CREDIT CARD USE AFTER THE FINAL MORTGAGE PAYMENT: DOES THE MAGNITUDE OF INCOME SHOCKS MATTER?

Barry Scholnick*
School of Business, University of Alberta
Edmonton, Alberta, Canada, T6G 2R6
(780) 492 5669
barry.scholnick@ualberta.ca

May 2009

Abstract

We test the hypothesis that the magnitude of expected income shocks will impact consumption smoothing, because individuals only adjust consumption intertemporally if future income shocks are large enough. We examine how the magnitudes of final mortgage payments (which increase disposable income) impact credit card consumption and debt. Our confidential bank account data allows us to identify the exact date and magnitude of the final mortgage payment, and also to exploit the random timing of final mortgage payments across individuals. As predicted, we find recipients of smaller expected income shocks increase consumption, but recipients of larger expected income shocks reduce debt.

*

Funding for this project was provided by the Social Sciences and Humanities Research Council of Canada (SSHRC) and the Federal Deposit Insurance Corporation (FDIC). We thank the Canadian Financial Institution for providing us with their confidential monthly statement data. Rasmus Fatum, Stuart Landon, Nadia Massoud, Connie Smith and Pavel Vacek provided valuable comments.

1. INTRODUCTION

The Life Cycle/Permanent Income Hypothesis (PIH) predicts that individuals should smooth consumption over time if future income shocks are predictable. For example, if an individual knew with certainty that she would receive $1000 in 6 months time, the PIH predicts that she should borrow today and then pay off this debt when she receives the predictable income shock in the future. This is so she can smooth consumption both before as well as after the date she receives the income shock. However, even though the PIH is central to much of modern consumption theory, and in spite of a very large number of empirical studies on consumption smoothing[1] , no consensus has emerged on whether consumption smoothing does or does not hold empirically. It remains a major outstanding puzzle to explain why consumption smoothing is sometimes accepted and sometimes rejected by the data.

A variety of authors (e.g. Kreinin, 1961, Souleles, 1999, Browning and Collado, 2001, Hsieh, 2003, Coulibaly and Li, 2006, Stephens, 2008) have suggested that one possible solution to this puzzle involves the *magnitude* of the predictable income shock. This argument (which we term the "magnitude hypothesis") states that consumption smoothing will hold if the size of the predictable income shock is *large* enough, but will not hold if these predictable income shocks are *small*. One popular explanation for the magnitude hypothesis in is bounded rationality. Browning and Collado (2001) argue that individuals "do smooth (consumption) …if there are large and predictable income changes" (p. 682) but that they "will not bother to adjust optimally to small income changes since the utility cost of doing so is small" (p. 690). Similarly, Hsieh (2003) summarizes the bounded rationality argument by noting that there may be "costs associated with the mental processing of these forecastable income changes" (p. 404).

To extend our example above, if the amount of the certain future income shock was small (say $100), then the magnitude hypothesis suggests that the individual may

[1] A large literature has attempted to test this hypothesis by examining individual level consumption patterns following various predictable income shocks. Examples of this literature include (Agarwal, Liu, & Souleles, 2007; Bodkin, 1959; Browning & Collado, 2001; Coulibaly & Li, 2006; Hsieh, 2003; Johnson, Parker, & Souleles, 2006; Kreinin, 1961; Musto & Souleles, 2006; Parker, 1999; Shapiro & Slemrod, 1995; Shapiro & Slemrod, 2003; Shea, 1995; Souleles, 1999; Souleles, 2000; Souleles, 2002; Stephens, 2001; Stephens, 2003; Stephens, 2006; Stephens, 2008).

“not bother” to arrange the credit needed to smooth consumption, or to engage in the “mental processing” needed to work out her optimal consumption patterns. On the other hand, if the magnitude of the future income shock was large (say $5000), then the magnitude hypothesis suggests that the individual is much more likely to smooth consumption by making use of credit and working out her optimal stream of consumption over time.

Table 1 provides a summary of some of the literature testing the PIH using identifiable income shocks. Panel A includes papers that discuss the magnitude hypothesis as a possible explanation for their results, while panel B includes papers that do not. An interesting observation from Table 1 is that many of the papers who have discussed the magnitude hypothesis as an explanation (panel A) find results that are consistent with the PIH, while a majority of papers who do not discuss the magnitude hypothesis (panel B) find results that are not consistent with the PIH. This would seem to suggest the importance of the magnitude hypothesis as an explanation for the PIH. Some of the papers listed in panel A, such as Browning and Collado, (2001), Hsieh, (2003) and Coulibaly and Li, (2006) do not set out to formally test the magnitude hypothesis, but rather suggest that their results may be consistent with the magnitude hypothesis, because the PIH tends to hold following income shocks that the authors consider are “large”. Other papers such as Kreinin, (1961) and Souleles (1999) do formally test the magnitude hypothesis, but as we argue in Section 2 below, use data that is subject to important data concerns. The aim of our paper is to provide a new test of the magnitude hypothesis using a high quality new database.

Our data consists of a confidential individual level database provided by a Canadian bank. The data consists of monthly statement data for approximately 20 000 individuals for both their credit card as well as their mortgage accounts, over 19 months. We follow Coulibaly and Li (2006) and Stephens (2008) in arguing that the final mortgage payment of an individual can be analyzed as an expected disposable income shock. Our aim is to examine how credit card usage is impacted by the expected disposable income shock of a final mortgage payment. We measure the expected disposable income shock using our mortgage data, and we measure the individual’s consumption and debt response using our credit card data. Our main test of the magnitude hypothesis examines if consumption and debt responses are different for individuals with high compared to low expected disposable income shocks (i.e. the cessation of high versus low monthly mortgage payments).

Our use of monthly credit card data to examine issues around consumption smoothing follows a variety of recent papers including Gross and Souleles (2002a) and Agarwal, Liu and Souleles (2007) etc. We believe that our data set is unique, however, because our monthly credit card data is matched to monthly mortgage balance data. This allows us to be the first to use monthly bank account data to specifically test the magnitude hypothesis. Because our monthly mortgage account data is matched with monthly credit card statement data, we are able to exploit the wide variance in the magnitude of final mortgage payments over individuals, in order to test how the magnitude of an expected disposable income shock impacts credit card consumption.

There are a number of important advantages in using this database and research design to test the magnitude hypothesis. First, because we have monthly data on each individual's mortgage balance as it declines towards zero, we are able to isolate *exactly* which month a mortgage holder finally pays off their mortgage as well as the *exact* amount of the monthly payments. In other words we have a remarkably precise measure of both the timing and magnitude of each individual's expected future income shock as measured by the final monthly mortgage payment. This differs from those papers in the literature that have identified either the timing or magnitude of income shocks using survey based databases (such as the Consumer Expenditure Survey (CEX) or the Survey of Consumer Finance (SCF)), which are subject to various well known measurement issues inherent in the use of survey based data. Essentially, the monthly bank account data we observe concerning the timing and magnitude of the income shock is the same data observed by the individual in the study.

Second, we exploit the fact that the dates of final mortgage payments are randomly distributed across individuals over time. In this regard, our use of final mortgage payments as an expected income shock differs from examining government payments (e.g. tax rebate payments or fiscal stimulus payments) which have been extensively examined in the consumption smoothing literature (see Table 1). As highlighted by Agarwal, Liu and Souleles (2007), government payments tend to be clustered for all individuals in a few months of the year, thus it may be difficult to disentangle whether each individual's consumption on that date was responding to that specific government payment, or to any other macroeconomic factor that occurred at the same time, e.g. stock exchange or interest rate developments. In our research design, we are able to exploit the random distribution of the date of the final mortgage payment across individuals to identify exactly when specific individuals received this disposable income shock relative to all other individuals in our sample. Furthermore, we are able to use our data to only include instances where the date of an individual's final mortgage payment is predetermined, an important element of identification in our tests.

Third, we are able to extend the existing monthly credit card statement based literature (e.g. Gross and Souleles, 2002a, Agarwal et al 2007 etc) by adding census based measures of variables such as income. Our monthly bank statement data includes the Canadian postal code of each individual in our sample, thus we are able to match this data with Canadian Census data which provides post code level data on a variety of demographic variables. In particular, we use the post code level income data to test a variation of the magnitude hypothesis – that income shocks should be classified as large or small *relative* to the agent's income.

Our research also has important policy implications. An important motivation of the large literature examining consumption and debt responses to income shocks, concerns measuring the impacts of fiscal policies such as tax rebates and cuts, as well as fiscal stimuli programs (such as the 2008 US Government stimulus package, where each individual was sent a check in an attempt to increase consumption). However, as described above, very little evidence exists on how the dollar *magnitude* of such expected income shocks impact individual consumption and debt response. In other words, an important policy issues is whether a larger stimulus payment check (of say $1000) will have different impacts than a smaller stimulus payment check (of say $300). Stephens (2008), argues that "the *smaller* income changes, that are not smoothed, are typically the focus of stimulative fiscal measures (e.g. tax rebates and permanent tax cuts)" (italics added p. 241). Even though this paper uses data on mortgage payments, rather than fiscal stimuli, we argue that the policy relevance of the magnitude hypothesis in the context of fiscal stimuli payments is an important additional motivation for our research.

2. **RELATIONSHIP TO THE MAGNITUDE HYPOTHSSIS LITERATURE**

Even among the limited group of papers that have discussed the magnitude hypothesis, there is disagreement about whether the magnitude hypothesis is backed by the data. On the one hand, a group of recent papers (e.g. Hsieh (2003) Browing and Collado (2001) and Coulibali and Li (2006)) have argued that the magnitude hypothesis is consistent with their data. However, none of these papers formally test the magnitude hypothesis, but rather speculate in the concluding sections of their papers that the magnitude hypothesis is a possible reason for why they find consumption smoothing, following income shocks that these authors consider to be "large". On the other hand, more rigorous tests of the magnitude hypothesis are provided by Kreinin (1961), and Souleles (1999), but both reject the magnitude hypothesis. These two papers examine individual consumption across a large number of individuals after each received the same type of income shock[2] but where there is a wide variance in the magnitude of these shocks across individuals. Both these authors distinguish between large and small payments by squaring the income shock term, and both reject the magnitude hypothesis because the income squared term is insignificant.

Our study follows the approach of Kreinin (1961) and Souleles (1999) in examining a single type of income shock (final mortgage payments), where there is a wide variance in the magnitudes of the shocks. However, we argue that the data used by these authors is subject to important data concerns. Firstly, both authors use survey based data, and as argued by Gross and Souleles (2002a) and Agarwal, Liu and Souleles (2007) etc., such surveys are subject to significantly greater measurement problems compared to the monthly bank statement data that we use. Second, as emphasized by Agarwal, Liu and Souleles (2007), a key element of testing consumption smoothing across individuals is that the date of the expected income shock be randomized across individuals. However, the data used by both Kreinin (1961) and Souleles (1999) to test the magnitude hypothesis does not allow for such randomization of timing. As described above, our data

[2] Kreinin (1961) examines Israeli reparations payments using the Israeli Survey of Family Savings and Souleles (1999) examines tax rebates using the Consumer Expenditure Survey (CEX).

and research methodology allow us to specifically account for both the measurement accuracy as well as the randomized timing issues.

In terms of theoretical explanations for the magnitude hypothesis, at least three separate psychological theories have been proposed in the literature to explain why magnitudes may matter. These are (1) bounded rationality (e.g. Kreinin, 1961, Browning and Collado (2001) and Hsieh (2003)), (2) mental accounting (e.g Souleles (1999) following (Thaler, 1990)) and (3) inattention (e.g. Coulibali and Li (2006) following (Reis, 2006))[3]. The literature has not, however, been able to provide empirical evidence to distinguish between these three theories. The aim of this paper is to document empirically whether magnitudes do impact consumption smoothing decisions. As in the literature, however, our data does not allow us to distinguish empirically between the various behavioral theories (e.g. bounded rationality, mental accounting, inattention etc).

3. DATA

3.1 Individual Level Monthly Bank Account Data

Our main database consists of individual level monthly credit card and mortgage statements provided to us confidentially by an individual Canadian bank. While a number of recent papers have used monthly credit card statement data[4], our data is unique in that it is matched with monthly mortgage account data. We are thus able to provide the first formal test of the magnitude hypothesis by using individual level monthly bank statement data. We use credit card statement data to measure credit card consumption and credit card debt, and monthly mortgage statements to measure predictable income shocks. The full data base consists of data for more than 75 000 individuals for 19 months. Our primary focus is on the approximately 20 000 individuals who hold *both* mortgage as

[3] Bounded rationality, is based on the argument that individuals will not make optimal intertemporal adjustments to consumption if the amount of the future income shock is too small, because of the mental costs involved. The mental accounting argument is based on the idea that if individuals receive a large income shock they will choose to save it, but if they receive a small income shock they will choose to consumer it. Inattention, is based on the argument that individuals will be more attentive to larger shocks.

[4] A variety of papers have also used individual level credit card monthly statement data to examine a variety of issues. These papers include (Agarwal, Chomsisengphet, Liu, & Souleles, 2006; Agarwal et al., 2007; Agarwal, Driscoll, Gabaix, & Laibson, 2008; Gross & Souleles, 2002a; Gross & Souleles, 2002b; Musto & Souleles, 2006).

well as credit card accounts. Our dependent variables are individual level credit card behavior (the dollar value of either credit card consumption or the reduction in credit card debt), and our independent variables are contemporaneous and lagged values of the dollar magnitude of the expected disposable income shock (i.e. final mortgage payments).

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, including investments, mortgages, credit cards and deposit and checking accounts. The bank has not targeted any particular consumer segment, but like most Canadian banks is active across all consumer segments. It is active in both consumer and business banking. The bank is a very well established and has been active for many decades. For confidentiality reasons we are not able to provide any more information about the characteristics of the bank. The period of our data runs from December 2004 to June 2006. This was a period of rapid economic growth in Canada. Like most other Canadian banks, this bank was able to deal with the financial turbulence of 2008 without any official assistance.

As described by Gross and Souleles (2002a) and Agarwal, Liu and Souleles (2007), the use of monthly credit card data to examine consumption smoothing provides a number of important advantages in terms of measurement accuracy, over survey type data (such as CEX or SCF). However, as noted by Gross and Souleles (2002a) and Agarwal, Liu and Souleles (2007), the unit of analysis in monthly credit card statement data is the account holder and not necessarily the individual, because the individual can hold multiple credit card accounts. In this regard we follow the strategies used by Gross and Souleles (2002a) and Agarwal, Liu and Souleles (2007), by firstly, only including "active" credit cards in our analysis (i.e. cards for which there is regular monthly activity), and secondly, including FICO scores as a control variable (which measures credit quality across all credit cards). However, we argue that our study has one important additional advantage over the studies of Gross and Souleles (2002a) and Agarwal, et al (2007) in this regard, because the credit cards used in our study are, by definition, all attached to individual mortgage accounts at the same bank. We argue that because of "relationship lending" or "product bundling", individuals will often receive greater benefits in using a credit card that is issued by the same bank that sells them other consumer finance products (such as mortgages etc). For this reason, individuals may have a strong incentive to use the credit card in our study (which is attached to their mortgage account), rather than other credit cards they may own issued by other financial institutions[5].

3.2. Census Data on Income – Testing the Relative Magnitude Hypothesis

Our main hypothesis of interest in this paper is that the magnitude of an expected income shock impacts the consumption or debt response of individuals. In the existing literature on the magnitude hypothesis, however, it is unclear whether consumers respond to the *absolute magnitude* of the expected income shock, or the *relative magnitude* of the income shock – that is the size of the expected income shock relative to total income. Our strategy in this paper is to empirically examine both the absolute as well as relative magnitude hypotheses.

Our monthly bank statement data described above does not include a direct measure of the individual's income. However, the bank account data does include the Canadian Postal Code for each individual. This Postal Code data allows us to match our bank account data with Canadian Census data, which provides disaggregate data on a variety of demographic variables including income, at the Postal Code level. In other words, this procedure allows us to measure the postal code level income for each individual in our data. By dividing the amount of the final mortgage payment by the postal code level measure of the individual's income, we can measure the relative magnitude of the expected income shock.

Appendix 1 describes in detail the procedures used to match these databases, while Table 2 provides detailed summary statistics of all variables used in our analysis. 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. In this paper we use the terms dissemination area (DA) or "postal code" interchangeably to refer to a DA area of 200 households.

[5] This is borne out by our discussions with managers of our data providing bank, who indicated that individuals with strong relationships with the bank (i.e. mortgage holders) are indeed more likely to receive "preferential treatment" in their credit card accounts, relative to individuals who do not hold a mortgage.

4. EMPIRICAL METHODOLOGY

In this section we first describe our baseline tests of consumption smoothing (i.e. ignoring the magnitude hypothesis). We then describe how we test the absolute as well as the relative versions of the magnitude hypothesis.

4.1. Baseline Test of Consumption Smoothing

Standard theory of consumption smoothing distinguishes between income shocks that are either anticipated or unanticipated and also that are either permanent or temporary. Broadly speaking, the theory suggests that only unanticipated shocks should impact consumption. However, if there is a consumption response, theory suggests that the consumption response to permanent shocks should be larger and longer lasting than the consumption response to temporary shocks. In this paper we examine anticipated disposable income shocks (the final mortgage payment), which implies theoretically that there should be no consumption response at the time of the shock because of consumption smoothing. However, it is important to note that our final mortgage payment is a permanent shock to disposable income. For this reason we examine the dynamics of consumption over time.

Consumption smoothing with anticipated shocks implies two empirically testable hypotheses. First, if an individual has smoothed consumption, then there should be no significant difference in consumption on the date of the receipt of the expected income shock relative to consumption on other dates. Second, consumption smoothing implies that the individual accesses credit in advance of the expected future income shock, and then pays down that credit when the income shock has been received. In order to test these hypotheses we estimate the following models. Model (1) examines the impact of the final mortgage payment on credit card consumption (CONS); while model (2) examines the impact of the final mortgage payment on the change in credit card debt (ΔDEBT).

(1) $$CONS_{i,t} = \alpha_1 ' time_t + \alpha_2 ' CustID_i + \sum_{s=0}^{n} \chi_s FINAL_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

(2) $$\Delta DEBT_{i,t} = \alpha_1 ' time_t + \alpha_2 ' CustID_i + \sum_{s=0}^{n} \beta_s FINAL_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

In these two equations, the key variable of interest is FINAL, which captures the exact month and exact dollar magnitude of the final mortgage payment of an individual's mortgage contract. The vast majority of data points in the FINAL variables are zero, except for the month *t* of the final mortgage payment for individual *i*, in which case the variable includes the dollar magnitude of the final payment. Equations (1) and (2) also include a number of other control variables (Z) which we describe in detail below, as well as month fixed effects (time) and individual fixed effects (CustID). Following (Petersen, 2008) all our panel data results use clustered robust standard errors. The structure of these models is very similar to those used by Gross and Souleles (2002a) and Agarwal, Liu and Souleles (2007), whose data has a very similar structure to ours (i.e. monthly individual bank accounts). Following Gross and Souleles (2002a) and Agarwal et al (2007) equation (2) uses the change in credit card debt rather than the level of credit card debt as the dependent variable. These authors argue that while consumption is a flow variable, debt is a stock variable, thus it is more appropriate to examine the change in debt.

Each of these equations provides a test of consumption smoothing. First, consumption smoothing implies that the χ coefficients in equation (1) are insignificant because the expected income shock following the final mortgage payment should not have a significant impact on monthly consumption relative to other months. Secondly, if an individual pays down his/her credit card debt in the month(s) after the final mortgage payment, as predicted by credit smoothing, then we would expect negative β coefficients in equation (2).

As described by Gross and Souleles (2002a) and Aggarwal et al (2007), the distributed lags on FINAL in equations (1) and (2) can be interpreted as event studies. For example, in the case of the consumption equation (1), the coefficient $\chi 0$ measures the instantaneous response of consumption. We can also examine the marginal coefficients $\chi 1$, $\chi 2$, $\chi 3$ etc which measure the additional response of consumption in the months after the final mortgage payment. We can thus measure the cumulative (or long term) response of consumption to the final mortgage payment by examining $\Sigma\chi$ over multiple lagged months. Similarly, in equation (2) we can also measure the instantaneous, marginal and cumulative impacts of final mortgage payment on the change in the level of credit card debt, by examining $\beta0$, the individual lagged βs as well as $\Sigma\beta$ over multiple lagged months. The cumulative measures of the impact of FINAL are of particular interest, because the income shock we are considering (the final mortgage payment) can be considered as a permanent increase in the individuals disposable income.

Both of the dependent variables in equations (1) and (2) as well as the main independent variable of interest (FINAL) in these equations are measured in dollars. Thus the coefficients on FINAL from these equations are direct measures of the impact that FINAL has on either consumption (eq 1) or the change in credit card debt (eq 2). This is different from some of the consumption smoothing literature which has only been able to measure future income shocks as a dummy variable. Our ability to measure FINAL in dollars, is the key reason why we are able to modify equations (1) and (2) below, to test the magnitude hypothesis (i.e. larger FINAL has a different impact than smaller FINAL).

Another important element of equations (1) and (2) is that they include fixed effects for both time (19 months), as well as for each individual bank customer. By including time fixed effects, we can account for any exogenous macro shocks (e.g. recession, stock market returns) which could impact the consumption of all individuals in a particular month. Similarly, by including individual fixed effects, we control for any individual level factors which could impact consumption (or change in card debt).

4.2. Ensuring the timing of FINAL is Predetermined

An important issue in testing consumption smoothing is that the timing of predictable future income shock needs to be exogenous (e.g. a shock that emanates from the government or an employer) or predetermined (e.g. where the individual does not control the timing of the shock). If, however, the individual is able to determine the timing of when she receives the income shock, then the income shock is endogenous, and equations (1) and (2) above are no longer valid. In this paper we are able to utelise the data that we have to ensure that we only examine final mortgage payments that are predetermined, and we exclude all data where the date of the final mortgage payment is endogenously determined by the individual. Stephens (2008) followed a very similar strategy in his car loan study by excluding all individuals who paid of their car loans before the final due date. He comments that “this exclusion is very important for the identification strategy as it restricts the analysis to those loan repayments …that are predetermined” (p. 244).

Based on discussions with the bank, we define two separate types of mortgage payers, based on the pattern of their final months of mortgage payments. We label these two groups “amortizers” and “lump-sum payers”. The “amortizers” are individuals who have worked out with the bank a steady stream of *equal* mortgage payments (including interest and capital) which continues until the final payment. We argue that individuals, who choose this amortization approach to the stream of mortgage payments, know in advance the exact magnitude of their final mortgage payment as well as the exact month of their final mortgage payment. Econometrically speaking, the final mortgage payment can then be considered predetermined to these individuals.

On the other hand, the bank informed us that certain mortgage holders have the right to pre-pay their mortgage by certain amounts (typically a function of the opening balance of the mortgage). For example, consider an individual who makes regular mortgage payments of $500, but then makes a final payment of $10 000 to pay off the mortgage in full. It would clearly be inappropriate in the context of testing consumption smoothing to define such a “lump-sum payer” as somebody who has made a predetermined final mortgage payment.

Because of the exact nature of our monthly payment data, we are able to distinguish very precisely between “lump-sum payers” and “amortizers” in our data. For the purposes of this paper we define an individual who amortizers her monthly mortgage payments, as occurring when no single monthly payment differs from any other monthly payment by more than 10%. These “amortizers“ are the individuals that we include in our study because the date and magnitude of their final mortgage payment can be considered pre-determined. Based on these characteristics, we are able to identify 147 individuals in our sample who made final mortgage payments that where predetermined. The dollar magnitudes of these final payments are included in our FINAL variable. As a comparison, Coulibali and Li (2006) identify 286 individuals who have paid off their mortgages (in one year of data), out of their total sample of 39515 mortgage holders.

4.3. Tests of the Absolute Magnitude Hypothesis

Once we have specified the standard consumption smoothing models in equations (1) and (2), it is possible to adapt these specifications in order to test the main hypothesis of this paper – the magnitude hypothesis. This section examines the absolute magnitude hypothesis, i.e. that the magnitude of FINAL impacts consumption smoothing. The following section examines the relative magnitude hypothesis, i.e. where FINAL is divided by income.

The key prediction of the magnitude hypothesis is that smaller sized predictable shocks will have different outcomes compared to larger predictable shocks. Specifically, the magnitude hypothesis predicts that consumption smoothing will hold when predictable shocks are large (i.e. that on the date of the predictable shock there will be no significant impact on consumption, but will be a reduction in credit card debt). On the other hand the magnitude hypothesis predicts that if the size of the predictable shock is small, then consumption smoothing will not hold (i.e. that when the predictable income shock is manifested there will be an increase in consumption, and there will not be a decline in credit card debt). We test the magnitude hypothesis by adjusting our baseline consumption smoothing models (equations (1) and (2) above) for both credit card consumption as well as the change in credit card debt.

In order to test the magnitude hypothesis we utilize two different specifications to differentiate between "large" and "small" final mortgage payments (FINAL). Our first specification is simply to divide the FINAL measures into large and small categories based on whether they are above or below the mean value of FINAL (i.e. $751). We refer to those expected income shocks that are greater than $751 as FINAL_HI , and those expected income shocks that are smaller than $751 as FINAL_LO. We then modify our baseline equations 1 and 2 above to run separate equations for large shocks and for small shocks. Equations 3 and 4 are modified forms of equation 1 and provide the specifications for the credit card consumption models.

$$(3)\, CONS_{i,t} = \alpha_1 'time_t + \alpha_2 'CustID_i + \sum_{s=0}^{n} \chi^{HI}{}_s FINAL\_HI_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

$$(4)\, CONS_{i,t} = \alpha_1 'time_t + \alpha_2 'CustID_i + \sum_{s=0}^{n} \chi^{LO}{}_s FINAL\_LO_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

The magnitude hypothesis predicts that consumption smoothing should hold if FINAL is large. Thus the magnitude hypothesis predicts that the χ^{HI} coefficients in equation (3) should be insignificant, because smoothed consumption would not be significantly different in the periods before and after FINAL. The magnitude hypothesis also predicts that consumption would respond if the magnitude of FINAL was small, thus the χ^{LO} coefficients in equation (4) should be significant and positive.

One possible concern with specifications (3) and (4) is that the difference between large and small that we chose (i.e. the mean level of FINAL across individuals) may not be the actual turning point. Our second approach to testing the magnitude hypothesis does not predetermine the turning point. This second specification formulates the magnitude hypothesis as an "inverted U" specification, and thus includes square terms in the model. The standard way of modeling such an "inverted U" specification is to include squared terms for FINAL (i.e. FINAL_SQ) in addition to the level terms.

(5)

$$CONS_{i,t} = \alpha_1 'time_t + \alpha_2 'CustID_i + \sum_{s=0}^{n} \chi_n FINAL_{i,t-n} + \sum_{s=0}^{m} \chi_m FINAL\_SQ_{i,t-m} + \delta Z_{i,t} + \varepsilon_{i,t}$$

The "inverted U" specification implies that when the magnitude of the expected income shock is less than turning point, then there should be a positive relationship between the expected income shock and consumption. However, after the turning point, as the magnitude of the expected income shock increases its impact on consumption should decline. An inverted U specification implies that the FINAL coefficients in (5) are significantly positive and the FINAL_SQ coefficients in (5) are significantly negative.

Our specifications to examine the impact of the magnitude of FINAL on the change in credit card debt, are very similar to those used above to examine the magnitude of FINAL on credit card consumption. Our first specification is to examine the impact of FINAL_HI and FINAL_LO (as defined in equations (3) and (4) above) when the dependent variable is change in credit card debt, rather than credit card consumption. This results in equations (6) and (7).

(6) $$\Delta DEBT_{i,t} = \alpha_1 'time_t + \alpha_2 'CustID_i + \sum_{s=0}^{n} \beta^{HI}{}_s FINAL\_HI_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

(7) $$\Delta DEBT_{i,t} = \alpha_1' time_t + \alpha_2' CustID_i + \sum_{s=0}^{n} \beta^{LO}{}_s FINAL\_LO_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

Because the independent variables FINAL_HI and FINAL_LO are the same in both the consumption equations (3) and (4) as well as the debt equations (6) and (7), we can examine how these variables impact both consumption and debt. The magnitude hypothesis implies that individuals will smooth consumption when FINAL is large. This implies that the individual should use the expected increase in disposable income (after the final mortgage payment) to pay down existing credit card debt (i.e. β^{HI} in equation (6) would be negative and significant) rather than to increase consumption (χ^{HI} in (3) is insignificant). On the other hand, if the individual did not smooth consumption (as the magnitude hypothesis predicts for small magnitudes of the final mortgage payment) then the individual could use the increase in disposable income to increase consumption (i.e. χ^{LO} in (4) is significant and positive), but not to pay down their credit card debt (i.e. β^{LO} in (7) is insignificant).

It is also possible that some combination of both debt payback, as well as increased consumption could occur after the final mortgage payment. Our empirical specification allows us to test for this (i.e. if we find that both the χ coefficients are significant and positive (i.e. consumption increase) and the β coefficients are significant and negative (i.e. reduction in debt).

As in the case of the consumption equations we specify quadratic equation (8) as an alternative test of the magnitude hypothesis (6) and (7). The only difference between (8) and (5) is that the dependent variable is the change in debt rather than the level of consumption.

(8)

$$\Delta DEBT_{i,t} = \alpha_1' time_t + \alpha_2' CustID_i + \sum_{s=0}^{n} \beta_n FINAL_{i,t-n} + \sum_{s=0}^{m} \beta_m FINAL\_SQ_{i,t-m} + \delta Z_{i,t} + \varepsilon_{i,t}$$

As described for the case of equation (5) above, equation (8) allows us to examine if an “inverted U” specification applies to the change in debt. If the coefficients on the FINAL_SQ term are significant and negative, then this implies as that as the magnitude of FINAL gets larger, so there will be an increasing rate of the reduction of credit card debt as predicted by the magnitude hypothesis.

4.4. Test of the Relative Magnitude Hypothesis

The tests conducted in equations (1) to (8) above all have as the independent variable of interest FINAL, which examines the absolute impact that the final mortgage payment has on consumption or credit card debt. In this section we test the hypothesis that the *relative* size of final (relative to income) will impact the response of consumption and debt. Existing discussions of the magnitude hypothesis in the literature (see Table 1) state that the magnitude of the shock should impact the response of consumption and debt, but do not specify whether this magnitude is in absolute terms or relative to income. In this paper, therefore, we conduct tests for both the absolute as well as relative specifications.

Essentially our tests of the relative magnitude hypothesis are similar to our tests of the absolute magnitude hypothesis in equations (1) to (8) above with the one exception that in each case the variable FINAL is replaced by FINAL/INC, where FINAL is divided by the postal code level income variable for each individual in the sample.[6] Our measure of income is taken from the Statistics Canada Census database which provides postal code level measures of income. Full details of the use of this data are provided in the data appendix below.

4.5.Control Variables (Z)

As robustness tests, in all of the models we are also able to add two control variables specified as Z. In our results section below we report results that both include and don't include these control variables. Our first control variable is the credit utilization rate – i.e. the ratio of the individual's credit card debt outstanding relative to their credit card credit limit for each month. An individual whose credit utilization rate is relatively high (i.e. their level of debt is high relative to their credit card credit limit) may make different consumption and debt repayment decisions relative to an individual whose credit utilization ratio is low. Including the credit card credit utilization rate allows us to control for this. Our second control variable is the log of the individuals credit card credit limit. The credit card credit limit is set by the bank for each individual, and changes periodically. Once again we include this variable to control against the possibility that the

[6] This includes all variations of FINAL, including FINAL_HI, FINAL_LO and FINAL_SQ.

credit card credit limit could impact individual consumption and debt repayment decisions.

4.6. Excluding Alternative Explanations – Credit Constraints

While the main focus of this paper is on testing the magnitude hypothesis, another important explanation for the lack of consumption smoothing has been credit constraints. As is evident from Table 1, a large proportion of the consumption smoothing literature has rejected consumption smoothing because of credit constraints. A key assumption of the LC/PIH is that the individual has access to credit in order to borrow in advance of the future certain income shock, and thus smooth consumption. Therefore consumption smoothing may not occur because of credit constraints. Thus before we can conclude that consumption smoothing is a result of the magnitude hypothesis, it is necessary to ensure that our results are not being driven by the alternative hypothesis of credit constraints.

Our data allows us to rigorously exclude those individuals who may be credit constrained. Following Gross and Souleles (2002a), we can define individuals who are credit constrained if their credit card utilization ratio (i.e. monthly credit card debt divided by their credit limit) is greater than 90%. All individuals who are credit constrained are excluded from our FINAL group. It is not surprising that the number of individuals excluded from FINAL because of credit constraints is very small[7]. Given that the individuals in this group have access to at least *two* sources of credit, (mortgage and credit card) and furthermore have just paid off their mortgage, it does not seem likely that many in the FINAL group will be credit constrained. By excluding these (relatively few) credit constrained individuals, we are able to focus only on the magnitude hypothesis as an explanation for the lack of consumption smoothing.

4.7. Selection Bias

An important issue in tests such as ours, which examine the behavior of some individuals (i.e. final mortgage payers) relative to other mortgage papers, is whether there is any selection bias in the choice of those specific individuals. We argue that this

[7] Between 6 and 8 individuals who have just made their final mortgage payment also have a credit card utilization rate of above 90% (depending on whether the utilization rate is measured over a single month or averaged over multiple months).

selection process should not generate selection bias that could impact the results of our tests. Every individual in our sample is both a credit card as well as a mortgage holder. The only systematic difference between the individuals in our FINAL group and all the other individuals in our sample is the fact that these individuals are making their final mortgage payment while the others continue to pay their mortgages. Furthermore, the date of the final mortgage payment will be randomly determined, based on issues such as the starting date of the contract and the amount of monthly payments. In due course every mortgage holder will come to the end of the mortgage contract, thus the selection criteria that a final payment has been made on a mortgage should not be a characteristic of a particular sub group in the sample. For these reasons we argue that we provide an appropriate test of comparing credit card consumption and debt between individuals who have paid off their mortgage, and those who are still paying their mortgage.

5. RESULTS

5.1 Absolute Magnitude Hypothesis

Our absolute magnitude results for the credit card consumption equations are presented in Tables 3 to 6. A summary of the consumption equation results are provided in Figure 1. Tables 7 to 10 and Figure 2 replicate these tests for credit card debt. Following a Agarwal et al, (2008) and Gross and Souleles, (2002a), we report marginal coefficients where the lag (s) is from 0 to 8 as well as the cumulative (or long run) coefficient which is the sum of all lags from 0 to 8.

Table 3 reports the baseline case (equation 1) where the FINAL variable is included without any differentiation between large or small magnitudes. Tables 4 and 5 replace FINAL with FINAL_HI (equation (3)) and FINAL_LO (equation (4)) respectively. Figure 1 graphically displays the cumulative magnitudes of the coefficients on FINAL, FINAL_HI and FINAL_LO taken from Tables 3, 4 and 5 respectively, as the lags increase from 0 to 8. Our main conclusion from Tables 3, 4, and 5 (as displayed in Figure 1) is that when the magnitude of the final mortgage payment is large (FINAL_HI) there is no significant impact on consumption from the final mortgage payment. On the other hand, when the magnitude of the final mortgage payment is small (FINAL_LO) there is a strongly significant and positive impact on consumption. These results can be seen graphically as well as by examining the significance of the cumulative FINAL coefficients in Tables 4 and 5. The cumulative FINAL_HI coefficient (Table 4) is insignificant while the cumulative FINAL_LO coefficient (Table 5) is and positive and significant at 5%.These findings are thus consistent with the magnitude hypothesis.

The economic magnitudes of these coefficients are also of interest. Recall that both our dependent and independent variables of interest are measured in dollar terms, thus the magnitude of the coefficients can be easily interpreted. Furthermore, recall that the final mortgage payment can be considered as a *permanent* shock to disposable income, thus it is possible for the shock to have an increasing cumulative impact on consumption over time. From Table 5 it can be seen that the instantaneous response (lag s=0) of consumption to FINAL_LO is 0.93. This indicates that when the final mortgage payment is small, individuals consume 93% of the increase of disposable income in month s=0. For the following 8 months, the marginal impacts are considerably smaller, but nevertheless the cumulative impact over 8 months on total consumption is 2.1 times the value of one month's increase in disposable income from paying off the mortgage.

Tables 8 and 9, and Figure 2, display our key results on the impact of FINAL_HI and FINAL_LO on the change in credit card debt. The cumulative coefficient on all the lagged FINAL_HI coefficients in Table 8 is negative and significant, but the cumulative coefficient on the FINAL_LO coefficients in Table 9 is insignificant. This can be seen graphically in Figure 2. In other words these results show that when the magnitude of the final mortgage payment is large, individuals use this expected increase in disposable income to pay down debt. On the other hand, when the magnitude of the final mortgage payment is small, individuals do not significantly pay down their credit card debt.

In Tables 6 and 10 we implement the quadratic specification for the consumption and debt equations, with 4 lags of both the level term of FINAL as well as the Square term FINAL_SQ[8]. Our key finding in Table 6 is that the cumulative coefficient for the level term is significant and positive, while the cumulative coefficient for the square term is significant and negative. In other words, our results support the hypothesis of an inverted U shaped relationship between consumption and the magnitude of FINAL. As

[8] Our results are robust to alternative lag structures.

FINAL increases from a low magnitude, consumption increases. However, once FINAL increases beyond a certain magnitude, consumption begins to decline. In other words, this specification is consistent with the magnitude hypothesis that as the size of the expected income shock increases beyond a certain point, so the impact of that shock on consumption will be reduced. Similar findings are apparent in the debt quadratic equation in Table 10, which shows that the cumulative term for the FINAL_SQ coefficients is negative and significant as are several of the marginal lag terms.

Our two sets of results for consumption and reduction in debt clearly complement each other. We argued that when an individual receives an increase in disposable income (from a final mortgage payment) this disposable income can be used either to increase consumption or to reduce debt or a combination of both. Our results show that when the magnitude of the final mortgage payment is large, individuals significantly reduce their credit card debt, but there is no significant impact on consumption. On the other hand when the magnitude of the final mortgage payment is small individuals significantly increase consumption, but there is no significant impact on the reduction in credit card debt. These results are consistent with the magnitude hypothesis.

5.2. Relative Magnitude Hypothesis

The results for the relative magnitude hypothesis (where all the FINAL coefficients are divided by income) are reported in Tables 11 to 13. These results replicate the results for the absolute magnitude hypothesis above (except we do not report results that include the control variables Z in order to save space). Table 11 reports on both the FINAL/INC_HI as well as FINAL/INC_LO specifications for consumption. Table 12 reports on these two specifications for debt, while Table 13 reports on the quadratic specifications for consumption and debt.

The results for the HI and LO equations in Tables 11 and 12 are somewhat weaker than those reported above in the case of the absolute magnitude hypothesis with few of the cumulative estimates significant.. However the results reported in the quadratic specifications in Table 13 are relatively strong, and are consistent with the magnitude hypothesis. In particular, Table 13 shows that in both the case of consumption and the change in debt the cumulative coefficients are significant for both the level and square terms. In both cases the results suggest an inverted U relationship for consumption and the change in debt as the size of FINAL increases. These results are consistent with the magnitude hypothesis that at low levels of FINAL, consumption (and the change in debt) may increase, but at high levels of FINAL debt will decrease (along with consumption). In other words, even after we divide the magnitude of FINAL by income, we still find support for the magnitude hypothesis.

5.3. Robustness Tests

We replicate our results above using a variety of robustness tests. First we experiment with different lag lengths on the FINAL variables. Our results are robust to different lag lengths. Second, instead of using as our control group the 20 000 individuals in our sample who have both a credit card as well as an outstanding mortgage, we extend the control group to include all 75 000 individuals in our sample. All these individuals have a credit card account, irrespective of whether or not they hold a mortgage. Our main results are robust to this change in control group.

5.4. The Characteristics of HI and LO Mortgage Payers

Finally, we examine if there are systematic differences between mortgages payers in the FINAL_HI and FINAL_LO groups. If there is a systematic reason for why individuals sort into HI and LO groups, then this reason could be the underlying cause of our results concerning the differences in the behavior of these groups.

The amount of a monthly mortgage payment is a function of a variety of factors including total mortgage size, type of interest rate, and amortization period chosen. Thus, it can be argued that there are a number of alternative reasons why some individuals may pick a low monthly mortgage payment and others may pick a high monthly mortgage payment. For example, lower income individuals, whose total mortgage debt may be lower, may have a lower monthly mortgage payment. Alternatively, higher income individuals, even with a larger total mortgage debt, may also choose a lower monthly mortgage payment (using a longer amortization period) in order to build up an investment portfolio in other assets[9]. Thus theoretically, it can be argued that there is not a single determinant of individuals choosing higher or lower monthly payment groups.

We can also examine this empirically by using our available census and bank account data to conduct difference in mean t tests to examine if there are differences in the high and low groups. We conduct these tests for both the absolute magnitude (FINAL_HI and FINAL_LO) groups as well as the relative magnitude groups (FINAL/INCOME_HI and FINAL/INCOME_LO). These results are reported in Table 14. Using postcode level census data, we are able to compare these individuals both in terms of total income, but also in terms of the proportion of total income from investments, as well as the proportion of total income from government sources (e.g. government pensions and unemployment insurance). We find that for both the absolute and relative models, individuals who choose low monthly mortgage payments have higher investment income – consistent with the argument that some individuals may choose to invest in other assets rather than rapidly paying down their mortgages. On the other hand we also show that individuals with lower total income, greater percentage of income from government sources and lower FICO scores have lower monthly mortgage payments. In other words, this data shows that there does not seem to be a single systematic reason for which individuals choose high or low monthly mortgage payments.

6. CONCLUSION

We test the hypothesis that the magnitude of expected future income shocks impacts consumption and debt responses. We examine the impact of a single kind of income shock (final mortgage payments) on credit card consumption and debt repayment, where there is a wide variance in the magnitude of these shocks across individuals. We use a confidential database consisting of monthly bank credit card and mortgage statements for about 20 000 individuals over 19 months, provided to us by a Canadian bank. This data is able to provide an exact measure of both the timing as well as the magnitude of the final mortgage payment (the future income shock). Furthermore, our

[9] In the Canadian banking system, borrowers typically have the choice of changing the amortization period of the mortgage by changing the magnitude of the monthly payment.

data exploits the fact that the timing of the final mortgage payment is randomly distributed across individuals. We are also able to use each individual's postal code to match the bank account data with postal code level census data.

Our results show that if the magnitude of the final mortgage payment is relatively small, then individuals use this increase in disposable income to increase credit card consumption and not to pay down credit card debt. On the other hand, if the magnitude of the final mortgage payment is relatively large, then we find that individuals use this increase in disposable income to pay down their credit card debt, but not to increase consumption. In other words, our result are consistent with consumption smoothing occurring when expected income shocks are large but not when they are small, as predicted by the magnitude hypothesis.

The magnitude hypothesis could also have policy implications. Some attempts at fiscal stimulus involve preannounced future income shocks to individuals. While the income shocks in our study (final mortgage payments) are very different from fiscal stimulus income shocks, our results concerning the *magnitude* of these income shocks could be of use in terms of the design of fiscal stimulus programs. Our results show that recipients of relatively smaller expected income shocks are likely to use this money to increase consumption, while the recipients of relatively larger expected income shocks are likely to use this money to pay down debt.

FIGURE 1: SPEND MORE AFTER SMALL SHOCK
Coefficients on Consumption (Cumulative)
From Tables 3,4,5

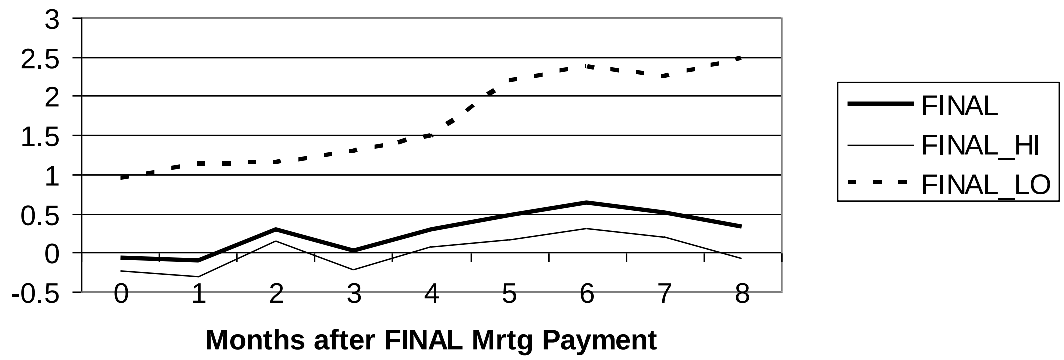

FIGURE 2: DEBT DOWN AFTER LARGE SHOCK
Coefficients on Change in Debt (Cumulative)
From Tables 7,8,9

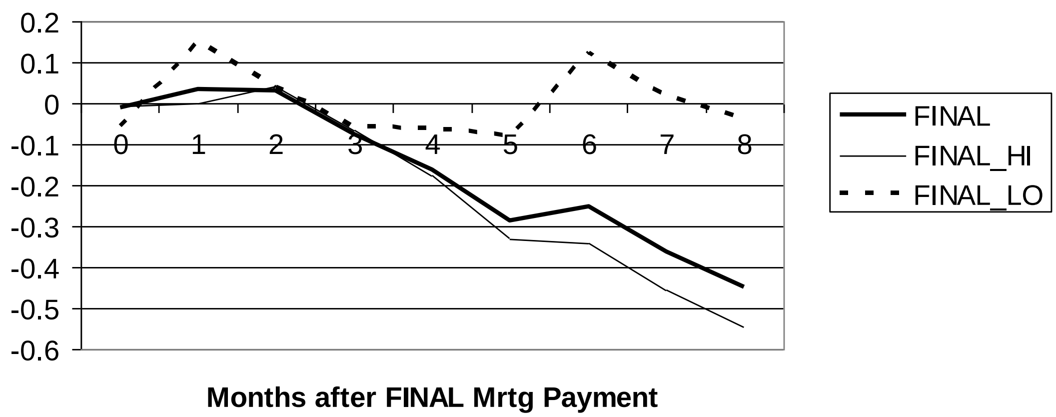

TABLE 1: LITERATURE REVIEW:
TESTS OF THE PERMANENT INCOME HYPOTHESIS (PIH) USING IDENTIFIABLE INCOME SHOCKS

Authors	Jrnal	Date	Income Shock	Data	Support PIH	Explanations for Findings
A: MAGNITUDE HYPOTHESIS EXPLANATIONS						
Coulibali and Li	REStat	2006	Final Mrtg Paymnt	CEX	Yes	Magnitude Hypothesis – Discussed but not Tested
Hsieh	AER	2003	Alaska Perm Fund	CEX	Yes	Magnitude Hypothesis – Discussed but not Tested
Browning, Collado	AER	2001	Annual Bonus	Spanish Household Cons	Yes	Magnitude Hypothesis – Discussed but not Tested
Souleles	AER	1999	Income Tax Refunds	CEX	No	Liquidity Constraints (Magnitude Hypothesis Rejected)
Kreinin	AER	1961	Reparations Payments	Israeli Data	Yes	Magnitude Hypothesis Rejected
B: OTHER EXPLANATIONS						
Stephens	REStat	2008	Car Loan Repayment	CEX	No	Liquidity Constraints
Agarwal, Liu, Souleles	JPE	2007	2001 Tax Rebates	Credit Card Accounts	No	Liquidity Constraints
Johnson, Parker, Souleles	AER	2006	2001 Tax Rebates	CEX plus Special Qs	No	Liquidity Constraints
Stephens	EJ	2006	Paycheck Date	UK Fam Expen Survey	No	Liquidity Constraints
Shapiro and Slemrod	AER	2003	2001 Tax Rebates	Michigan Survey	No	No Clear Explanation
Stephens	AER	2003	Social Security	CEX Diary	No	Liquidity Constraints
Souleles	JPubE	2000	College Tuition	CEX	Yes	Consumption Smoothing
Parker	AER	1999	Social Sec Taxes	CEX	No	Intertemporal Elasticity of Substitution
Shapiro and Slemrod	AER	1995	1992 Tax Change	Michigan Survey	No	Myopia or Rule of Thumb
Shea	AER	1995	Union Based Wage	PSID	No	Loss Aversion
Bodkin	AER	1959	Life Insurance	Survey of Cons Exp	No	

These papers examine how individual consumption responds to a specific identifiable income shock. They form only a fraction of the very large PIH literature.

TABLE 2: Descriptive Statistics				
	Obs	Median	Mean	Std Dev
A: Individual Level Monthly Bank Balance Sheet Data				
1: Credit Card Data				
Credit Card Debt ($ /month)	1496451	681.38	2050.73	3497.93
Credit Card Consumption ($ /month)	1496451	151.99	577.34	1865.78
Card Debt/Limit (%)	1494969	25.76	38.28	39.38
Credit Card Credit Limit ($)	1496451	5000.00	6147.33	6271.31
FICO Score	1399828	741	723.78	100.13
2: Mortgage Data				
Monthly Reduction in Mrtg Balance ($)	255249	800.00	950.22	887.36
FINAL (Final Predetermined Monthly Mortgage Payment) ($)	147	627.01	751.46	507.93
FINAL/INCOME (Final Predetermined Monthly Mortgage Payment/ Total Annual Income)	142	0.0281	0.0331	0.021
B: Post Code Level Census Data (Matched to Credit Card Data)				
Total Annual Income ($)	1460288	21626.00	22221.38	7651.05
Income from Invest & Bus (% of total)	1458721	7.6	8.46	5.47
Income from Govt Sources (% of total)	1460288	10.8	11.83	7.47

TABLE 3: CREDIT CARD CONSUMPTION – Baseline Specification

$$CONS_{i,t} = \alpha_1 ' time_t + \alpha_2 ' CustID_i + \sum_{s=0}^{n} \chi_s FINAL_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

CONS is dollar credit card consumption for month t and individual i. FINAL is the dollar magnitude of the final mortgage payment in the month of the final payment, and 0 otherwise. We report marginal effects on consumption for lags s= 0 to 8 months as well as long-run cumulative effects. Control variables (Z) are either included or excluded. Regressions include time fixed effects (time) for each month, as well as individual fixed effects for each individual (CustID). Panel data are estimated using clustered standard errors.

	Exclude Control Vars (Z)		**Include Control Vars (Z)**	
Indep Var (lag)	**Coeff**	**Std Err**	**Coeff**	**Std Err**
FINAL-0	-0.06487	0.192646	-0.03251	0.177882
FINAL -1	-0.03471	0.158254	-0.01122	0.142841
FINAL -2	0.388979	0.268022	0.367988	0.237387
FINAL -3	-0.27362	0.128863**	-0.07599	0.141125
FINAL -4	0.270009	0.227694	0.307797	0.203673
FINAL -5	0.194517	0.262607	0.18429	0.221888
FINAL -6	0.149209	0.146244	0.170481	0.136269
FINAL -7	-0.11382	0.183289	-0.08933	0.176135
FINAL -8	-0.17764	0.104327*		
Constant	838.1835	9.542072***	-3600.81	362.4254***
Card Balan/Limit			9.29232	0.685149***
Card Limit			467.6358	41.22759***
n		184238		184219
F		21.44		33.89
R2		74.30		74.35

TABLE 4: CREDIT CARD CONSUMPTION – Large Final Mortgage Payment

$$CONS_{i,t} = \alpha_1 ' time_t + \alpha_2 ' CustID_i + \sum_{s=0}^{n} \chi_s FINAL\_HI_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

CONS is dollar credit card consumption for month t and individual i. FINAL_HI is the dollar magnitude of the final mortgage payment in the month of the final payment, if that magnitude is greater than $751, and 0 otherwise. We report marginal effects on consumption for lags s= 0 to 8 months as well as long-run cumulative effects. Control variables (Z) are either included or excluded. Regressions include time fixed effects (time) for each month, as well as individual fixed effects for each individual (CustID). Panel data are estimated using clustered standard errors.

	Exclude Control Vars (Z)		**Include Control Vars (Z)**	
Indep Var (lag)	**Coeff**	**Std Err**	**Coeff**	**Std Err**
FINAL_HI-0	-0.22946	0.192618	-0.24323	0.185888
FINAL_HI -1	-0.07983	0.184231	-0.09829	0.172746
FINAL_HI -2	0.467359	0.325573	0.471932	0.311456
FINAL_HI -3	-0.36497	0.145438***	-0.3182	0.136709**
FINAL_HI -4	0.284174	0.262429	0.289916	0.250076
FINAL_HI -5	0.087982	0.312486	0.075094	0.292426
FINAL_HI -6	0.143971	0.168811	0.13739	0.16235
FINAL_HI -7	-0.10324	0.220835	-0.10699	0.209078
FINAL_HI -8	-0.26824	0.107961**	-0.26193	0.102123***
Constant	838.236	9.540474***	-3953.38	401.3633***
Card Balan/Limit			9.968774	0.760745***
Card Limit			504.888	46.23405***
n		184238		184219
F		22.22		33.91
R2		74.29		75.05
Cumulative FINAL_HI	-0.06226	0.876685	-0.05431	0.837705

TABLE 5: CREDIT CARD CONSUMPTION – Small Final Mortgage Payment

$$CONS_{i,t} = \alpha_1 ' time_t + \alpha_2 ' CustID_i + \sum_{s=0}^{n} \chi_s FINAL\_LO_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

CONS is dollar credit card consumption for month t and individual i. FINAL_LO is the dollar magnitude of the final mortgage payment in the month of the final payment, if that magnitude is less than $751, and 0 otherwise. We report marginal effects on consumption for lags s= 0 to 8 months as well as long-run cumulative effects. Control variables (Z) are either included or excluded. Regressions include time fixed effects (time) for each month, as well as individual fixed effects for each individual (CustID). Panel data are estimated using clustered standard errors.

	Exclude Control Vars (Z)		**Include Control Vars (Z)**	
Indep Var (lag)	**Coeff**	**Std Err**	**Coeff**	**Std Err**
FINAL_LO- 0	0.934964	0.538585*	0.827091	0.499692*
FINAL_LO -1	0.192705	0.179591	0.072039	0.181487
FINAL_LO -2	0.023043	0.14042	-0.03172	0.127922
FINAL_LO -3	0.140298	0.227944	0.135241	0.218091
FINAL_LO -4	0.194753	0.325484	0.220824	0.309766
FINAL_LO -5	0.697684	0.403379*	0.712415	0.386857*
FINAL_LO -6	0.187568	0.225042	0.205078	0.212282
FINAL_LO -7	-0.1277	0.194069	-0.07928	0.180772
FINAL_LO -8	0.232768	0.259916	0.297768	0.253234
Constant	837.9654	9.539819***	-3954.3	401.3767***
Card Balan/Limit			9.969319	0.760803***
Card Limit			504.9599	46.23519***
n		184238		184219
F		20.71		32.44
R2		74.29		75.05
Cumulative FINAL_LO	2.183447	1.05726**	2.359457	1.174559**

TABLE 6: CREDIT CARD CONSUMPTION - Quadratic Specification

$$CONS_{i,t} = \alpha_1 ' time_t + \alpha_2 ' CustID_i + \sum_{s=0}^{n} \chi_n FINAL_{i,t-n} + \sum_{s=0}^{m} \chi_m FINAL\_SQ_{i,t-m} + \delta Z_{i,t} + \varepsilon_{i,t}$$

CONS is dollar credit card consumption for month t and individual i. FINAL is the dollar magnitude of the final mortgage payment in the month of the final payment, and 0 otherwise. FINAL_SQ is the square of FINAL. We report marginal effects on consumption for lags s= 0 to 4 months as well as long-run cumulative effects. Control variables (Z) are either included or excluded. Regressions include time fixed effects (time) for each month, as well as individual fixed effects for each individual (CustID). Panel data are estimated using clustered standard errors.

	Exclude Control Vars (Z)		Include Control Vars (Z)	
Indep Var (lag)	Coeff	Std Err	Coeff	Std Err
FINAL -0	0.602339	0.327023*	0.565289	0.310219*
FINAL -1	0.285683	0.246276	0.228393	0.232235
FINAL -2	0.566332	0.320451*	0.522268	0.308139*
FINAL -3	-0.18408	0.246195	-0.17051	0.234673
FINAL -4	0.562823	0.347351*	0.567103	0.334518*
FINAL_SQ – 0	-0.00042	0.000169**	-0.00041	0.000159***
FINAL_SQ – 1	-0.00022	0.000149	-0.0002	0.000136
FINAL_SQ – 2	-0.00025	0.000165	-0.00022	0.00016
FINAL_SQ – 3	6.53E-05	0.000191	6.01E-05	0.000181
FINAL_SQ – 4	-0.0002	0.000212	-0.0002	0.000204
Constant	832.8823	9.276118***	-2520.599	260.5603***
Card Balan/Limit			8.539506	0.5359267***
Card Limit			346.5123	29.28572***
n		211180		211145
F		20.44		33.53
R2		72.20		72.89
Cumulative FINAL	1.833099	0.777345**	1.712547	0.736884**
Cumulative FINAL_SQ	-0.001017	0.000496**	-0.000971	0.000463**

TABLE 7: CHANGE IN CREDIT CARD DEBT – Baseline Specification

$$\Delta DEBT_{i,t} = \alpha_1 ' time_t + \alpha_2 ' CustID_i + \sum_{s=0}^{n} \beta_s FINAL_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

$\Delta DEBT$ is the change in Credit Card Debt from month t-1 to month t, for individual i. FINAL is the dollar magnitude of the final mortgage payment in the month of the final payment, and 0 otherwise. We report marginal effects on change in credit card debt for lags s= 0 to 8 months as well as long-run cumulative effects. Control variables (Z) are either included or excluded. Regressions include time fixed effects (time) for each month, as well as individual fixed effects for each individual (CustID). Panel data are estimated using clustered standard errors.

	Exclude Control Vars (Z)		Include Control Vars (Z)	
Indep Var (lag)	Coeff	Std Err	Coeff	Std Err
FINAL - 0	-0.0118	0.069097	-0.01118	0.066779
FINAL -1	0.046447	0.055077	0.03357	0.051743
FINAL -2	-0.00334	0.046072	-0.00244	0.047221
FINAL -3	-0.10762	0.046146**	-0.10225**	0.046612
FINAL -4	-0.08629	0.051928*	-0.07405	0.052269
FINAL -5	-0.12437	0.068502*	-0.11783*	0.066455
FINAL -6	0.03508	0.064379	0.031486	0.06347
FINAL -7	-0.11182	0.06451*	-0.10249	0.065374
FINAL -8	-0.0849	0.06934	-0.0766	0.069581
Constant	21.44403	2.891382***	-1640.4***	95.84722
Card Balan/Limit			3.706753***	0.411581
Card Limit			175.637***	10.92172
n		150260		150242
F		26.06		38.57
R2		19.25		22.49

TABLE 8: CHANGE IN C. CARD DEBT – Large Final Mortgage Payment

$$\Delta DEBT_{i,t} = \alpha_1 ' time_t + \alpha_2 ' CustID_i + \sum_{s=0}^{n} \beta_s FINAL\_HI_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

$\Delta DEBT$ is the change in Credit Card Debt from month t-1 to month t, for individual i. FINAL_HI is the dollar magnitude of the final mortgage payment in the month of the final payment, if that magnitude is greater than $751, and 0 otherwise. We report marginal effects on change in credit card debt for lags s= 0 to 8 months as well as long-run cumulative effects. Control variables (Z) are either included or excluded. Regressions include time fixed effects (time) for each month, as well as individual fixed effects for each individual (CustID). Panel data are estimated using clustered standard errors.

	Exclude Control Vars (Z)		Include Control Vars (Z)	
Indep Var (lag)	Coeff	Std Err	Coeff	Std Err
FINAL_HI -0	-0.00622	0.078004	-0.00364	0.075268
FINAL_HI -1	0.007162	0.058221	0.001244	0.054608
FINAL_HI -2	0.041826	0.052143	0.049835	0.05285
FINAL_HI -3	-0.10806	0.05338**	-0.09994*	0.053981
FINAL_HI -4	-0.11142	0.056979**	-0.09691*	0.056995
FINAL_HI -5	-0.15522	0.084347*	-0.15174*	0.081832
FINAL_HI -6	-0.01113	0.0804	-0.01881	0.079821
FINAL_HI -7	-0.11072	0.076219	-0.10077	0.076962
FINAL_HI -8	-0.09137	0.082927	-0.09106	0.082936
Constant	21.40466	2.890888***	-1640.98***	95.85848
Card Balan/Limit			3.707192***	0.411623
Card Limit			175.6987***	10.9232
n		150260		150242
F		25.81		38.42
R2		19.17		22.47
Cumulative FINAL_HI	-0.54515	0.270129**	-0.51179	0.271711*

TABLE 9: CHANGE IN C. CARD DEBT – Small Final Mortgage Payment

$$\Delta DEBT_{i,t} = \alpha_1 ' time_t + \alpha_2 ' CustID_i + \sum_{s=0}^{n} \beta_s FINAL\_LO_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

$\Delta DEBT$ is the change in Credit Card Debt from month t-1 to month t, for individual i. FINAL_LO is the dollar magnitude of the final mortgage payment in the month of the final payment, if that magnitude is less than $751, and 0 otherwise. We report marginal effects on change in credit card debt for lags s= 0 to 8 months as well as long-run cumulative effects. Control variables (Z) are either included or excluded. Regressions include time fixed effects (time) for each month, as well as individual fixed effects for each individual (CustID). Panel data are estimated using clustered standard errors.

	Exclude Control Vars (Z)		**Include Control Vars (Z)**	
Indep Var (lag)	**Coeff**	**Std Err**	**Coeff**	**Std Err**
FINAL_LO -0	-0.05538	0.109406	-0.0639	0.105585
FINAL_LO -1	0.208533	0.126908*	0.169544	0.123952
FINAL_LO -2	-0.11385	0.095523	-0.13249	0.096532
FINAL_LO -3	-0.09952	0.084625	-0.10487	0.083068
FINAL_LO -4	-0.00308	0.109951	0.000872	0.112978
FINAL_LO -5	-0.01529	0.101716	0.000409	0.098197
FINAL_LO -6	0.202599	0.109773*	0.212544	0.107401**
FINAL_LO -7	-0.10606	0.12222	-0.10132	0.124588
FINAL_LO -8	-0.05557	0.125456	-0.02929	0.126256
Constant	21.29318	2.891817***	-1640.94	95.87362***
Card Balan/Limit			3.707641	0.411686***
Card Limit			175.6784	10.92506***
n		150260		150242
F		25.61		38.24
R2		19		22.47
Cumulative FINAL_LO	-0.03764	0.359275	-0.04851	0.387198

TABLE 10: CHANGE IN C. CARD DEBT – Quadratic Specification

$$\Delta DEBT_{i,t} = \alpha_1 ' time_t + \alpha_2 ' CustID_i + \sum_{s=0}^{n} \beta_n FINAL_{i,t-n} + \sum_{s=0}^{m} \beta_m FINAL\_SQ_{i,t-m} + \delta Z_{i,t} + \varepsilon_{i,t}$$

$\Delta DEBT$ is the change in Credit Card Debt from month t-1 to month t, for individual i. FINAL is the dollar magnitude of the final mortgage payment in the month of the final payment, and 0 otherwise. FINAL_SQ is the square of FINAL. We report marginal effects on change in credit card debt for lags s= 0 to 4 months as well as long-run cumulative effects. Control variables (Z) are either included or excluded. Regressions include time fixed effects (time) for each month, as well as individual fixed effects for each individual (CustID). Panel data are estimated using clustered standard errors.

	Exclude Control Vars (Z)		**Include Control Vars (Z)**	
Indep Var (lag)	**Coeff**	**Std Err**	**Coeff**	**Std Err**
FINAL -0	0.011183	0.117795	0.000906	0.116052
FINAL -1	0.228019***	0.091287	0.203818	0.087243***
FINAL -2	-0.00263	0.097372	-0.01576	0.096495
FINAL -3	-0.0143	0.078884	-0.02072	0.077976
FINAL -4	0.082111	0.090426	0.083102	0.090848
FINAL_SQ -0	-2.3E-05	8.37E-05**	-2.1E-05	8.28E-05
FINAL_SQ -1	-0.0001	4.71E-05	-9.6E-05	4.49E-05**
FINAL_SQ -2	2.54E-05	6.62E-05	3.14E-05	6.58E-05
FINAL_SQ -3	-1.2E-05	4.15E-05	-9.42E-06	4.03E-05
FINAL_SQ -4	-9.5E-05	4.21E-05**	-9.3E-05	4.31E-05**
Constant	20.34565	2.770388***	-996.099	48.46922***
Card Balan/Limit			3.178236	0.235454***
Card Limit			103.1162	5.381023***
n		192410		192376
F		24.16		40.79
R2		15.91		18.79
Cumulative FINAL	0.30438	0.218945	0.251347	0.217417
Cumulative FINAL_SQ	-0.00021	0.000129*	-0.00019	0.000125

TABLE 11: RELATIVE MAGNITUDE HYPOTHESIS: Consumption

$$CONS_{i,t} = \alpha_1 'time_t + \alpha_2 'CustID_i + \sum_{s=0}^{n} \chi^{HI}{}_s FINAL/INC\_HI_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

$$CONS_{i,t} = \alpha_1 'time_t + \alpha_2 'CustID_i + \sum_{s=0}^{n} \chi^{HI}{}_s FINAL/INC\_LO_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

CONS is credit card consumption. FINAL/INC is the FINAL variable divided by Total Income (from Census Data). FINAL/INC is split into FINAL/INC_LO and FINAL/INC_HI based on the mean value of FINAL/INC. We report marginal effects on consumption for lags s= 0 to 8 months as well as long-run cumulative effects. Regressions include time fixed effects (time) for each month, as well as individual fixed effects for each individual (CustID). Panel data are estimated using clustered standard errors.

	FINAL/INC_HI		**FINAL/INC_LO**	
Indep Var (lag)	**Coeff**	**Std Err**	**Coeff**	**Std Err**
FINAL/INCOME-0	188.8365	6122.238	39929.24	20649.41*
FINAL/INCOME -1	-1792.74	3908.749	5630.041	6650.271
FINAL/INCOME -2	10675.82	4951.31**	-7675.58	4533.884*
FINAL/INCOME -3	-2973.57	3320.09	-4873.24	5309.334
FINAL/INCOME -4	6362.045	5859.569	3785.914	10371.53
FINAL/INCOME -5	3831.745	6370.776	18433.07	13729.62
FINAL/INCOME -6	4121.215	3773.921	6090.555	7061.278
FINAL/INCOME -7	-4023.04	5096.972	-4213.07	5349.383
FINAL/INCOME -8	-3697.14	2542.001	3966.343	6758.383
n		175328		184238
F		22.02		21.11
R2		74		74
Cumulative FINAL/INC	10711.59	20395.22	26774.07	32815.78

TABLE 12: RELATIVE MAGNITUDE HYPOTHESIS: Change in Debt				

$$\Delta DEBT_{i,t} = \alpha_1 ' time_t + \alpha_2 ' CustID_i + \sum_{s=0}^{n} \beta^{HI}{}_s FINAL / INC\_HI_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

$$\Delta DEBT_{i,t} = \alpha_1 ' time_t + \alpha_2 ' CustID_i + \sum_{s=0}^{n} \beta^{LO}{}_s FINAL / INC\_LO_{i,t-s} + \delta Z_{i,t} + \varepsilon_{i,t}$$

Debt is credit card debt. FINAL/INC is the FINAL variable divided by Total Income (from Census Data). FINAL/INC is split into FINAL/INC_LO and FINAL/INC_HI based on the mean value of FINAL/INC. We report marginal effects on change in credit card debt for lags s= 0 to 8 months as well as long-run cumulative effects. Regressions include time fixed effects (time) for each month, as well as individual fixed effects for each individual (CustID). Panel data are estimated using clustered standard errors.

	FINAL/INC_HI		**FINAL/INC_LO**	
Indep Var (lag)				
FINAL/INCOME-0	-2330.98	1356.849*	3201.717	4727.227
FINAL/INCOME -1	860.413	1133.599	4035.344**	2489.124
FINAL/INCOME -2	494.392	1274.187	-4324.01	2042.703
FINAL/INCOME -3	-1681.94	1164.789	-3416.38	2368.319
FINAL/INCOME -4	-1953.96	1267.441	694.3739	2902.342
FINAL/INCOME -5	-2868.88	1754.227	426.0734	3110.957
FINAL/INCOME -6	208.8903	1663.332	3075.798	2867.504
FINAL/INCOME -7	-1719	1553.75	-3870.37	2845.243
FINAL/INCOME -8	-3247.73	1805.729*	2945.625	2861.354
n		142969		150260
F		26.24		25.87
R2		19		19
Cumulative FINAL/INC	-9047.41	5360.8*	3601.799	10158.43

TABLE 13: RELATIVE MAGNITUDE HYPOTHESIS: Quadratic Specifications

$$CONS_{i,t} = \alpha_1 'time_t + \alpha_2 'CustID_i + \sum_{s=0}^{n} \chi_n FINAL/INC_{\ i,t-n} + \sum_{s=0}^{m} \chi_m FINAL/INC\_SQ_{i,t-m} + \delta Z_{i,t} + \varepsilon_{i,t}$$

$$\Delta DEBT_{i,t} = \alpha_1 'time_t + \alpha_2 'CustID_i + \sum_{s=0}^{n} \beta_n FINAL/INC_{\ i,t-n} + \sum_{s=0}^{m} \beta_m FINAL/INC\_SQ_{i,t-m} + \delta Z_{i,t} + \varepsilon_{i,t}$$

CONS is credit card consumption and DEBT is credit card debt. FINAL/INC is the FINAL variable divided by Total Income (from Census Data). FINAL/INC_SQ is FINAL/INC squared. We report marginal effects for both FINAL/INC and FINAL/INC_SQ for lags s= 0 to 4, months as well as long-run cumulative effects. Regressions include time fixed effects (time) for each month, as well as individual fixed effects for each individual (CustID). Panel data are estimated using clustered standard errors.

	CONSUMPTION		**D DEBT**	
Indep Var (lag)				
FINAL/INCOME -0	5452.101	6519.527	1042.611	2415.558
FINAL/INCOME -1	6555.374	5348.821	4210.681	1951.243**
FINAL/INCOME -2	8456.939	7207.733	-552.309	2281.63
FINAL/INCOME -3	-2614.19	4639.249	405.1141	1769.835
FINAL/INCOME -4	17615.66	6751.975**	2184.214	2130.456
FINAL/INCOME_SQ -0	-44582.3	98619.62	-38620.6	36777.49
FINAL/INCOME_SQ -1	-125258	86045.23	-39637.6	21881.77*
FINAL/INCOME_SQ -2	-64537.1	81131.34	14609	37603.58
FINAL/INCOME_SQ -3	36680.21	79048.66	-11135.1	22937.21
FINAL/INCOME_SQ -4	-180989	106895.5*	-50116.6	23546.57**
n		258343		211830
F		20.48		23.70
R2		72		15.86
Cumulative FINAL/INC	36569.16	17716.76**	10458.38	5344.631**
Cumulative FINAL/INC_SQ	-459362	262698.9*	-125918	60945.05**

TABLE 14: DIFFERENCES BETWEEN HIGH AND LOW MORTGAGE PAYERS

T tests of Differences in Mean

Panel A: Absolute Magnitudes

	FINAL_LO		FINAL_HI		t test of Diff in Mean
	Mean	Std Err	Mean	Std Err	
Bank Account Data (Individual)					
Credit Card Debt/Limit (%)	32.38	3.48	28.4	3.93	0.739
FICO Score	742.97	7.95	765.48	5.44	2.05**
Census Data (Post Code Level)					
Invest & Bus Income (% of total income)	8.08	0.46	6.46	0.54	3.05***
Govt Transfer Payments (% of total income)	12.59	0.7	9.83	0.95	2.35**
Total Income (C$)	21245	701.51	23976	1030.45	2.26**

Panel B: Relative Magnitudes

	FINAL/INCOME_LO		FINAL/INCOME_HI		t test of Diff in Mean
	Mean	Std Err	Mean	Std Err	
Bank Account Data (Individual)					
Credit Card Balance/Limit (%)	33.02	4.15	30.27	3.58	0.5
FICO Score	737.04	9.69	766.28	5.48	2.65***
Census Data (Post Code Level)					
Invest & Bus Income (% of total income)	8.71	0.53	6.68	0.43	2.94***
Govt Transfer Payments (% of total income)	11.48	0.62	12.2	0.94	0.62
Total Income (C$)	23698	820.25	22233	641.79	1.41

*, ** and *** indicate 10%, 5% and 1% confidence levels

Appendix 1: Postal Code Level Census Data

Our main 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 match our data on credit card mistakes with postal code level census data provided by Statistics Canada. The Statistics Canada Census data provides us with various proxies for different components of income. In order to match the two 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 neighboring 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). A full description of the geographic concept of the Dissemination Area is provided by Statistics Canada, (2001). 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, 2001, p. 7).

References

Agarwal, S., Chomsisengphet, S., Liu, C., & Souleles, N. S. (2006). *Do consumers choose the right credit contracts?* Federal Reserve Bank of Chicago, Working Paper Series: WP-06-11.

Agarwal, S., Driscoll, J. C., Gabaix, X., & Laibson, D. (2008). *Learning in the credit card market* National Bureau of Economic Research, Inc, NBER Working Papers: 13822.

Agarwal, S., Liu, C., & Souleles, N. S. (2007). The reaction of consumer spending and debt to tax rebates--evidence from consumer credit data. *Journal of Political Economy, 115*(6), 986-1019.

Bodkin, R. G. (1959). Windfall income and consumption. *American Economic Review, 49*, 602-614.

Browning, M., & Collado, M. D. (2001). The response of expenditures to anticipated income changes: Panel data estimates. *American Economic Review, 91*(3), 681-692.

Coulibaly, B., & Li, G. (2006). Do homeowners increase consumption after the last mortgage payment? An alternative test of the permanent income hypothesis. *Review of Economics and Statistics, 88*(1), 10-19.

Gross, D. B., & Souleles, N. S. (2002a). Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data. *Quarterly Journal of Economics, 117*(1), 149-185.

Gross, D. B., & Souleles, N. S. (2002b). An empirical analysis of personal bankruptcy and delinquency. *Review of Financial Studies, 15*(1), 319-347.

Hsieh, C. (2003). Do consumers react to anticipated income changes? Evidence from the Alaska permanent fund. *American Economic Review, 93*(1), 397-405.

Johnson, D. S., Parker, J. A., & Souleles, N. S. (2006). Household expenditure and the income tax rebates of 2001. *American Economic Review, 96*(5), 1589-1610.

Kreinin, M. E. (1961). Windfall income and consumption: Additional evidence. *American Economic Review, 51*, 388-390.

Musto, D. K., & Souleles, N. S. (2006). A portfolio view of consumer credit. *Journal of Monetary Economics, 53*(1), 59-84.

Parker, J. A. (1999). The reaction of household consumption to predictable changes in social security taxes. *American Economic Review, 89*(4), 959-973.

Petersen, M. A. (2008). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies,* Reis, R. (2006). Inattentive consumers. *Journal of Monetary Economics*, *53*(8), 1761-1800.

Shapiro, M. D., & Slemrod, J. (1995). Consumer response to the timing of income: Evidence from a change in tax withholding. *American Economic Review*, *85*(1), 274-283.

Shapiro, M. D., & Slemrod, J. (2003). Consumer response to tax rebates. *American Economic Review*, *93*(1), 381-396.

Shea, J. (1995). Union contracts and the life-Cycle/Permanent-income hypothesis. *American Economic Review, 85*(1), 186-200.

Souleles, N. S. (1999). The response of household consumption to income tax refunds. *American Economic Review, 89*(4), 947-958.

Souleles, N. S. (2000). College tuition and household savings and consumption. *Journal of Public Economics*, *77*(2), 185-207.

Souleles, N. S. (2002). Consumer response to the Reagan tax cuts. *Journal of Public Economics, 85*(1), 99-120.

Statistics Canada (2001). "Introducing the Dissemination Area for the 2001 Census**:** An Update".

Stephens, M.,Jr. (2001). The long-run consumption effects of earnings shocks. *Review of Economics and Statistics, 83*(1), 28-36.

Stephens, M.,Jr. (2003). '3rd of tha month': Do social security recipients smooth consumption between checks? *American Economic Review, 93*(1), 406-422.

Stephens, M.,Jr. (2006). Paycheque receipt and the timing of consumption. *Economic Journal, 116*(513), 680-701.

Stephens, M.,Jr. (2008). The consumption response to predictable changes in discretionary income: Evidence from the repayment of vehicle loans. *Review of Economics and Statistics, 90*(2), 241-252.

Thaler, R. H. (1990). Saving, fungibility, and mental accounts. *Journal of Economic Perspectives, 4*(1), 193-205.