EUROPEAN CENTRAL BANK

EUROSYSTEM

RETAIL PAYMENTS:
INTEGRATION AND INNOVATION

WORKING PAPER SERIES

NO 1142 / DECEMBER 2009

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DOES THE MAGNITUDE OF INCOME SHOCKS MATTER?

by Barry Scholnick

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In 2009 all ECB publications feature a motif taken from the €200 banknote.

This paper can be downloaded without charge from http://www.ecb.europa.eu or from the Social Science Research Network electronic library at http://ssrn.com/abstract_id=1358457.

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Retail payments: integration and innovation

“Retail payments: integration and innovation” was the title of the joint conference organised by the European Central Bank (ECB) and De Nederlandsche Bank (DNB) in Frankfurt am Main on 25 and 26 May 2009. Around 200 high-level policy-makers, academics, experts and central bankers from more than 30 countries of all five continents attended the conference, reflecting the high level of interest in retail payments.

The aim of the conference was to better understand current developments in retail payment markets and to identify possible future trends, by bringing together policy conduct, research activities and market practice. The conference was organised around two major topics: first, the economic and regulatory implications of a more integrated retail payments market and, second, the strands of innovation and modernisation in the retail payments business. To make innovations successful, expectations and requirements of retail payment users have to be taken seriously. The conference has shown that these expectations and requirements are strongly influenced by the growing demand for alternative banking solutions, the increasing international mobility of individuals and companies, a loss of trust in the banking industry and major social trends such as the ageing population in developed countries. There are signs that customers see a need for more innovative payment solutions. Overall, the conference led to valuable findings which will further stimulate our efforts to foster the economic underpinnings of innovation and integration in retail banking and payments.

We would like to take this opportunity to thank all participants in the conference. In particular, we would like to acknowledge the valuable contributions of all presenters, discussants, session chairs and panellists, whose names can be found in the enclosed conference programme. Their main statements are summarised in the ECB-DNB official conference summary. Twelve papers related to the conference have been accepted for publication in this special series of the ECB Working Papers Series.

Behind the scenes, a number of colleagues from the ECB and DNB contributed to both the organisation of the conference and the preparation of this conference report. In alphabetical order, many thanks to Alexander Al-Haschimi, Wilko Bolt, Hans Brits, Maria Foskolou, Susan Germain de Urday, Philipp Hartmann, Päivi Heikkinen, Monika Hempel, Cornelia Holthausen, Nicole Jonker, Anneke Kosse, Thomas Lammer, Johannes Lindner, Tobias Linzert, Daniela Russo, Wiebe Ruttenberg, Heiko Schmiedel, Francisco Tur Hartmann, Liisa Väisänen, and Pirjo Väkeväinen.

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Abstract

We test the hypothesis that consumption smoothing occurs after large, but not small, expected future income shocks. Even though this hypothesis has often been discussed, formal evidence in support of it is rare. We use individual level, monthly, bank account data to examine how expected income shocks from final mortgage payments impact credit card consumption, and the repayment of credit card debt. Our data allows us to identify the exact magnitude and date of final mortgage payments, and also to exploit the random timing of these expected income shocks across individuals. Our results are consistent with the magnitude hypothesis.

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 the predictable income shock is *small*. One popular explanation for the magnitude hypothesis 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 future income shock was small (say $100), then the magnitude hypothesis suggests that the individual may "not bother"

[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).

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. This Table shows that there is little consensus among those papers that have addressed the magnitude hypothesis (Panel A of Table 1). On the one hand, a group of recent papers that discuss the magnitude hypothesis, such as Browning and Collado, (2001), Hsieh, (2003) and Coulibaly and Li, (2006), do not formally test this hypothesis (e.g. by comparing large and small shocks). Rather, these authors suggest that their results may be consistent with the magnitude hypothesis, because the PIH tends to hold following income shocks that can be considered "large". On the other hand, the two papers (Kreinin, (1961) and Souleles (1999)), that have both formally tested the magnitude hypothesis (by comparing large and small shocks), both reject the hypothesis. However, as we argue in Section 2 below, both these papers use data that is subject to various data concerns. In other words, even though much recent discussion has focused on the magnitude hypothesis as a possible explanation for why the PIH may hold (e.g. Browning and Collado, (2001), Hsieh, (2003) and Coulibaly and Li, (2006)), those papers who have formally tested it (e.g. by comparing large and small shocks) have not found evidence to support it (Kreinin, (1961) and Souleles (1999)). The aim of our paper is to address these conflicting elements in the literature, by providing 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 payment of a long term debt contract 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. Because of this, 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 (the final mortgage payment) impacts credit card consumption and debt.

There are two main 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 (see Table 1) 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.

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 of various kinds 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 is responding to that specific government payment, or to any other macroeconomic factor that occurred at the same time, e.g. stock exchange or monetary policy 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.

Section 2 of the paper examines the contribution of our paper relative to the existing literature, while Section 3 details the data we use. Section 4 describes the methodology and Section 5 provides results.

2. RELATIONSHIP TO THE LITERATURE

As described above, there is disagreement in the literature about the relevance of the magnitude hypothesis. On the one hand, a group of recent papers (e.g. Hsieh (2003) Browing and Collado (2001) and Coulibali and Li (2006)) speculate that the magnitude hypothesis is one possible reason for consumption smoothing, following income shocks that these authors consider to be "large". However, none of these papers formally compare large and small shocks. On the other hand, Kreinin (1961), and Souleles (1999), both reject the magnitude hypothesis by examining individual consumption across a large number of individuals, after each received the same type of income shock but where there is a wide variance in the magnitude of these shocks across individuals. 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). Both these authors distinguish between large and small shocks by squaring the income shock term, and both reject the magnitude hypothesis because the income shock 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 across individuals. 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. Our data 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 behavioral 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)). 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. 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[2], our data is unique in that it is matched with monthly mortgage account data. Because of the variance in the size of final mortgage payments across individuals, we are thus able to provide the first formal test of the magnitude hypothesis 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. Our primary focus is on the approximately 20 000 individuals who hold *both* mortgage as well as credit card accounts at the bank. Our dependent variables are individual level credit card behavior (the dollar value of either credit card consumption or the change 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, partly because the provision of sub-prime mortgages was extremely rare in Canada.

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

[2] 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).

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 sources of credit and not just the credit card in our study). Furthermore, we argue that our study has one important additional advantage over existing studies 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[3].

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

[3] 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.

individual in our data. By dividing the amount of the final mortgage payment by the postal code level measure of individual 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. It is important to emphasise that the size of this Canadian post code area (200 households) is orders of magnitude smaller than US Zip codes, thus providing us with very fine grained measures of income etc.

4. EMPIRICAL METHODOLOGY

In this section we first describe our baseline tests of consumption smoothing (i.e. ignoring issues of magnitude). 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

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 after 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).

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

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

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. Those individuals, for whom FINAL is zero, act as a control group. 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 and interpretation 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. Furthermore, we closely follow the event study interpretation of these models used by Gross and Souleles (2002a) and Agarwal, Liu and Souleles (2007) in that the individual's consumption or debt in the period(s) after FINAL are being compared to the period(s) before FINAL.

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). The distributed lags on FINAL in equations (1) and (2) can be interpreted as in event studies. For example, in the case of the consumption equation (1), the coefficient $\chi 0$ measures the instantaneous response of consumption and the marginal coefficients $\chi 1$, $\chi 2$, $\chi 3$ etc 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 $\Sigma\chi$ summed 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 $\beta 0$, the individual lagged βs as well as the cumulative measure $\Sigma\beta$ summed 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 individual's disposable income. Once the individual has finished paying their final mortgage payment, the individual receives a permanent increase in disposable income each month into the future. For this reason we focus on the cumulative measures (i.e. the sum of all lags).

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 or the change in credit card debt. This is different from some of the consumption smoothing literature which has only been able to measure future income shocks as a dummy variable.

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 consumption smoothing study by excluding all individuals who paid off 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.

Similarly, it would also be inappropriate to include individuals who have defaulted or who are delinquent on their mortgages in our FINAL group. Our data allows us to observe such individuals and exclude them. If for any reason the outstanding mortgage balance increases (or stays constant) between any two months, that individual is not included in our FINAL group.

Because of the exact nature of our monthly payment data, we are able to identify very precisely the "amortizers" in our data who have paid off the mortgage in full. Specifically, the criteria we use to include an individual in our FINAL group is that the outstanding mortgage balance must decline in equal monthly increments (which we define as within 10%) over time until it reaches zero. We only use data if at least four previous months of data are available before the mortgage balance reaches zero. Based on these characteristics, we are able to identify 147 individuals in our sample who made final mortgage payments that were 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.

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)

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

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

As above, 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).

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 (or FINAL_HI or FINAL_LO) is replaced by FINAL/INC, where FINAL is divided by the postal code level income variable for each individual in the sample. 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)

In all of the models we add various control variables specified as Z in the equations above. 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 credit card credit limit could impact individual consumption and debt repayment decisions. Our third control variable is the FICO score for each individual. The FICO score is an external measure provided by a credit rating agency and captures past credit behavior by the individual across all credit products. This variable thus allows us to examine how credit behavior in other credit products besides the credit card in our study impact credit card consumption and debt decisions. Our final control variable is a measure of Age taken from post code level census data. A large literature has examined the impact of age on individual consumption and debt behavior in the context of consumption smoothing etc, thus it is appropriate to include age as a control variable in our tests.

4.6. Excluding Alternative Explanations – Credit Constraints

While the main focus of this paper is on testing the magnitude hypothesis, 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 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[4]. 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. those who receive the "treatment" of a final mortgage payment) relative to a "control group" (all other mortgage payers), is whether there is any selection bias in the choice of those specific individuals into the FINAL group. We argue that selection into the FINAL group should not generate selection bias. 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 control group is the fact that these individuals are making their final mortgage payment, while the others continue to pay their mortgages (those who prepay or who default are excluded). In due course every mortgage holder will come to the end of the mortgage contract.

[4] 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).

It may be possible that individuals in our FINAL group are older on average than all other individuals who are still paying their mortgage. However, as described above, we control for this by including Age as a control variable in all our tests. 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.

An alternative selection issue could occur if individuals select into FINAL_HI or FINAL_LO groups for some systematic reason. We discuss this issue in more detail, as well as providing evidence against this, in section 5.4 below.

5. RESULTS

5.1 Absolute Magnitude Hypothesis

Our results for the Absolute Magnitude hypothesis are presented in Tables 3, 4 and 5. Following Agarwal et al, (2008) and Gross and Souleles, (2002a), we report both marginal coefficients for each lag as well as the cumulative (or long run) coefficient which shows the significance of the sum of all lags from 0 to n. Because the income shock we are examining (final mortgage payments) is a permanent rather than temporary shock, we are specifically interested in the significance of the long run cumulative coefficient (i.e. the sum of all lags).

Tables 3 and 4 can be considered together. Table 3 includes three specifications for credit card consumption; the baseline case where the FINAL variable is included without any differentiation between large or small magnitudes, as well as the separate cases of large final mortgage payments and small final mortgage payments. Table 4 examines the same three specifications for the change in credit card debt. Table 3 (final row) shows that the cumulative FINAL coefficient for the impact of small final mortgage payments on consumption is significant and positive, while the cumulative coefficient for large final mortgage payments is insignificant. On the other hand, Table 4 (final row) shows that the cumulative FINAL coefficient for the impact of large final mortgage payments of the change in card debt is significant and negative, while the cumulative coefficient for small final mortgage payments is insignificant.

These results are consistent with the magnitude hypothesis. Individuals with large final mortgage payments do not have significantly higher consumption after the final mortgage payment, but they do significantly reduce their credit card debt – actions that are consistent with consumption smoothing. On the other hand, individuals with small final mortgage payments do have significantly higher consumption, but do not significantly lower their debt – actions which are not consistent with consumption smoothing. Thus as predicted by the magnitude hypothesis, the evidence in Tables 3 and 4 is consistent with consumption smoothing for larger rather than small expected permanent income shocks.

The importance of taking into account the magnitude of expected income shocks can be seen by examining the baseline specifications in Tables 3 and 4, where all final mortgage payments are included irrespective of magnitude. In the case of both the baseline consumption models as well as the baseline debt models, all estimates of cumulative FINAL coefficients are insignificant. In other words, without taking magnitudes into account, the erroneous conclusion could have been reached that FINAL mortgage payments have no significant permanent impact on either credit card consumption or credit card debt. It is only by distinguishing between large and small magnitudes that we can conclude that consumption smoothing occurs for large but not small income shocks, as predicted by the magnitude hypothesis.

The magnitudes of the significant cumulative coefficients in Tables 3 and 4 are also of interest (recall that the consumption and debt variables as well as the FINAL variable are all measures in dollars). In Table 3 the significant cumulative FINAL_LO consumption coefficient for small final mortgage payments is 2.18 (or 2.48 with controls). This implies that, if the final mortgage payment is small, the cumulative increase in credit card consumption for the 8 months after the final mortgage payment will be 2.18 (or 2.48) times the magnitude of the monthly mortgage payment. Similarly, in Table 4, the significant cumulative FINAL_HI debt coefficient is -0.76 (without controls) and -0.72 (with controls). This implies that if that final mortgage payment is large, cumulative change in credit card debt in the 8 months after the final mortgage payment will be -0.76 (or -0.72 with controls) times the magnitude of the final mortgage payment,.

Table 5 reports results for the quadratic specification. In the case of credit card consumption we find that the cumulative FINAL variable is positive and significant and the cumulative FINAL_SQ variable is negative and significant. In other words, our results support the hypothesis of an inverted U shaped relationship between consumption and the magnitude of FINAL. 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, which shows that the cumulative term for the FINAL_SQ coefficients is negative and significant. In other words, as the magnitude of FINAL increases so there is a larger negative impact on the cumulative change in debt outstanding.

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 6, 7 and 8. The results for the HI and LO equations in Tables 6 and 7 are weaker than those reported above in the case of the absolute magnitude hypothesis, with no cumulative FINAL/INC coefficients significant in Tables 6 and 7. However the results reported in the quadratic specifications in Table 8 are relatively strong, and are consistent with the magnitude hypothesis. In particular, Table 8 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/INC increases. These results are consistent with the magnitude hypothesis that at low levels of FINAL/INC, consumption and the change in debt may increase, but at high levels of FINAL/INC, 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 in the quadratic specification.

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. As described by various authors who use similar types of data, we face a trade-off in determining the lag length, because the greater the lag length the greater the number of individuals that will be excluded because monthly various data points are missing from the dataset. Our lag lengths are similar to those used in the existing literature. 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 who 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 use our data to examine if there are systematic differences between mortgage payers in the FINAL_HI and FINAL_LO groups. As described above, if there is a systematic reason for why individuals sort into HI and LO groups, then this could cause selection bias, which could impact the interpretation of our results.

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[5]. Thus theoretically, it can be argued that there is not a single determinant (e.g. income) of individuals choosing higher or lower monthly payments. Rather, we argue that the magnitude of the monthly mortgage payment is a function of a large number of factors including but not limited to income, the size of the mortgage as well as the overall investment goals and priorities of each individual.

[5] 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.

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 9. 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

The Permanent Income Hypothesis is central to much modern economics, including consumption and saving theory and many macroeconomic models. Despite its importance, empirical evidence on the hypothesis remains unsettled. One possible explanation for why the PIH only sometimes holds is the magnitude hypothesis, which states that consumption smoothing occurs after large but not small expected future income shocks. While a variety of papers have discussed the magnitude hypothesis, those few papers that have formally tested it by comparing large and small income shocks have rejected the hypothesis.

The main contribution of this paper is to provide a new test of the magnitude hypothesis, using a high quality new dataset that addresses some of the data concerns in the previous literature. We examine the impact of a single kind of income shock (final mortgage payments) 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. Furthermore, our data exploits the fact that the timing of the final mortgage payment is randomly distributed across individuals.

Our data is unique in that monthly mortgage account data is matched with monthly credit card statement data, thus we can test the magnitude hypothesis by examining the impact of final mortgage payments on credit card consumption and debt. We test both the absolute magnitude hypothesis as well as the relative magnitude hypothesis (where the size of the expected shock is divided by income).

Our results show that if the magnitude of the final mortgage payment is small, then the final payment is followed by a significant increase in credit card consumption but not a significant reduction in credit card debt. On the other hand, if the magnitude of the final mortgage payment is large, then the final payment is followed by a significant reduction in credit card debt, but not a significant increase in 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.

TABLE 1: LITERATURE REVIEW:
TESTS OF THE PERMANE NT 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
Age	1462827	41.23	41.11	5.88

Table 3. Credit Card Consumption – Absolute Magnitude Hypothesis

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

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. 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. 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.

	All Final Mortgage Payments				**Large Final Mortgage Payments**				**Small Final Mortgage Payments**			
FINAL Specification	**FINAL**				**FINAL_HI**				**FINAL_LO**			
	No Controls (Z)		With Controls (Z)		No Controls (Z)		With Controls (Z)		No Controls (Z)		With Controls (Z)	
Indep Var (lag)	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.
FINAL -0	-0.06487	0.192646	-0.09276	0.186236	-0.22946	0.192618	-0.2472	0.187255	0.934964	0.538585*	0.8383	0.502774*
FINAL -1	-0.03471	0.158254	-0.0659	0.149171	-0.07983	0.184231	-0.09734	0.173638	0.192705	0.179591	0.101159	0.180595
FINAL -2	0.388979	0.268022	0.391143	0.258089	0.467359	0.325573	0.480519	0.3144	0.023043	0.14042	-0.01559	0.12864
FINAL -3	-0.27362	0.128863**	-0.24308	0.1207**	-0.36497	0.14543***	-0.32616	0.1358**	0.140298	0.227944	0.140402	0.219564
FINAL -4	0.270009	0.227694	0.275124	0.219133	0.284174	0.262429	0.283895	0.252293	0.194753	0.325484	0.235399	0.31402
FINAL -5	0.194517	0.262607	0.179083	0.248996	0.087982	0.312486	0.060523	0.296626	0.697684	0.403379*	0.74182	0.392043*
FINAL -6	0.149209	0.146244	0.137325	0.138744	0.143971	0.168811	0.125078	0.159516	0.187568	0.225042	0.212262	0.216001
FINAL -7	-0.11382	0.183289	-0.11852	0.174159	-0.10324	0.220835	-0.12439	0.209729	-0.1277	0.194069	-0.06117	0.186393
FINAL -8	-0.17764	0.104327*	-0.17787	0.10221*	-0.26824	0.107961**	-0.27989	0.105***	0.232768	0.259916	0.294315	0.261165
Constant	838.1835	9.54207***	3849.669	5.84E+08	838.236	9.54047***	3849.302	5.96E+08	837.9654	9.53981***	3851.753	5.71E+08
Card Balan/Limit			9.898972	0.79145***			9.898968	0.791***			9.899631	0.79150***
Card Limit			491.9109	46.8441***			491.9377	46.84***			492.0514	46.8467***
FICO			0.71557	0.10772***			0.715769	0.107***			0.714668	0.10771***
Age			-202.12	1.44E+07			-202.119	1.47E+07			-202.193	1.41E+07
n		184238		175810		184238		175810		184238		175810
F		21.44		30.31		22.22		31.58		20.71		29.59
R^2		74.30		74.9		74.29		74.9		74.29		74.9
Cumulative FINAL	0.338057	0.786513	0.284559	0.745246	-0.06226	0.876685	-0.12497	0.8307	2.183447	1.05726**	2.486904	1.2096**

Table 4. Change in Credit Card Debt – Absolute Magnitude Hypothesis

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

Δ 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_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. 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 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.

	All Final Mortgage Payments				**Large Final Mortgage Payments**				**Small Final Mortgage Payments**			
FINAL Specification	**FINAL**				**FINAL_HI**				**FINAL_LO**			
	No Controls (Z)		With Controls (Z)		No Controls (Z)		With Controls (Z)		No Controls (Z)		With Controls (Z)	
Indep Var (lag)	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.
FINAL -0	-0.08514	0.098075	-0.07989	0.096972	-0.10691	0.114537	-0.099	0.113545	-0.00683	0.125866	-0.01121	0.117253
FINAL -1	0.005377	0.066151	-0.00135	0.064171	-0.06043	0.070951	-0.05839	0.068822	0.26828	0.174245	0.227773	0.170686
FINAL -2	-0.09896	0.095219	-0.08291	0.094516	-0.13188	0.116306	-0.1077	0.115641	0.023351	0.111309	0.012822	0.11317
FINAL -3	-0.15009	0.060291	-0.136	0.060**	-0.19283	0.071***	-0.17323	0.0726**	0.01768	0.118411	0.012314	0.11202
FINAL -4	-0.04109	0.067068	-0.01779	0.066858	-0.07533	0.07865	-0.05023	0.077905	0.087119	0.111252	0.107389	0.113104
FINAL -5	-0.10616	0.078553	-0.10281	0.075721	-0.15433	0.094697	-0.16274	0.09161*	0.074054	0.136969	0.120121	0.131623
FINAL -6	0.031118	0.07561	0.026081	0.072564	-0.01873	0.090335	-0.03139	0.08685	0.229294	0.14744	0.254254	0.14840*
FINAL -7	0.002862	0.093021	-0.01032	0.089061	0.067795	0.107092	0.052563	0.100861	-0.21683	0.153083	-0.22584	0.151683
FINAL -8	-0.01591	0.093415	-0.01076	0.096431	-0.08988	0.101368	-0.09483	0.104786	0.187911	0.191589	0.223887	0.198815
Constant	37.72215	3.706116	3570.363	1.00E+09	37.716	3.705***	3570.826	1.00E+09	37.50305	3.705***	3571.046	9.96E+08
Card Balan/Limit			5.800071	0.610***			5.799922	0.610***			5.800703	0.61***
Card Limit			255.8538	14.89***			255.8906	14.89***			255.8987	14.89***
FICO			0.569418	0.052***			0.569088	0.052***			0.569404	0.052***
Age			-157.458	2.47E+07			-157.471	2.46E+07			-157.49	2.45E+07
n		161368		153815		161368		153815		161368		153815
F		27.56		42.42		27.84		42.68		27.3		42.2
R^2		16.25		21.1		16.2		21.1		16.2		21.1
Cumulative FINAL	-0.45798	0.302546	-0.41575	0.316804	-0.76253	0.3714**	-0.72494	0.38209*	0.664027	0.462075	0.721515	0.520675

Table 5. Quadratic Specification – Absolute Magnitude Hypothesis

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

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

CONS is dollar credit card consumption for month t and individual i. Δ 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 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.

	Credit Card Consumption				**Change in Credit Card Debt**			
	No Controls (Z)		With Controls (Z)		No Controls (Z)		With Controls (Z)	
Indep Var (lag)	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.
FINAL -0	0.602339	0.327023*	0.572831	0.314201*	-0.05117	0.129357	-0.04082	0.128514
FINAL -1	0.285683	0.246276	0.23433	0.235335	0.248678	0.13002*	0.230068	0.126549*
FINAL -2	0.566332	0.320451*	0.528294	0.312946*	0.024528	0.12625	0.018965	0.125833
FINAL -3	-0.18408	0.246195	-0.18096	0.235968	-0.02385	0.093975	-0.02105	0.091454
FINAL -4	0.562823	0.347351*	0.567507	0.339607*	0.167426	0.106049	0.190696	0.104902*
FINAL_SQ -0	-0.00042	0.000169**	-0.00041	0.00016***	-9.87E-06	8.75E-05	-1.6E-05	8.73E-05
FINAL_SQ -1	-0.00022	0.000149	-0.0002	0.000136	-0.00014	7.E-05**	-0.00013	6.79E-05**
FINAL_SQ -2	-0.00025	0.000165	-0.00022	0.00016	-3.4E-05	7.69E-05	-2.8E-05	7.72E-05
FINAL_SQ -3	6.53E-05	0.000191	6.67E-05	0.00018	-2E-05	4.77E-05	-1.9E-05	4.58E-05
FINAL_SQ -4	-0.0002	0.000212	-0.0002	0.000206	-0.00013	5.E-05***	-0.00014	5.E-05***
Constant	832.8823	9.27611***	-2398.7	2.49E+08	34.87975	3.548***	-1518.95	1.12E+07
Card Balan/Limit			8.473163	0.55833***			4.996803	0.35274***
Card Limit			334.5328	28.1536***			155.5982	7.1877***
FICO			0.656012	0.07884***			0.473962	0.0341***
Age			-12.199	6139431			-8.38512	276879.7
n		271180		258826		238241		227129
F		20.44		32.21		25.95		47.32
R^2		72.20		72.9		13.46		17.81
Cumulative FINAL	1.833099	0.777345**	1.721998	0.7489**	0.365606	0.275411	0.377863	0.277845
Cumulative FINAL_SQ	-0.001017	0.000496**	-0.00097	0.0004**	-0.00034	0.00014***	-0.00033	0.00014**

Table 6. Credit Card Consumption – Relative Magnitude Hypothesis

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

CONS is dollar credit card consumption for month t and individual i. FINAL/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. 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.

	All Final Mortgage Payments				**Large Final Mortgage Payments**				**Small Final Mortgage Payments**			
FINAL Specification	**FINAL/INC**				**FINAL/INC_HI**				**FINAL/INC_LO**			
	No Controls (Z)		With Controls (Z)		No Controls (Z)		With Controls (Z)		No Controls (Z)		With Controls (Z)	
Indep Var (lag)	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.
FINAL/INC -0	3352.874	5932.477	2574.201	5805.408	205.0162	6125.384	-424.53	6024.249	39929.24	20649.4*	36711.03	1879205*
FINAL/INC -1	-950.875	3569.513	-1567.12	3410.405	-1786.81	3907.957	-2260.7	3720.749	5630.041	6650.271	3857.782	6969.251
FINAL/INC -2	8743.459	4416.443	9011.456	4279.4**	10674.27	4955.4**	11017.34	4804.5**	-7675.58	4533.88*	-7920.63	4495.97
FINAL/INC -3	-3226.47	2983.534	-2612.33	2851.377	-2972.36	3321.187	-2335.12	3169.535	-4873.24	5309.334	-4287.42	5236.236
FINAL/INC -4	6146.287	5360.871	6277.488	5186.985	6358.478	5860.947	6343.791	5664.108	3785.914	10371.53	5215.901	10028.99
FINAL/INC -5	5581.403	5843.726	5161.921	5563.328	3837.827	6374.036	3214.151	6076.992	18433.07	13729.62	19517.54	12981.04
FINAL/INC -6	4416.12	3430.724	4098.038	3254.537	4126.777	3771.771	3592.117	3573.674	6090.555	7061.278	7356.95	6665.967
FINAL/INC -7	-3989.46	4531.664	-3895.27	4341.307	-4011.62	5098.909	-4211.72	4888.012	-4213.07	5349.383	-2011.43	5000.683
FINAL/INC -8	-2682.67	2413.803	-2650.01	2341.95	-3699.74	2541.4	-3698.24	2450.801	3966.343	6758.383	4409.982	6821.01
Constant	838.0461	9.543***	3849.804	5.43E+08	838.1156	9.542***	3849.096	4.87E+08	838.1591	9.537***	3849.244	5.19E+08
Card Balan/Limit			9.899243	0.791***			9.899727	0.7***			9.898848	0.791***
Card Limit			491.9142	46.84***			491.9179	46.84***			491.8555	46.84***
FICO			0.715628	0.107***			0.715708	0.107***			0.715675	0.107***
Age			-202.129	1.34E+07			-202.112	1.20E+07			-202.101	1.28E+07
N		184238		175810		184238		175810		184238		175810
F		21.10		30.10		21.32		30.15		21.11		29.93
R^2		74.30		74.98		74.30		74.98		74.30		74.98
Cumulative FINAL	13086.92	18604.02	12257.07	18022.16	10740.01	20403.33	9400.922	19728.83	26774.07	32815.78	29996.45	32471.78

Table 7. Change in Credit Card Debt – Relative Magnitude Hypothesis

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

Δ 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 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.

	All Final Mortgage Payments				**Large Final Mortgage Payments**				**Small Final Mortgage Payments**			
FINAL Specification	**FINAL/INC**				**FINAL/INC_HI**				**FINAL/INC_LO**			
	No Controls (Z)		With Controls (Z)		No Controls (Z)		With Controls (Z)		No Controls (Z)		With Controls (Z)	
Indep Var (lag)	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.
FINAL/INC -0	-2784.44	1877.812	-2850.59	1721.12*	-3030.71	2003.639	-3100.31	1832.18*	-888.009	5328.286	-1142.38	5141.959
FINAL/INC -1	1202.663	1342.67	955.8	1345.991	620.6284	1347.68	442.9396	1348.598	5267.826	5247.154	4534.627	5214.567
FINAL/INC -2	-2299.77	2317.524	-1980.01	2279.874	-2367.28	2615.584	-2026.91	2574.193	-2087.7	2689.23	-1824.25	2704.818
FINAL/INC -3	-2712.19	1388.7*	-2447.44	1387.33*	-2998.12	1547.97*	-2702.53	1552.14*	-1090.29	3031.154	-924.909	2929.671
FINAL/INC -4	-329.244	1494.926	146.9051	1497.975	-748.407	1594.175	-278.679	1598.887	2316.539	3831.497	2899.57	3776.493
FINAL/INC -5	-1574.66	1843.848	-1533.42	1811.833	-1512.76	2038.978	-1730.2	2025.232	-2017.06	3929.395	-246.009	3515.868
FINAL/INC -6	710.5546	1673.733	626.3997	1624.992	737.7512	1826.33	436.5139	1779.692	728.3061	4096.81	2015.085	4024.373
FINAL/INC -7	66.71955	1980.09	-4.19451	1883.418	766.8251	2119.603	511.3905	2000.837	-4407.75	5020.04	-3294.62	5055.091
FINAL/INC -8	-633.95	1952.546	-433.804	2007.851	-2550.11	2075.926	-2413.84	2155.373	6838.503	5016.723	7644.922	5043.299
Constant	37.66716	3.70***	3569.736	9.95E+08	37.65777	3.705***	3569.751	9.89E+08	37.55556	3.706***	3570.51	1.00E+09
Card Balan/Limit			5.800172	0.610***			5.800124	0.610***			5.800643	0.61***
Card Limit			255.8557	14.89***			255.8562	14.89***			255.884	14.89***
FICO			0.5696	0.052***			0.569632	0.05***			0.56943	0.052***
Age			-157.448	2.45E+07			-157.448	2.43E+07			-157.473	2.47E+07
N		161368		153815		161368		153815		161368		153815
F		27.41		42.30		27.41		42.32		27.29		42.23
R^2		16.25		21.10		16.25		21.11		16.25		21.11
Cumulative FINAL	-4367.21	6359.015	-3713.96	6668.097	-7430.84	6750.874	-7318.37	7124.022	10816.19	18083.45	15339.05	18183.44

Table 8. Quadratic Specification – Relative Magnitude Hypothesis

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

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

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.

	Credit Card Consumption				Change in Credit Card Debt			
	No Controls (Z)		With Controls (Z)		No Controls (Z)		With Controls (Z)	
Indep Var (lag)	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.	Coeff	s.e.
FINAL/INC -0	5467.441	6520.081	4943.616	6217.623	-170.301	2739.558	136.3628	2603.008
FINAL/INC -1	6557.282	5349.85	5452.798	5139.461	4915.476	2787.45*	4591.102	2733.11*
FINAL/INC -2	8450.431	7209.684	7997.201	7072.307	405.5828	3029.062	379.4706	3001.862
FINAL/INC -3	-2615.3	4639.521	-2491.52	4478.062	158.5124	2160.297	286.4102	2098.344
FINAL/INC -4	17625.79	6753***	17703.31	6603***	4137.479	2476.17*	4660.463	2448.63*
FINAL/INC_SQ -0	-44638.2	98630.03	-45727	94219.09	-29758.7	40033.95	-35334.3	36317.22
FINAL/INC_SQ -1	-125335	86041.16	-116140	79298.22	-62680.2	38797.56	-61534	37829.7*
FINAL/INC_SQ -2	-64550.9	81184.18	-57467.9	79627.46	-20734.9	46587.66	-18848.4	46301.72
FINAL/INC_SQ -3	36681.14	79062.72	35933.63	74813.26	-15127.5	26612.05	-15569.3	25536.28
FINAL/INC_SQ -4	-181231	106900.*	-180053	103490*	-68995.9	28477**	-71410.8	28802**
Constant	832.8172	9.276***	-2400.79	2.30E+08	34.85747	3.548***	-1519.25	1.15E+07
Card Balan/Limit			8.473289	0.558***			4.996997	0.352***
Card Limit			334.5402	28.15***			155.6173	7.188***
FICO			0.656064	0.078***			0.47404	0.034***
Age			-12.1517	5663246			-8.3841	284029.4
n		271180		258826		238241		227129
F		20.18		32.05		25.62		46.93
R^2		72.20		72.94		13.47		17.81
Cumulative FINAL	36575.49	17719**	34114.59	17310**	14532.53	6833**	14508.55	6765**
Cumulative FINAL_SQ	-459771	262669*	-433868	248691*	-230219	80933***	-228897	83540***

TABLE 9: 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).

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