.[14]

4.4.2. Causality

In our tests causality runs from individual characteristics (e.g. wealth, credit history etc) to overlimit or delinquent mistakes. This section examines the possibility of reverse causality. For example, an individual who makes a financial mistake can lower his/her wealth in the future. We argue, however, 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, postal code level census data represents average wealth level measured in the 2001 census, while our data on financial mistakes is measured later, between 2004 and 2006. Furthermore, it seems highly unlikely that a specific individual's financial mistake will impact the average wealth of a postal code area. It seems more 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 financial mistake.

[14] In addition to the various alternative specifications described here, we have also examined other specifications which we don't report to conserve space. We examine a variety of alternative specifications for the land titles registry property variables including nominal dollar values of property prices, percentage growth rates of property prices as well as the clustering of property by region rather than by postal code or DA. All of these alternative specifications are insignificant in our mistakes regressions. We also changed the specification of the percentage of total income paid by government from a percentage to a nominal dollar value. These results were broadly similar.

In terms of our control variables which reflect an individual's credit history (i.e. FICO and Credit Card credit limit) it might be argued that being overlimit or delinquent can negatively affect the FICO score or credit limit, (which is the reverse causality of our specification). This could happen if the bank decided to reduce the individuals FICO or credit limit in the same month in response to a card mistake. An important advantage of the panel nature of our data is that we can control for this by lagging the FICO Score and Credit Limit of each individual in our sample by three months. Table 10 repeats Tables 5 and 6 with the exception that the FICO score and Credit Limit on Credit Card are lagged three months Even though our sample size is significantly reduced by the lagging operation, our results are highly robust in terms of the significance and economic magnitude of the effects from these variables.

In addition, the institutional timing of fee charges within our data supplying bank also mitigate against the possibility of reverse causality (i.e. mistakes causing FICO and credit limit). Discussions with bankers suggest that being overlimit or delinquent only impacted FICO scores and credit limits after multiple payment problem episodes by the consumer, and further that usually there would be a lag of some months between overlimit/delinquent episode(s) and a negative impact on his/her FICO or credit limit.

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[15]. This had no impact on any of our findings in Tables 5 and 6.

4.4.3. Alternative Econometric Specifications

All of the results reported above use robust standard errors clustered by individual (see Petersen (2008)). For robustness purposes Tables 11, 12 and 13 replicate Tables 5, 6 and 7 with the key exception that they use robust standard error clustering by the DA measure of postal code rather than clustering by individual. The key finding from these Tables is that the results are very similar whether we cluster by individual or by postal code (DA) across all of these models. Furthermore, following Petersen (2008) we also

[15] These results are not reported to save space.

reran the models in Tables 5, 6 and 7 using random effects instead of the robust clustered standard error models reported above[16]. Overall the results between the robust clustered standard errors models and the random effects models are very similar.

4.5 Strategic Default

An individual can always decide to strategically default on his/her credit card debt because of the possible advantages of bankruptcy protection. An individual who is attempting to strategically default can therefore decide to be delinquent or overlimit, even if the individual has sufficient balances in his/her deposit account. It is important therefore to ensure that the mistakes we are examining here are not caused by strategic default.

An important advantage of the panel nature of our data (i.e. individual accounts over 19 months) is that we can examine how individuals behave with respect to delinquency in the months after a "mistake" has been made to determine if the individual is attempting to strategically default. Furthermore, our data allows us to distinguish between bankruptcy (which can be declared by the individual) and charge off (which is declared by the bank). 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 or have declared bankruptcy. Out of a total sample of more than 75 000 individuals, only 3502 made a delinquency mistake for three months in a row. Of those only 49 went on to be charged off and only 3 declared bankruptcy. Indeed many others declared bankruptcy or were charged off *without* making the kinds of mistake we are examining here. Thus strategic default appears to be an extremely rare occurrence in our dataset.

5. CONCLUSIONS

Inattention occurs when agents do not fully utilize information available to them and thus incur a cost. A large and growing literature has examined the causes and consequences of inattention. Existing, psychologically based theory, however, is not able to make a clear prediction about the impacts of wealth on inattention. Indeed it is

[16] These results are not reported to save space.

theoretically possible that both richer and/or poorer individuals are inattentive because each could be facing competing demands on their limited supplies of attention.

This paper investigates this issue empirically by examining the impact of inattention in the context of credit card repayments and the payment of penalty fees. We define inattention as occurring when individuals mistakenly incur credit card penalty fees (for being delinquent or overlimit) *even though* they simultaneously held sufficient deposit balances to have been able to avoid these penalty fees.

Our research is based on an account level credit card database of more than a million data points, provided to us by a Canadian financial institution. In order to examine the impact of wealth on credit card mistakes, we match our account level credit card data to postal code level data taken from the Canadian Census as well as Land Titles Registries. 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.

Our findings are particularly important in light of other recent research in the household finance literature that shows that poorer individuals are also likely to have lower levels of financial literacy (i.e. the ability to make appropriate choices in areas such as investments, pensions and mortgages). Our results complement this existing research by showing that not only may poorer individuals have lower levels of financial literacy but they are also more inattentive to their personal finances, as measured by credit card repayments.

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[17].

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[18].

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

[17] 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.

[18] 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)[19].

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

[19] 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: Percentage Occurrences of Credit Card Mistakes

This Table provides the percentage occurrences of various credit card mistakes. All percentages are a proportion of almost 1 million month/consumer data points. Full discussion of these definitions is provided in part 3.1 of the text.

	Delinquent	**Overlimit**	**Cash Advance**	**Delinquent and Overlimit in Single Month**
Row 1: Raw Total Ignoring Deposits	10.3%	5.8%	4.6%	2.5%
Row 2: Mistakes- (Definition 1) Unnecessary Cost when Sufficient Deposits Available	6.6%	3.2%	2.7%	1%
Row 3: Mistakes – (Definition 2) Precautionary Balances function of standard deviation of deposits.	4.1%	1.8%	1.5%	0.5%
Row 4: Mistakes – (Definition 3) Precautionary Balances function of standard deviation of deposits *and* bottom quintile of deposits	4.0%	1.7%	1.5%	0.5%
Row 5: Mistakes – (Definition 4) *Consecutive* Months of Definition 3 Mistakes	0.6%	0.4%	0.3%	0.09%

Table 2: Correlation between Credit Card Mistakes

These correlations are from data using Definition 2 in Table 1 (i.e. precautionary balances based on one standard deviation of deposits). Results are similar for other definitions of precautionary balances in Table 1.

	Delinquent	**Overlimit**	**Cash Advance**
Delinquent	1.0		
Overlimit	0.1795	1.0	
Cash Advance	0.0255	0.1432	1.0

Table 3: 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 ($)	1 387 456	730.23	73.5	369	880
Credit Limit on Credit Card ($)	1 496 451	6147.33	6271.31	0	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 ($)	1 399 227	2689.39	2338.82	0	64983.6
Residence Rent/Own Status (% Rent)	1 460 288	24.6	21.38	0	100
Annual Family Income Total ($)	1 449 534	62636.85	25961.28	0	435103
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 4: 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 5. IMPACT OF WEALTH ON DELINQUENT AND OVERLIMIT MISTAKES.

LOGIT MODEL WITH CLUSTERD STANDARD ERRORS (CLUSTERED BY INDIVIDUAL)

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 Logit Methodology with Clustered Robust Standard Errors (as in Petersen, forthcoming) . Clustered by Individual. Dependent Variables are (1) Unnecessary Delinquency and (2) Unnecessary Over-Limit. For each model both logit coefficients as well as elasticity is reported. 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.

	DELINQUENT		**OVERLIMIT**	
	Coefficient	**Elasticity**	**Coefficient**	**Elasticity**
Residential Property Value ($)	-0.0190	0.0032	0.0001	0.0000
Government Income (% of Total)	0.0070***	0.0832	0.0027	0.0332
Business & Investment Income ($)	-0.0130	-0.0958	-0.0611**	-0.4616
Residence Rent/Own Status (% Rent)	0.0017***	0.0405	0.0040***	0.0950
Annual Family Income Total ($)	0.0078	0.0822	-0.0250	-0.2717
Credit Rating –FICO Score	-0.0023***	-1.6438	-0.0034***	-2.4197
Credit Limit on Credit Card ($)	-0.1406***	-1.1160	-0.4020***	-3.2719
Type of Credit Card (No Fee Dummy)	-0.0036	-0.0023	-0.2241***	-0.1476
High School (% in DA)	0.0028	0.0314	-0.0008	-0.0089
Some Post Secondary (% in DA)	0.0011	0.0608	0.0067***	0.3816
Bachelor or Higher Degree (% in DA)	-0.0028*	-0.0348	-0.0105***	-0.1342
Age 0 to 19 (% in DA)	0.0059*	0.1602	0.0026	0.0734
Age 20 to 34 (% in DA)	0.0002	0.0049	0.0063	0.1279
Age 35 to 54 (% in DA)	0.0029	0.0829	0.0070	0.2057
Age 55 to 64 (% in DA)	0.0064	0.0512	0.0133*	0.1083
Population per Household	-0.0220	-0.0563	0.0246	0.0646
Immigrant (% in DA)	-0.0015	-0.0157	0.0021	0.0222
Constant	-0.7541**		1.4358***	
Number of Observations	970774		970774	
Wald Chi2	4074.05		9582.17	
Psuedo R2	0.02		0.06	

Table 6. IMPACT OF WEALTH ON DELINQUENT AND OVERLIMIT MISTAKES.

LOGIT MODEL WITH CLUSTERD STANDARD ERRORS (CLUSTERED BY INDIVIDUAL)

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 Logit Methodology with Clustered Robust Standard Errors (as in Petersen, forthcoming) . Clustered by Individual. Dependent Variables are (1) Unnecessary Delinquency and (2) Unnecessary Over-Limit. For each model both logit coefficients as well as elasticity is reported. 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.

	DELINQUENT		**OVERLIMIT**	
	Coefficient	**Elasticity**	**Coefficient**	**Elasticity**
Residential Property Value ($)	-0.0175	0.0030	-0.0012	0.0002
Government Income (% of Total)	0.0070***	0.0841	0.0035	0.0430
Business & Investment Income ($)	-0.0131	-0.0965	-0.0702***	-0.5307
Residence Rent/Own Status (% Rent)	0.0016**	0.0365	0.0040***	0.0956
Annual Family Income Total ($)	0.0054	0.0572	-0.0267	-0.2909
Credit Rating –FICO Score	-0.0023***	-1.6522	-0.0033***	-2.4121
Credit Limit on Credit Card ($)	-0.1269***	-1.0082	-0.3881***	-3.1607
Type of Credit Card (No Fee Dummy)	-0.0050	-0.0032	-0.2312***	-0.1523
High School (% in DA)	0.0026	0.0293	-0.0018	-0.0213
Some Post Secondary (% in DA)	0.0011	0.0620	0.0066***	0.3773
Bachelor or Higher Degree (% in DA)	-0.0027*	-0.0335	-0.0099***	-0.1265
Age 0 to 19 (% in DA)	0.0055	0.1507	0.0015	0.0414
Age 20 to 34 (% in DA)	0.0001	0.0029	0.0071*	0.1434
Age 35 to 54 (% in DA)	0.0023	0.0650	0.0075	0.2214
Age 55 to 64 (% in DA)	0.0062	0.0493	0.0159**	0.1300
Population per Household	-0.0237	-0.0607	0.0508	0.1335
Immigrant (% in DA)	-0.0015	-0.0161	0.0017	0.0186
Constant	-0.8214**	0.0030	1.2695**	0.0002
Number of Observations	970774		970774	
Wald Chi2	3902.00		9335.25	
Psuedo R2	0.02		0.06	

Table 7. IMPACT OF WEALTH ON DELINQUENT AND OVERLIMIT MISTAKES.

LOGIT MODEL WITH CLUSTERD STANDARD ERRORS (CLUSTERED BY INDIVIDUAL)

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 Logit Methodology with Clustered Robust Standard Errors (as in Petersen, forthcoming) . Clustered by Individual. Dependent Variables are (1) Unnecessary Delinquency and (2) Unnecessary Over-Limit. For each model both logit coefficients as well as elasticity is reported. 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.

	DELINQUENT		**OVERLIMIT**	
	Coefficient	**Elasticity**	**Coefficient**	**Elasticity**
Residential Property Value ($)	-0.0618	0.0108	0.0015	0.0127
Government Income (% of Total)	0.0100	0.1242	0.0015	0.1023
Business & Investment Income ($)	0.0171	0.1300	-0.0500	0.4181
Residence Rent/Own Status (% Rent)	0.0014	0.0333	0.0051**	0.0595
Annual Family Income Total ($)	0.0214	0.2344	-0.0584	0.5200
Credit Rating –FICO Score	-0.0032***	-2.3344	-0.0035***	0.0419
Credit Limit on Credit Card ($)	-0.1148***	-0.9428	-0.2953***	0.1958
Type of Credit Card (No Fee Dummy)	-0.0546	-0.0363	-0.0688	0.0448
High School (% in DA)	0.0047	0.0556	0.0018	0.0811
Some Post Secondary (% in DA)	0.0052	0.2996	0.0099***	0.2311
Bachelor or Higher Degree (% in DA)	-0.0088	-0.1128	-0.0117**	0.0731
Age 0 to 19 (% in DA)	0.0137	0.3879	0.0067	0.2777
Age 20 to 34 (% in DA)	0.0021	0.0436	0.0021	0.1446
Age 35 to 54 (% in DA)	0.0053	0.1588	0.0027	0.2486
Age 55 to 64 (% in DA)	0.0099	0.0817	0.0188	0.1118
Population per Household	-0.1616	-0.4280	-0.0774	0.4290
Immigrant (% in DA)	0.0054*	0.0578	0.0052	0.0432
Constant	-2.9959		-0.4499	
Number of Observations	970774		970774	
Wald Chi2	4505.08		6873.62	
Psuedo R2	0.03		0.05	

Table 8. IMPACT OF WEALTH ON DELINQUENT AND OVERLIMIT MISTAKES.

DELINQUENT AND OVERLIMIT IN SAME MONTH

LOGIT MODEL WITH CLUSTERD STANDARD ERRORS (CLUSTERED BY INDIVIDUAL)

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 Logit Methodology with Clustered Robust Standard Errors (as in Petersen, forthcoming) . Clustered by Individual. Dependent Variables are (1) Unnecessary Delinquency and Unnecessary Over-Limit. In the same month. 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.

	Single Months		**Consecutive Months**
Precautionary Balances	**1 std dev**	**1 std dev plus low quintile**	**1 std dev**
Residential Property Value ($)	0.0338	0.0180	0.0330
Government Income (% of Total)	0.0000	-0.0013	0.0071
Business & Investment Income ($)	-0.0871*	-0.0929**	-0.0946
Residence Rent/Own Status (% Rent)	0.0040*	0.0040*	0.0075
Annual Family Income Total ($)	-0.0754**	-0.0761**	-0.1096
Credit Rating –FICO Score	-0.0034***	-0.0034***	-0.0038***
Credit Limit on Credit Card ($)	-0.5429***	-0.5251***	-0.4558***
Type of Credit Card (No Fee Dummy)	-0.0322	-0.0345	0.0547
High School (% in DA)	-0.0010	-0.0016	0.0035
Some Post Secondary (% in DA)	0.0065*	0.0067*	0.0108
Bachelor or Higher Degree (% in DA)	-0.0109***	-0.0107***	-0.0164*
Age 0 to 19 (% in DA)	0.0032	0.0016	0.0263
Age 20 to 34 (% in DA)	-0.0024	-0.0030	-0.0003
Age 35 to 54 (% in DA)	-0.0035	-0.0040	0.0025
Age 55 to 64 (% in DA)	0.0045	0.0053	0.0279
Population per Household	-0.0440	-0.0326	-0.3247
Immigrant (% in DA)	-0.0001	-0.0002	0.0049
Constant	2.7277***	2.6793***	0.0391
Number of Observations	970774	970774	970774
Wald Chi2	8917.53	8798.86	5828.01
Psuedo R2	0.08	0.07	0.07

Table 9. IMPACT OF WEALTH ON CASH ADVANCE MISTAKES.

LOGIT MODEL WITH CLUSTERD STANDARD ERRORS (CLUSTERED BY INDIVIDUAL)

PRECAUTIONARY BALANCES PROXIED BY 1 STANDARD DEVIATION OF DEPOSITS AND LOWEST QUINTLE OF DEPOSITS ($240).

Data is panel data and dependent variable is binary (1 = mistake and 0 = no mistake). Use Panel Logit Methodology with Clustered Robust Standard Errors (as in Petersen, forthcoming) . Dependent Variables Cash Advance Errors. 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.

	Single Months		**Consecutive Months**
Precautionary Balances	**1 std dev**	**1 std dev plus low quintile**	**1 std dev**
Residential Property Value ($)	0.0359	0.0260	0.1367
Government Income (% of Total)	0.0087	0.0084	0.0107
Business & Investment Income ($)	-0.0518	-0.0519	-0.0360
Residence Rent/Own Status (% Rent)	0.0057***	0.0058***	0.0056**
Annual Family Income Total ($)	0.0811	0.0771	0.1337
Credit Rating –FICO Score	-0.0022***	-0.0021***	-0.0019***
Credit Limit on Credit Card ($)	-0.1557***	-0.1504***	-0.0583*
Type of Credit Card (No Fee Dummy)	-0.3291***	-0.3274***	-0.2393***
High School (% in DA)	0.0031	0.0037	0.0037
Some Post Secondary (% in DA)	0.0075*	0.0073**	0.0054
Bachelor or Higher Degree (% in DA)	-0.0156***	-0.0151***	-0.0178***
Age 0 to 19 (% in DA)	-0.0019	-0.0020	0.0080
Age 20 to 34 (% in DA)	0.0100*	0.0101**	0.0121
Age 35 to 54 (% in DA)	0.0031	0.0028	0.0025
Age 55 to 64 (% in DA)	0.0114	0.0123	0.0182
Population per Household	0.1645	0.1642	0.0654
Immigrant (% in DA)	0.0009	0.0009	0.0003
Constant	-2.9445***	-2.9728***	-5.8783***
Number of Observations	970774	970774	970774
Wald Chi2	1625.32	1555.58	377..09
Psuedo R2	0.02	0.02	0.01

Table 10. IMPACT OF WEALTH ON DELINQUENT AND OVERLIMIT MISTAKES.

LOGIT MODEL WITH CLUSTERD STANDARD ERRORS (Clustered by Individual)

THREE MONTH LAGS OF FICO SCORE AND CREDIT LIMIT

Data is panel data and dependent variable is binary (1 = mistake and 0 = no mistake). Use Panel Logit Methodology with Clustered Robust Standard Errors (as in Petersen, forthcoming) . Dependent Variables are (1) Unnecessary Delinquency and (2) Unnecessary Over-Limit. Clustered by Individual. 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.

	DELINQUENT		**OVERLIMIT**	
PRECAUTINARY BALANCES	**1 SD**	**1 SD AND $240**	**1 SD**	**1 SD AND $240**
Residential Property Value ($)	-0.01514	-0.015068	0.010584	0.006832
Government Income (% of Total)	0.006696**	0.006637**	0.003688	0.004446
Business & Investment Income ($)	-0.02574	-0.026151	-0.068774**	-0.078846***
Residence Rent/Own Status (% Rent)	0.001758**	0.001625**	0.005121***	0.005062***
Annual Family Income Total ($)	0.000528	-0.000352	-0.009331	-0.015005
Credit Rating –FICO Score [lag 3 mnth]	-0.00258***	-0.00257***	-0.0036***	-0.003582***
Credit Limit on Credit Card ($) [lag 3 mnth]	-0.14205***	-0.130812***	-0.350372***	-0.339984***
Type of Credit Card (No Fee Dummy)	0.024468	0.02041	-0.163698***	-0.175402***
High School (% in DA)	0.002183	0.002003	0.000413	-0.000424
Some Post Secondary (% in DA)	0.001551	0.001528	0.006905**	0.006741***
Bachelor or Higher Degree (% in DA)	-0.00277*	-0.002677	-0.010221***	-0.009312***
Age 0 to 19 (% in DA)	0.004807	0.004046	0.003381	0.00291
Age 20 to 34 (% in DA)	-0.00084	-0.001016	0.006049	0.00672
Age 35 to 54 (% in DA)	0.002481	0.002006	0.006935	0.007334
Age 55 to 64 (% in DA)	0.007061	0.006652	0.018741**	0.021286***
Population per Household	-0.0219	-0.01925	0.042437	0.05951
Immigrant (% in DA)	-0.00208	-0.002189	0.001976	0.001874
Constant	-0.3592	-0.424922	0.845514	0.773196
Number of Observations	772231	772231	772231	772231
Wald Chi2	3366.1	3201.1	6710	6561.7
Psuedo R2	0.02	0.02	0.06	0.06

Table 11. IMPACT OF WEALTH ON DELINQUENT AND OVERLIMIT MISTAKES.

LOGIT MODEL WITH CLUSTERD STANDARD ERRORS (CLUSTERED BY DA)

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 Logit Methodology with Clustered Robust Standard Errors (as in Petersen, forthcoming) . Clustered by DA. Dependent Variables are (1) Unnecessary Delinquency and (2) Unnecessary Over-Limit. For each model both logit coefficients as well as elasticity is reported. 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.

	DELINQUENT		**OVERLIMIT**	
	Coefficient	**Elasticity**	**Coefficient**	**Elasticity**
Residential Property Value ($)	-0.01896	0.0032	9.36E-05	-1.6E-05
Government Income (% of Total)	0.006955***	0.083189	0.002705	0.033178
Business & Investment Income ($)	-0.01301	-0.09582	-0.06109	-0.46156
Residence Rent/Own Status (% Rent)	0.001729**	0.040484	0.003956	0.095024
Annual Family Income Total ($)	0.007755	0.082196	-0.025	-0.27174
Credit Rating –FICO Score	-0.00234***	1.643811	-0.00335	2.419703
Credit Limit on Credit Card ($)	-0.14061***	-1.116	-0.40198	-3.2719
Type of Credit Card (No Fee Dummy)	-0.00364	-0.00234	-0.22415	-0.14756
High School (% in DA)	0.002761	0.031444	-0.00077	-0.00894
Some Post Secondary (% in DA)	0.001093	0.060819	0.006688	0.381577
Bachelor or Higher Degree (% in DA)	-0.0028*	-0.03481	-0.01052	-0.13424
Age 0 to 19 (% in DA)	0.005874	0.16024	0.002625	0.073423
Age 20 to 34 (% in DA)	0.000248	0.004886	0.006336	0.127881
Age 35 to 54 (% in DA)	0.002873	0.082882	0.006953	0.205726
Age 55 to 64 (% in DA)	0.006426	0.051153	0.013259	0.108253
Population per Household	-0.02199	-0.05629	0.024619	0.064621
Immigrant (% in DA)	-0.00151	-0.01574	0.002085	0.02222
Constant	-0.75406**		1.435789	
Number of Observations	970774		970774	
Wald Chi2	3835		9419	
Psuedo R2	0.02		0.06	

Table 12. IMPACT OF WEALTH ON DELINQUENT AND OVERLIMIT MISTAKES.

LOGIT MODEL WITH CLUSTERD STANDARD ERRORS (CLUSTERED BY DA)

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 Logit Methodology with Clustered Robust Standard Errors (as in Petersen, forthcoming) . Clustered by DA. Dependent Variables are (1) Unnecessary Delinquency and (2) Unnecessary Over-Limit. For each model both logit coefficients as well as elasticity is reported. 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.

	DELINQUENT		**OVERLIMIT**	
	Coefficient	**Elasticity**	**Coefficient**	**Elasticity**
Residential Property Value ($)	-0.01747	0.002951	-0.0012	0.000208
Government Income (% of Total)	0.007021***	0.084072	0.0035	0.042964
Business & Investment Income ($)	-0.01309	-0.09654	-0.0702**	-0.5307
Residence Rent/Own Status (% Rent)	0.001556*	0.036489	0.003977***	0.09558
Annual Family Income Total ($)	0.005392	0.057213	-0.02674	-0.29086
Credit Rating –FICO Score	-0.00235***	-1.65221	-0.00334***	-2.4121
Credit Limit on Credit Card ($)	-0.12689***	-1.00822	-0.38806***	-3.16066
Type of Credit Card (No Fee Dummy)	-0.005	-0.00321	-0.23122***	-0.15232
High School (% in DA)	0.002568	0.029287	-0.00182	-0.02125
Some Post Secondary (% in DA)	0.001114	0.062042	0.006609**	0.377306
Bachelor or Higher Degree (% in DA)	-0.00269*	-0.03347	-0.00991***	-0.12647
Age 0 to 19 (% in DA)	0.005519	0.150715	0.001477	0.041354
Age 20 to 34 (% in DA)	0.000147	0.0029	0.007101*	0.143416
Age 35 to 54 (% in DA)	0.002252	0.065044	0.007479	0.221423
Age 55 to 64 (% in DA)	0.006186	0.0493	0.015911**	0.129988
Population per Household	-0.02368	-0.06069	0.05081	0.133453
Immigrant (% in DA)	-0.00154	-0.01607	0.001746	0.018619
Constant	-0.82137		1.26953	
Number of Observations	970774		970774	
Wald Chi2	3656		9078	
Psuedo R2	0.02		0.05	

Table 13. IMPACT OF WEALTH ON DELINQUENT AND OVERLIMIT MISTAKES.

LOGIT MODEL WITH CLUSTERD STANDARD ERRORS (CLUSTERED BY DA)

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 Logit Methodology with Clustered Robust Standard Errors (as in Petersen, forthcoming) . Clustered by DA. Dependent Variables are (1) Unnecessary Delinquency and (2) Unnecessary Over-Limit. For each model both logit coefficients as well as elasticity is reported. 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.

	DELINQUENT		**OVERLIMIT**	
	Coefficient	**Elasticity**	**Coefficient**	**Elasticity**
Residential Property Value ($)	-0.06183	0.010798	0.001518	-0.00027
Government Income (% of Total)	0.010033	0.124183	0.001471	0.018236
Business & Investment Income ($)	0.017059	0.130045	-0.05**	-0.38173
Residence Rent/Own Status (% Rent)	0.001373	0.033275	0.005067	0.122976
Annual Family Income Total ($)	0.021369	0.234352	-0.05837	-0.64112
Credit Rating –FICO Score	-0.00321***	-2.33438	-0.00345***	-2.51822
Credit Limit on Credit Card ($)	-0.1148***	-0.94279	-0.29531***	-2.42896
Type of Credit Card (No Fee Dummy)	-0.05464	-0.03629	-0.06882	-0.04578
High School (% in DA)	0.004714	0.055559	0.001772	0.020911
Some Post Secondary (% in DA)	0.005204	0.299572	0.009875**	0.569335
Bachelor or Higher Degree (% in DA)	-0.00876***	-0.11276	-0.01174**	-0.15131
Age 0 to 19 (% in DA)	0.013742*	0.387901	0.006743	0.19063
Age 20 to 34 (% in DA)	0.002141	0.043596	0.002054	0.041902
Age 35 to 54 (% in DA)	0.005321	0.158835	0.002705	0.080869
Age 55 to 64 (% in DA)	0.009918	0.081697	0.018825	0.155305
Population per Household	-0.1616	-0.42797	-0.07745	-0.20542
Immigrant (% in DA)	0.005378	0.057837	0.005188	0.055877
Constant	-2.99592***		-0.44987	
Number of Observations	970774		970774	
Wald Chi2	4495		6827	
Psuedo R2	0.03		0.05	

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