Over Indebtedness and Depression: Sad Debt or Sad Debtors?

Daniel Hojman[*] Alvaro Miranda [†] Jaime Ruiz-Tagle[‡]

First Version: December, 2011
This version: October, 2013

Abstract

In the last decades, consumer debt experienced a marked increase in the United States, Latin America and other emerging countries, spurring a debate about the real costs and benefits of household credit. This paper explores the psychological costs of over indebtedness. Using a unique dataset with detailed health and balance sheet information of a large sample of Chilean households we construct depression measures based on a questionnaire used in standardized medical diagnosis. We find causal evidence that over indebtedness increases depression and that the effect is large, comparable to half the effect of the loss of a family member. Most of the impact seems to be associated with non-mortgage debt -primarily consumer credit supplied by large retail chains- or late mortgage payments. We explore some of the behavioral and cognitive channels that make over indebtedness psychologically harmful. The probability of over indebtedness is found to be higher for individuals that exhibit self-regulation problems (gambling, smoking, drinking), leading to higher depression. This is a measure of the cost of debt explained by impulsivity in terms of an objective psychological well-being indicator. Individuals with higher numeracy skills are also associated with higher over indebtedness but -ceteris paribus- their overall depression measures are lower. Our findings suggest that self-control and cognitive abilities play a role in explaining sad debt.

Keywords. debt, over indebtedness, credit, depression, subjective well-being.
JEL Classification: D14, G2.

[*]dhojman@fen.uchile.cl. Department of Economics, University of Chile.
[†]amirandas@fen.uchile.cl. Department of Economics, University of Chile.
[‡]jaimert@fen.uchile.cl. Department of Economics, University of Chile

1 Introduction

In the last decades, large segments of the world population have increased their access to credit. In the United States, between 1983 and 2004 the household median debt to income ratio nearly quadrupled and lower to middle income households gained access to mortgages and consumption credit.[1] In Latin America and other emerging countries, the rise of the new middle classes and poverty exit by millions of people over the last decade is a remarkable social change that has also been accompanied by a massive rise of credit uptake.[2] Some of the potential benefits of credit of availability are consumption smoothing and the financing of productive investments such as education or working capital. At the same time, increased access to credit by lower or middle income individuals can be associated to high interest rates, non-bank credit, and, in some cases, predatory credit. Some have argued that expensive liquidity could cause more harm than good, leading to over indebtedness, financial distress (White, 2007; Skiba and Tobacman, 2009), and even underinvestments in health and education (Melzer, 2011).

This has fueled a debate in two fronts. First, on the positive side, it seems important to understand the real costs of credit. Specifically, borrowing and debt burden may not reveal optimal choices but can instead be associated with self-control problems, overconfidence and cognitive limitations that lead to mistakes; or they could be associated with market failures -poor credit screening, lack of consumer information and financial literacy, or predatory credit.[3] Second, in the aftermath of a crisis sparked by the the collapse of subprime credit, it has spurred a policy debate on the potential economic and social impact of household over borrowing on financial stability and the regulation credit supply and access (IMF, 2006; Zinman, 2010).

This paper explores the psychological costs of over indebtedness. We use a unique dataset of Chilean households and show a robust causal effect of over indebtedness

[1]The median debt service to income ratio among all households rose from 5% in 1983 to 13% in 2007; the share of households with debt service obligations that exceeded 40% of income rose from 4% in 1983 to 11% in 2007. The share of households with debt increased more for lower-income households than higher-income households (Dynan, 2009). The percentage of the lowest quintile having a positive credit card debt increased from 12.3% in 1983 to 29% in 2004 (Scholz and Seshadri, 2009) .

[2]The growth of household debt in the last fifteen years is common to Latin America and other emerging countries (IMF, 2006, chapter 2). In Brazil, for example, debt service to income increased from 16% in 2005 to 36% in 2011 (IMF, 2013). Colombia and Chile show similar growth rates in the last decade.

[3]Laibson et al. (2003, 2007) and Gross and Souleles (2002) provide evidence supporting the view that self-control can be central to explain debt increase in the United States. The importance of bounded cognition in financial decisions has been widely documented by a body of work behavioral finance (Thaler, 1993, 2005; Thaler and Benartzi, 2004). A recent discussion of the interaction between behavioral biases, information asymmetries and financial regulation can be found in Campbell et al. (2011). See also Bertrand and Morse (2011).

on psychological well-being. The Chilean case is interesting to explore for several reasons. First, since the 1990s there has a been an explosive growth of consumer credit, especially in lower-middle and middle income households. This boom has been largely driven by non-banking credit provided by retail stores, supermarkets, pharmacy chains and large department stores. From 2003 to 2009, the ratio of debt to income increased 35% and consumer credit increased at a rate of 12% per year.[4] In 2008 the number of credit cards was more than 19 million, more than one per capita, where 50% was offered by retailers and other non-bank credit suppliers. Second, Chile has one of the highest rates of depression prevalence in the world. A striking 17% of the adult population is estimated to have suffered this illness in 2010.[5] Indeed, a comparative study with subjects from fifteen countries around the world showed that, in 1999, Santiago was the capital with the highest depression symptoms by a fair margin (Simon et al., 1999). Finally, our dataset is very rich and especially well suited for the question in hand. We use a large nationally representative longitudinal household survey, the Social Protection Survey (SPS), that includes complete household balance sheets, detailed health information and a rich set of controls (demographics, socioeconomic variables, labor history, household characteristics, medical history, time and risk preferences, among others). Our measure of over indebtedness is based on the ratio of unsecured debt on household income. To measure depression, we take advantage of a module of survey questions used to clinically diagnose depression in the mental health profession (CES-D short form as in the United States Health and Retirement Study). Each question has a binary score, allowing us to construct a depression index -that aggregates these answers for each individual- and resembles the ones used by physicians.

Our first set of results provide correlational evidence and show a positive and significant relationship between over indebtedness and depression. Interestingly, a decomposition of the different types of debt shows that the (conditional) correlation is driven by consumer debt and mortgage delinquency. Over indebtedness associated with non-delinquent mortgages is not significantly correlated with depression.

Next, we tackle the issue of causal identification. Identifying a causal effect of over indebtedness on depression is complicated given the possibility of reverse causality or a spurious correlation. Our identification strategy takes advantage of

[4] See Ruiz-Tagle et al. (2013) for a recent characterization of debt in Chile.

[5] A recent study showed that, for a sample of ten high-income countries that included France, Germany, Japan and the United States, among others, the mean 12-month prevalence of depression was 5.5%. The United States was at the top of this list with a prevalence of 8.3%. For eight low and middle income countries, including Brazil and Colombia, the mean of the 12-month prevalence found by the study was 5.9% and Brazil had the highest prevalence with 10.7% (Bromet et al., 2011). The Chilean prevalence rate nearly triples the average across countries and is significantly higher than the highest prevalence rate in the study. A similar picture arises if we consider the prevalence of depression over a lifetime. For the sample of high income countries the prevalence is 15,5%, for the low and middle sample it is 11%, and the number for Chile is estimated to be 21%.

the variation in geographical access to retail chain stores, the main non-bank credit providers. A key source of non-mortgage credit for most of the population is provided by retail chain stores.[6] Indeed, three out of four individuals that, according to our measure, fall in the group of those over indebted, have non-mortgage credit supplied by retailers. For this group, the median monthly income was $530 dollars, and the median non-mortgage debt was $1,876 dollars. On average, 60% of this consumer debt was with retail stores.[7] The instruments we use measure geographic access to commercial retailers -the number of retail stores located in the municipality and in the province where the individual resides- as an instrument for over indebtedness. We find a significant causal effect of large magnitude. As a robustness check, we use an entirely independent identification method -a non-linear bivariate probit model- that confirms the causal effect of over indebtedness on depression and the magnitude of this effect.

The final set of estimates identifies heterogeneous effects in the population. We are primarily interested in exploring the behavioral and cognitive channels that could make over indebtedness psychologically harmful. Specifically, two systematic departures from the traditional "homo economics" highlighted in the psychology and economics literature are limited self-control and limited cognitive resources. We distinguish between the direct effect that measures the impact of different behavioral characteristics on depressiveness and the indirect effect that measure the extent to which different behavioral characteristics are associated with different levels of over indebtedness and, affecting depression through excessive debt. The overall contribution of a behavioral characteristic on depression is the sum of these two effects. First, using different measures of individual self-control -measures of gambling, drinking and smoking habits- we find, as expected, that lower self-control is associated with a statistically significant higher probability of over indebtedness. We find that the direct effect of self-regulation on depression is weak or non-existing. Thus, self-regulation problems are associated with a higher depression index mostly due to a higher debt burden relative to individuals with lower inclination to behaviors often associated with impulsivity. More depression is a cost of the debt associated to lack of self-regulation. Second, we construct individual measures of numeracy skills derived from the responses to basic arithmetic questions in the survey. We show that individuals with higher scores are also associated with a higher probability of over indebtedness but, at the same time, they exhibit lower levels of depression as the direct effect more than compensates the indirect effect.

[6]As argued later, while the opening of retail stores is certainly associated to observable characteristics of a municipality -demographics, socioeconomic variables, property prices, etc.- it is uncorrelated with depression at the time of introduction.

[7]The annual interest rates associated to this consumer loans between 2009 and 2012 has ranged between 40 and 57%, the highest ones observed in the Chilean financial market. Thus, it seems fair to say that is this is probably a marginal source of credit for most of these debtors.

Our paper contributes to the literature of economic determinants of subjective well-being in economics and public health. While there is substantial recent work showing a correlational association between financial stress, indebtedness and negative physical and mental health (Brown et al., 2005; Drentea and Lavrakas, 2000; Drentea, 2000; Reading and Reynolds, 2001; Zimmerman and Katon, 2005) there are few papers that show a causal link. More closely related to our paper, Bridges and Disney (2010) estimate a recursive bivariate probit model to identify a causal link between a measure of self-reported depression and a subjective measure of financial stress and find a significant positive effect. Our work is complementary as it confirms their qualitative findings but differs in a number of dimensions. First, we use measures of depression based on the ones used by physicians to diagnose the illness and objective measures of financial strain based on households' balance sheets, i.e., our implications are not based on the relationship between two subjective reports. Second, the authors use a sample of families with children in the UK, where the respondent is normally a female, while we use sample representative of national adult population of Chile. Third, our identification is based on a novel instrumental variable approach that exploits variation in geographical access to non-bank credit providers in line with Melzer (2011). Finally, we estimate the "depression cost" that could be associated to self-control problems and bounded cognitive resources.

Importantly, our work tries to elicit some of the channels that could mediate the relation between over indebtedness and psychological discomfort and find that behavioral and cognitive channels such as impulsivity and cognitive abilities, may be an important determinant of the sad consequences of debt. In this sense, our paper contributes to a vast research agenda in psychology and economics that shows that impulsivity and bounded rationality can lead observed behavior to depart from welfare maximizing behavior (Schelling, 1984; Akerlof, 1991; Laibson, 1997; Bernheim and Rangel, 2009, Green and Hojman, 2009). Previous work in this area has emphasized that models that rationalize over borrowing at excessive interest rates -such as intensive and extensive credit card use and pay-day loans- are either consistent with present-biased motivation or overconfidence (Laibson, 1997; Angeletos et al., 2001; Skiba and Tobacman, 2008; Skiba and Tobacman, 2009). More recently, using pay-day loans data for the U.S., Melzer (2011) has shown that this type of credit is casually associated to costs such as lower investments in health and children education. Skiba and Tobacman (2009) show that pay-day loan creditors are more likely to engage in criminal behavior. Presumably, at least in some cases, these portfolio choices are associated with lower well-being. Our work finds direct evidence that one of the costs of over indebtedness at high interest rates is precisely lower psychological well being and, at least part of this suffering, seems consistent with the discrepancies between choice and welfare highlighted by previous work in psychology and economics.

The rest of the paper is organized as follows: Section 2 describes the data and introduces our measures of depression and over indebtedness. Section 3 presents the empirical strategy. Section 4 presents the estimation results. Section 6 concludes.

2 Data, Depression and Over Indebtedness Measures

The main source for our data is the Chilean Social Protection Survey (SPS; Encuesta de Protección Social). The SPS is a longitudinal household survey that aims to characterize the social protection and the labor market conditions in Chile for adult individuals. We use information from all four rounds of the SPS panel -2002, 2004, 2006 and 2009. For the year 2009, the only year containing a section with a depression diagnostic survey, the sample consists of 14,463 individuals and is representative of the population over 18 years old. The survey contains information on income, employment history, assets, debts, pensions, health, individual history, family events (e.g. births, divorce, deaths, changes in household composition), family history, cognitive and non-cognitive skills.

As mentioned earlier, there is no abundance of high-quality financial data combined with health data. In contrast to previous studies on the economic determinants of psychological well-being that rely on self-reported responses to mental illness, we are able to construct measures of psychological distress using clinical diagnostic questions included in the survey. At the same time, using household financial balance sheets, we are able to produce objective measures of over indebtedness, and decompose the different sources of credit. The SPS also allows for a rich set of controls. We now concentrate on explaining our psychological distress and financial stress measures.

2.1 Psychological distress measures

The measures of psychological distress that we use are based on a set of eight questions that aim to capture some aspects of the respondents depressive symptoms. The questionnaire coincides with the "Short Form of the Center for Epidemiological Studies Depression Scale (8 questions)". This scale is used to diagnose depression and has also been included in other surveys such as the "American Health and Retirement Study". The questions are the following:

(1) Have you felt depressed?
(2) Have you felt that everything you do is an effort?
(3) Have you felt that your sleep is restless?
(4) Have you ever felt alone?
(5) Have you felt happy?

(6) Have you felt that you enjoy life?
(7) Have you felt sad?
(8) Have you felt you could not get going?

The answers to these questions are used to generate a psychological distress measure, referred as the *depression index*. Specifically, for each respondent i and each question $j \in \{1, ..., 8\}$ a binary variable d_{ij}, is created, taking the value 1 if the answer to the question indicates a state of psychological distress and 0 otherwise.[8] The index for individual i, d_i, is defined as follows:

$$d_i = \sum_{j=1}^{8} d_{ij}. \tag{1}$$

That is, d_i is simply the sum of the binary variables associated with each question, d_{ij}, so that the index takes values between 0 and 8. The average of the index in our sample is 3.6 and its standard deviation is 2.4.

Using the depression index, we construct a *depression binary indicator* D_i, which takes the value of 1 if the individual has a score D_i greater than or equal to a threshold value $\hat{d}$, and zero otherwise. The indicator also allows for a "depression diagnostic" interpretation with some caution. Formally,

$$D_i = \begin{cases} 1 & \text{if } d_i \geq \hat{d}, \\ 0 & \text{if } d_i < \hat{d}. \end{cases}$$

The choice of the threshold value $\hat{d} \in \{1, 2, ..., 8\}$ comes from calibrating the index to the national diagnosed depression rate. In particular, $\hat{d}$ is such that the share of people with $D_i = 1$ -a "positive diagnosis"- is the smallest upper bound to the share of people diagnosed with depression in the Chilean adult population. According to the Chilean National Health Survey the prevalence of depression in Chile in the year 2009 was 17.2% of the population.[9] Given the distribution of the psychological distress index, we chose $\hat{d} = 6$ as the threshold, as it implies that 26% of the individuals in our sample have a psychological distress binary indicator equal to 1.[10]

[8] For example, if the answer to question 2 (*Have you felt that everything you do is an effort?*') is positive, then $d_{i1} = 1$; if the answer to question 6 (*Have you felt that you enjoy life?*) is negative, then $d_{i6} = 1$; and so on. A detailed account of this construction is presented in the Appendix A.

[9] The NHS considers a sample of 5,000 individuals representative of the Chilean population and identifies depression by the direct diagnosis of a mental health professional.

[10] Using $\hat{d} = 5$ yields a share of individuals with a psychological distress indicator equal to 1 of 38%, while $\hat{d} = 7$ yields a hare of 12.8%. Using the equivalent set of questions in the American Health and Retirement Study, Steffick (2000) uses a threshold of $\hat{d} = 4$ for a population of Americans aged 45 and over.

Importantly, our statistical results are robust to different choices of the threshold.[11]

We verify that our index and the binary indicator based on the survey questions is consistent with diagnosed depression. Indeed, the SPS asks respondents to report if they have ever been diagnosed with depression.[12] The simple correlation between the psychological distress index and a dummy variable that takes value 1 if the individual reports a diagnosis of depression and zero otherwise, is 0.32 and 0.30 for the binary indicator.

In addition, our measures show differences across basic socio demographic groups that are consistent with self-reported diagnosis and medical diagnosis, as seen in Table 1. Both the index and the binary indicator capture rather well the gender and educational level differences observed in the official depression figures in the 2009 National Health Survey: the index is consistently higher for women; the higher the educational level the lower the index value for both males and females. The higher psychological distress for older populations captured by our index is consistent with self-reports of diagnosed depression reported in the survey. In sum, we believe our psychological distress index and our binary indicator seem to capture rather well the main features of captured by medical data.[13]

Descriptive statistics of our data appear in Tables 2 and 3. Being a female, having a lower household income or education level, and being older are associated with a higher average depression index and with a greater percentage of individuals with a depression binary indicator equal to 1. The average value of the psychological distress index is greater for individuals who are unemployed or inactive relative to employed individuals. The same applies to widowers or separated individuals relative to those single or married. Having young children does not seem to be associated with greater psychological distress measures. However, those with older children have lower psychological well-being compared to individuals without children. The table also shows that the average of the psychological distress index is higher for obese individuals (Body Mass Index - BMI - of 30 or more),[14] those having a chronic disease, cancer, and those with inpatient treatment in the past two years. The same applies to individuals who have a family members diagnosed with depression or who have been diagnosed with depression at some point in life.

[11] Results using other threshold values are available upon request.

[12] The total share of the sample that responded affirmatively when asked about a previous diagnostic of depression is 9.3%, relatively low compared with the 21% from the NHS. This suggests considerable under-reporting of diagnosed depression. In contrast, the measures we construct rely on the current psychological state, finer information based on several questions, and a standardized scale used by the medical professionals to diagnose depression.

[13] We note that the NHS data shows a decline in depression rates for those above 65 years old that is not completely captured by our measures nor self-reported depression diagnosis.

[14] The survey includes information on self-reported height and weight that was used to calculate the BMI.

Table 1: Depression Index (d_i) , Depression Binary Indicator (D_i) and Depression prevalence by gender, educational level and age

	d_i SPS 2009			D_i SPS 2009 (% Prevalence)			Self-reported Diagnosed Depression SPS 2009 (% Prevalence)			Clinically Diagnosed Depression NHS 2009 (% Prevalence)		
	Male	Female	Total	Male	Female	Total	Male	Female	Total	Male	Female	Total
Primary Education	3.3	4.6	4.0	21.3	43.0	32.0	4.7	17.7	11.1	13	27	21
Secondary Education	2.9	4.0	3.4	16.1	31.8	23.9	2.2	12.8	7.5	8	29	18
Terciary Education	2.6	3.4	3.0	12.6	22.0	17.6	4.4	11.6	8.2	7	17	12
<24	2.6	3.8	3.2	17.6	25.7	21.5	1.4	5.7	3.5	8	22	14
25 to 44	2.8	3.9	3.4	15.7	29.9	23.0	2.8	11.4	7.2	11	28	19
45 to 64	3.1	4.4	3.8	18.5	39.1	28.8	3.5	17.9	10.7	7	30	19
65+	3.1	4.2	3.6	19.8	33.9	26.9	5.6	14.6	10.1	4	17	11
Total	3.0	4.1	3.6	17.6	34.3	26.0	3.6	14.5	9.1	9	26	17

Source: Author's calculations based on SPS 2009 and NHS 2009.

On average, the death of husband/wife and/or a child is associated with a higher value of the depression index. Finally we can observe that the index is higher for individuals that had a foster parent and those with no assets (such as cars, houses, machinery or financial assets).

Table 2: Depression Index (d_i) , Depression Binary Indicator (D_i) by individual characteristics

	%	d_i	D_i (%)
Total		3.6	26.0
Male	49.6	3.0	17.6
Female	50.4	4.1	34.3
$<$ 24 years old	1.2	3.2	21.5
25 to 44 years old	40.3	3.4	23.0
45 to 64 years old	40.6	3.8	28.8
65+ years old	17.9	3.6	26.9
Primary Education	40.5	4.0	32.0
Secondary Education	40.7	3.4	23.9
Terciary Education	18.7	3.0	17.6
Income Quintile I	20.2	4.0	33.7
Income Quintile II	19.9	3.8	29.0
Income Quintile III	20.2	3.6	26.7
Income Quintile IV	19.8	3.4	23.8
Income Quintile V	20.0	3.0	16.9
Employed	60.7	3.2	20.6
Unemployed	8.8	4.1	33.4
Inactive	30.5	4.1	34.7
Married	62.5	3.4	23.1
Separated	9.6	4.2	35.6
Widower	7.0	4.5	39.3
Single	21.0	3.5	25.8
No children	24.3	3.3	23.0
Has under 1 year old children	1.1	2.7	12.1
Has children between 2 and 4 years old	2.6	3.1	17.0
Has children between 5 and 13 years old	18.4	3.5	24.5
Has children between 14 and 18 years old	23.1	3.8	28.3
Has children over 18 years old	30.5	3.8	29.0
BMI$<$30	80.3	3.5	24.6
BMI$\geq$30	19.7	3.9	31.7

Source: Author's calculations based on SPS 2009.

Table 3: Depression Index (d_i) , Depression Binary Indicator (D_i) by individual characteristics (continuation)

		%	d_i	D_i (%)
Total			3.6	26.0
Drinks Alcohol	No	61.2	3.8	29.4
	Yes	38.8	3.3	20.6
Smokes	No	69.4	3.5	25.4
	Yes	30.6	3.7	27.4
Has a chronic disease	No	70.9	3.3	22.2
	Yes	29.1	4.2	35.4
Has cancer	No	98.0	3.6	25.7
	Yes	2.0	4.5	41.1
Has been inpatient in last 2 years	No	89.1	3.5	25.1
	Yes	10.9	4.1	33.8
Has newborn	No	98.4	3.6	26.0
	Yes	1.6	3.9	30.2
Relative diagnosed with depression	No	93.2	3.5	25.4
	Yes	6.8	4.3	34.7
Has been diagnosed with depression	No	90.9	3.3	22.0
	Yes	9.1	6.0	66.4
Close familiar passed away	No	97.3	3.5	25.5
	Yes	2.7	4.9	45.9
Had foster parents	No	97.4	3.6	25.8
	Yes	2.6	4.1	33.4
Fatherless	No	95.0	3.6	26.0
	Yes	5.0	3.7	26.2
Home owner	No	22.7	3.7	27.4
	Yes	77.3	3.6	25.6
Car owner	No	74.6	3.8	29.2
	Yes	25.4	3.0	16.8
Owns machinery	No	95.1	3.6	26.2
	Yes	4.9	3.4	22.7
Holds financial assets	No	75.4	3.6	27.4
	Yes	24.6	3.4	21.7

Source: Author's calculations based on SPS 2009.

2.2 Financial stress indicators

There is no consensus in the household finance literature on how to identify an over indebted household. Based on data availability, several measures have been proposed, including debt to income ratios, financial service ratios, number of debts and number of arrears, among others, with the primary goal of forecasting credit defaults. There are two main sources of households' indebtedness, mortgage debt and consumer debt. Although mortgage debt typically implies a large debt with a significant monthly debt service, in Chile, the majority of households do not hold mortgage debt. As seen in Table 4, only 11.6% of the households in our sample hold this type of debt. In parallel, consumer debt typically implies high interest rates and large service ratios with short-run repayment obligations, being much more spread out among households. According to our data, in 2009, 46.5% of Chilean households hold some consumer debt.

Previous studies have used proxies of subjective financial stress measures, mostly self-reported financial stress measures.[15] In this paper we use more precise measures of objective financial stress based on household balance sheets following the household finance literature. In particular, we use financial service to income ratio for consumer and mortgage debt, plus information on mortgage arrears.

Our financial stress indicators are based on the respondents' report of the amounts of consumer debt (bank consumer loans, bank credit cards, and retailers credit cards) and mortgage debt held by the interviewee and her/his spouse. With this information, and assuming an average interest rate for each type of debt and debt repayment deadlines, an average estimated monthly payment MP_i^k is computed for each type of debt k, for each household i in the survey.[16] We compute a measure of financial burden relative to monthly household income I_i for each type of debt k, the financial service ratio, as $FSR_i^k = MP_i^k / I_i$. Adding over all types of consumer debt we obtain the consumer debt financial service ratio FSR_i^C; the mortgage financial service ratio is denoted FSR_i^M, and total financial service ratio is FSR_i^T.[17]

[15] Bridges and Disney (2010) attempt to go one step further by incorporating 'objective' financial stress measures. They find a positive association between self-reported financial stress and objective measures of financial well-being. However, they find that the link between objective financial well-being and psychological stress is weak, in contrast to our findings. Still, the quality of the financial well-being measures in the Bridges and Disney data can be questioned as they do not have detailed information on balance sheets. Instead, they build financial stress measures based on saving accounts holding, credit card access, use of a formal loan, number of debt arrears, and amount of arrears.

[16] The standard formula for the monthly payment is $MP_i^k = \frac{Q_i^k}{\sum_{l=0}^{R^k} \frac{1}{(1+r^k)^l}}$, where Q_i^k is the amount of debt of type k held by household i, R^k is the average residual period (in months) of debt type k, and r^k is the monthly interest rate of debt type k. The interest rates and residual terms used are in Appendix B.1.

[17] We truncate outliers above 2 in FSR_i^T, FSR_i^M, and FSR_i^C.

Table 4: Indebtedness and Financial Stress Indicators

	% Households Holding Corresponding Debt	Average FSR All sample	Average FSR Debt Holders Only	Median FSR Debt Holders Only	% MA_i All sample	% Over Indebted All sample
Total Debt	50.9	0.24	0.48	0.25		
Mortgage Debt	11.6	0.03	0.26	0.19	2.0	
Consumer Debt	46.5	0.22	0.47	0.23		18.0
Consumer Debt Only						
Male	45.5	0.21	0.45	0.23	1.8	17.6
Female	47.5	0.23	0.48	0.23	2.3	18.5
< 24 years old	52.1	0.18	0.34	0.11	0.7	12.5
25 to 44 years old	52.8	0.25	0.48	0.25	2.6	21.0
45 to 64 years old	48.3	0.23	0.48	0.23	2.4	19.1
65+ years old	28.3	0.11	0.40	0.16	0.2	9.4
Primary Education	33.0	0.16	0.47	0.22	1.0	12.7
Secondary Education	51.8	0.26	0.50	0.25	3.0	21.6
Terciary Education	64.4	0.26	0.40	0.21	2.3	22.1
Income Quintile I	34.9	0.29	0.82	0.50	2.1	21.2
Income Quintile II	41.3	0.22	0.53	0.29	2.5	19.0
Income Quintile III	43.5	0.19	0.44	0.23	1.8	16.7
Income Quintile IV	51.3	0.19	0.37	0.19	2.3	16.8
Income Quintile V	61.8	0.20	0.32	0.16	1.4	16.6
Unemployed	53.8	0.23	0.43	0.22	2.4	19.8
Employed	39.2	0.28	0.72	0.41	2.5	21.3
Inactive	34.3	0.17	0.49	0.23	1.1	13.7
Married	50.4	0.24	0.48	0.24	2.5	20.1
Separated	44.8	0.26	0.57	0.25	2.7	19.1
Widower	25.7	0.10	0.39	0.15	0.6	8.2
Single	42.9	0.17	0.40	0.20	0.9	14.6
No children	38.8	0.16	0.41	0.19	0.5	12.5
Has under 1 year old children	59.1	0.25	0.42	0.21	0.8	18.2
Has children between 2 and 4 years old	55.9	0.24	0.43	0.26	2.5	20.7
Has children between 5 and 13 years old	53.5	0.27	0.51	0.27	2.8	22.8
Has children between 14 and 18 years old	53.1	0.27	0.50	0.25	3.9	22.2
Has children over 18 years old	42.3	0.19	0.45	0.21	1.4	16.2

Source: Author's calculations based on SPS 2009.

The descriptive statistics of our financial service ratio indicators are shown in Table 4. We can observe that, for the whole sample, the average FSR^T shows that households spend 24% of their monthly income in debt service. However, if we consider only those households that hold positive consumer debt, this figure increases to 48%. This is a large number as it indicates that almost half of monthly income is spent servicing debt. The figures for consumer debt (FSR^C) are similar, reaching 22% and 47% respectively. This reveals that most of the financial service comes from consumer debt. Nevertheless, it is important to note that the distribution of the FSR^C measure is highly skewed to the right, ie, the median is significantly lower than the mean, reaching only 25% for all debt, and 23% for consumer debt (among debtors). A number of features emerges from Table 4. A life-cycle pattern is suggested by the fact that middle-aged individuals exhibit larger FSR^C indicators, in line with the consumption/savings literature (Carroll, 1997; Laibson, 2001). Individuals with more education are more likely to hold consumer debt (reflecting a wider access for them), but tend to have lower indebtedness. The same pattern can be observed by income quintile. On the other hand, the needs effect on the demand is reflected in larger FSR^C for those with children of different ages.

Beyond the financial service ratio, we use mortgage arrears as an additional objective financial stress indicator, also reported in the survey. We use this information to compute a binary indicator MA_i equal to 1 if household i has mortgage arrears and 0 otherwise. We can observe from Table 4 that 2% of households report arrears. Those households are mostly middle aged, female household headed. Finally, in addition to the FSR^C, we consider a binary indicator of over indebtedness. This indicator, OI_i, is a dummy variable taking the value 1 if the FSR_i^C indicator is above a threshold value $\overline{FSR^C}$ and 0 otherwise. The interpretation is that $OI_i = 1$ corresponds to an over indebted individual. As discussed later, we choose $\overline{FSR^C} = 0.34$ using a statistical optimality criterion. We observe that 18% of our sample is classified as over indebted. Middle-aged and highly educated individuals are more likely to be over indebted. However, over indebtedness is relatively more frequent among low and middle income individuals.

2.3 Other controls

Our set of controls includes standard socioeconomic and demographic factors such as income, education, employment status, age and family composition. More importantly, given the multiplicity of factors present in the onset of depression, it is desirable to isolate the propensity to have depression as much as possible (Zimmerman and Katon, 2005). Since depression has a high biological and environmental component, we include controls for whether the respondent or any person in the family has ever been diagnosed with depression in their lives, and other controls related to non-cognitive skills coming from the TIPI test (Ten-Item Personality Inventory test, Gosling et al., 2003) that have been recently used in the economic literature (Heckman, 2011). Other medical factors such as the onset of cancer, other diseases, BMI, drinking habits, are also included. Moreover, we include important life events such as changes in the family composition, children ages, death of close relatives, divorce, among others. Given the multiple factors that can affect depression, an important strength of this paper is the large set of controls that we are able to incorporate.

3 Sad Debt

This section provides correlational evidence on the relationship between our measures of depression and over indebtedness. Our main focus is to identify the association between psychological distress and over indebtedness for specific types of debt. We estimate variations of the following linear model:

$$d_i = X_i'\beta + \delta f_i + \varepsilon_i, \tag{2}$$

where d_i is the psychological distress index defined in the previous sections, X_i corresponds to a vector of controls, f_i is a measure of financial stress, and ε_i is the error term. The variations considered differ either on the estimation method or on the measure of financial stress considered. Specifically, we consider two different methods, OLS and ordered probit estimation.[18]

The first measure of financial stress f_i we use is the ratio of financial service over income ratio (FSR^T) introduced in the previous section. An important variation of (2) considers a decomposition of the different types of financial burden. Specifically, we consider

$$d_i = X_i'\beta + \delta_1 FSR_i^M + \delta_2 FSR_i^C + \delta_3 MA_i + \varepsilon_i. \tag{3}$$

where FSR_i^M, FSR_i^C, and MA_i are measures of financial burden associated to mortgage, consumer debt and mortgage arrears, respectively, as presented in the previous section.

[18]The OLS strategy is the most straightforward but it assumes that the dependent variable is continuous. Since the psychological distress index takes discrete ordered values from 0 to 8, the ordered probit tackles this issue. For the ordered probit approach we can assume that there is a latent variable d_i^* that determines the level of psychological distress that the econometrician observes, d_i.

Table 5: OLS estimates for the effect of Total Financial Service Ratio on the Depression Index

Dependent Variable: Depression Index (d_i)					
FSR$_i^T$	0.300***	**Has under 1 year old children**	-0.402***	*Assets*	
	(0.0424)		(0.105)	**Car owner**	-0.314***
Socio Demographics		**Has children between 2 and 4 years old**	-0.0345		(0.0490)
Female	0.616***		(0.0735)	**Owns machinery**	0.0554
	(0.0464)	**Has children between 5 and 13 years old**	0.131**		(0.0903)
Age	0.0320***		(0.0509)	**Holds financial assets**	-0.0198
	(0.00928)	**Has children between 14 and 18 years old**	0.192***		(0.0451)
Squared age	-0.000385***		(0.0502)	**Home owner**	-0.119**
	(8.71e-05)	*Health problems*			(0.0473)
Income Quintile I	0.278***	**Has a chronic disease**	0.505***	**Relative Income**	0.0947**
	(0.0799)		(0.0492)		(0.0464)
Income Quintile II	0.266***	**Has cancer**	0.294**	*Personal History*	
	(0.0710)		(0.139)	**Family member recently passed away**	0.758***
Income Quintile III	0.120*	**Has been inpatient in last 2 years**	0.423***		(0.136)
	(0.0667)		(0.0632)	**Had Foster parents**	0.243**
Income Quintile IV	0.122*	**Has newborn**	0.467***		(0.123)
	(0.0626)		(0.156)	**Fatherless**	-0.0579
Years of Schooling	-0.0572***	**Relative diagnosed with depression**	0.440***		(0.0880)
	(0.00594)		(0.0760)	*Health risk factors*	
Unemployed	0.337***	**Has been diagnosed with depression**	1.846***	**Obesity**	0.170***
	(0.0763)		(0.0597)		(0.0499)
Inactive	0.300***	*Non cognitive skills*		**Smokes**	0.361***
	(0.0564)	**Emotional Stability**	-0.179***		(0.0444)
Family Characteristics			(0.0199)	**Drinks alcohol**	-0.0104
Married	-0.234***	**Agreeableness**	0.151***		(0.0435)
	(0.0595)		(0.0226)	**Constant**	2.961***
Separated	0.259***	**Openness to Experience**	-0.0464***		(0.361)
	(0.0826)		(0.0176)		
Widower	0.108	**Extraversion**	-0.154***	**Regional Dummies**	YES
	(0.106)		(0.0198)		
Has no children	-0.0886	**Conscientiousness**	0.00733	**Observations**	12,259
	(0.0576)		(0.0218)	**R-squared**	0.221

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The OLS estimates are shown in Table 5. The conditional correlation of indebtedness on the depression index is found to be positive and highly significant in the simple linear model. The parameter for total financial service ratio, FSR^T, is estimated at 0.30. Since the standard deviation of the psychological distress index is 2.4, the coefficient indicates that an increase of the financial service ratio indicator of one unit is expected to increase the depression index by 12.5% standard deviations (since the average of the index is 3.6, an increase of one the standard deviation raises the index to a value of 6, which is precisely the threshold we use for the depression indicator). This is a relatively large effect on depression as it amounts to 40% of the impact of the death of a close relative.

We use a long list of control variables that might affect psychological distress. Most of them are significant with the expected signs. First, we use general sociodemographic controls (column 1 in Table 5). We find a significant gender effect on psychological distress, consistent with the literature (Piccinelli and Wilkinson, 2000). Similarly, age has a positive and significant coefficient. We also observe a socioeconomic gradient as lower income quintiles are more likely to suffer from psychological distress (the omitted category is the the richest quintile). In addition, more educated individuals exhibit significantly less psychological distress. Labor status also seems to matter, as unemployed and inactive individuals are associated with higher psychological distress. Second, we use a set of family characteristics (columns 1 and 2). We observe that married individuals are associated with lower psychological distress, while separated individuals are associated with higher depressiveness. The age of children is statistically significant. Individuals with one-year-old children or younger are associated with a significantly lower depression index, in contrast to those with children between 5 and 18 years old.

Turning to the set of health controls (column 2 in Table 5) we find that chronic diseases, a previous diagnostic of depression, and having a relative diagnosed with depression, are all associated with a higher depression index. We also find that most variables measuring non-cognitive skills are significant -emotional stability, openness to experience, extraversion, agreeableness. On the other hand, assets (car and home ownership) significantly decrease psychological distress. Life events such as the recent death of a close relative significantly increases psychological distress. So does having had foster parents, while growing up fatherless has no significant effect. Finally, health risk factors such as obesity and smoking are significantly associated with a higher depression, while drinking is not statistically significant.

We next turn to a decomposition analysis that investigates if different sources of over indebtedness have different impacts on depression. We do so by estimating different variations of the original model. By separating the types of debt, we find that mortgage financial service ratio, FSR^M, has no significant effect on the depression index (column 2 in Table 6). In contrast, consumer debt financial service ratio, FSR^C, absorbs all of the economic and statistical significance of the relationship with the depression index. Nevertheless, mortgage arrears do have a significant impact on depression (column 3) doubling the effect of consumer debt.

Table 6: OLS estimates for the effect of Financial Stress Indicators on the Depression Index

Dependent Variable: Depression Index (d_i)				
	(1)	(2)	(3)	(4)
FSR$_i^T$	0.300***			
	(0.0424)			
FSR$_i^M$		0.166	-0.0260	
		(0.154)	(0.158)	
FSR$_i^C$		0.300***	0.300***	
		(0.0433)	(0.0433)	
MA$_i$			0.617***	0.608***
			(0.142)	(0.135)
OI$_i$				0.378***
				(0.0506)
Socio Demographics	Yes	Yes	Yes	Yes
Family Characteristics	Yes	Yes	Yes	Yes
Health problems	Yes	Yes	Yes	Yes
Non Cognitive Skills	Yes	Yes	Yes	Yes
Assets	Yes	Yes	Yes	Yes
Personal History	Yes	Yes	Yes	Yes
Health Risk Factors	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes
Observations	12,259	12,259	12,259	12,259
R-squared	0.221	0.221	0.223	0.223

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As mentioned above, there is no consensus in the household finance literature on how to define when an individual is over indebted. In contrast to previous work, that has proceeded by defining an arbitrary fixed threshold $\overline{FSR^C}$, in this paper the threshold is determined endogenously. We do so by selecting the model that maximizes the value of the likelihood function.[19] For this purpose, we use a grid search for the threshold $\overline{FSR^C}$ throughout our OI_i indicator (between 0.1% to 200%). The result of the search is specific to the specific variation of equation (2) considered. In particular, for the OLS estimate the threshold obtained is $\overline{FSR^C} = 0.34$. In the Appendix B.2 we show that the estimates are robust for a wide range of

[19] Disney et al. (2008) suggest that if a household spends more than 25% of its total monthly income on debt payments, it should be classified as over indebted. Others such as Ruiz-Tagle et al. (2013) suggest instead that the over indebtedness threshold should be evaluated considering the particular problem under study.

threshold choices.[20] Using the over indebtedness indicator, we find that it captures all of the effect of the financial service ratio indicator (the coefficient is estimated at 0.37 (column 4 in Table 6). This suggests that while over indebtedness is positively associated with psychological distress, holding a moderate debt service ratio may not be necessarily harmful for the individual.

The OLS estimation results are confirmed by the ordered probit estimates (columns 1 to 4 in Table 7). We observe a significant positive effect of total financial service ratio on depression, where all of the effect is captured by consumer debt (column 2). In addition, we find a significant coefficient for mortgage arrears, reinforcing the idea that arrears is what matters for psychological distress but not necessarily the mortgage debt per se.[21]

Table 7: Ordered Probit estimates of the effect of Financial Stress Indicators on the Depression Index (Coefficients reported)

Dependent Variable: Depression Index (d_i)				
	(1)	(2)	(3)	(4)
$\mathbf{FSR}_i^T$	0.146***			
	(0.0206)			
$\mathbf{FSR}_i^M$		0.0971	0.00556	
		(0.0773)	(0.0798)	
$\mathbf{FSR}_i^C$		0.146***	0.146***	
		(0.0210)	(0.0210)	
$\mathbf{MA}_i$			0.293***	0.293***
			(0.0678)	(0.0647)
$\mathbf{OI}_i$				0.180***
				(0.0245)
Socio Demographics	Yes	Yes	Yes	Yes
Family Characteristics	Yes	Yes	Yes	Yes
Health problems	Yes	Yes	Yes	Yes
Non Cognitive Skills	Yes	Yes	Yes	Yes
Assets	Yes	Yes	Yes	Yes
Personal History	Yes	Yes	Yes	Yes
Health Risk Factors	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes
Observations	12,259	12,259	12,259	12,259

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[20]In Appendix B.2 we present the point estimates and the confidence interval for the grid.

[21]Coincidentally, we found that the threshold value that maximizes the value of the likelihood function is the same as for the OLS model, ie, $\overline{FSR^C} = 0.34$.

Table 8: Marginal effects of Probit estimates of the effect of Total Financial Service Ratio on the Depression Binary Indicator

Dependent Variable: Depression binary indicator (D_i)					
FSR_i^T	0.0417***	**Has under 1 year old children**	-0.0708***	*Assets*	
	(0.00858)		(0.0215)	**Car owner**	-0.0516***
Socio Demographics		**Has children between 2 and 4 years old**	-0.0293*		(0.0101)
Female	0.0889***		(0.0154)	**Owns machinery**	-0.000799
	(0.00950)	**Has children between 5 and 13 years old**	0.0203*		(0.0200)
Age	0.00479**		(0.0111)	**Holds financial assets**	-0.0241**
	(0.00197)	**Has children between 14 and 18 years old**	0.0242**		(0.00962)
Squared age	-5.94e-05***		(0.0108)	**Home owner**	-0.0217**
	(1.84e-05)	*Health problems*			(0.0100)
Income Quintile I	0.0687***	**Has a chronic disease**	0.0647***	**Relative Income**	0.0135
	(0.0185)		(0.0106)		(0.00978)
Income Quintile II	0.0563***	**Has cancer**	0.0448	*Personal History*	
	(0.0165)		(0.0309)	**Family member recently passed away**	0.130***
Income Quintile III	0.0377**	**Has been inpatient in last 2 years**	0.0627***		(0.0323)
	(0.0153)		(0.0142)	**Had Foster parents**	0.0333
Income Quintile IV	0.0391***	**Has newborn**	0.0802**		(0.0256)
	(0.0147)		(0.0398)	**Fatherless**	-0.0182
Years of Schooling	-0.00909***	**Relative diagnosed with depression**	0.0408**		(0.0177)
	(0.00126)		(0.0172)	*Health risk factors*	
Unemployed	0.0544***	**Has been diagnosed with depression**	0.330***	**Obesity**	0.0299***
	(0.0163)		(0.0172)		(0.0105)
Inactive	0.0485***	*Non cognitive skills*		**Smokes**	0.0455***
	(0.0118)	**Emotional Stability**	-0.0309***		(0.00973)
Family Characteristics			(0.00417)	**Drinks alcohol**	-0.00878
Married	-0.0467***	**Agreeableness**	0.0250***		(0.00937)
	(0.0126)		(0.00479)		
Separated	0.0303*	**Openness to Experience**	-0.00815**	**Regional Dummies**	Yes
	(0.0171)		(0.00365)		
Widower	-0.00252	**Extraversion**	-0.0295***	**Observations**	12,259
	(0.0209)		(0.00404)		
Has no children	-0.0115	**Conscientiousness**	0.00185		
	(0.0119)		(0.00448)		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The nature of the psychological distress index makes it relatively difficult to interpret the size of the estimated coefficients from the OLS and Ordered Probit models in Tables 6 and 7. A more intuitive interpretation of the size of the relationship is obtained by using the psychological distress binary indicator presented in the previous section as the dependent variable, and estimating a probit model as the probability of suffering depression. The probit model we estimate is as follows:

$$\Pr(D_i = 1) \quad = \quad \Phi(X_i'\beta + \delta OI_i) \tag{4}$$

where D_i is depression binary indicator, OI_i the over indebtedness indicator, and $\Phi(\cdot)$ is the normal distribution of the probit model. The usefulness of this scheme is that the marginal effects can be interpreted as the change in the probability of having a depression binary indicator equal to one; or with some caution, as the change in the probability of suffering depression.

Table 9: Marginal effects of Probit estimates of the effect of Financial Stress Indicators on the Depression Binary Indicator

Dependent Variable: Depression binary Indicator (D_i)				
	(1)	(2)	(3)	(4)
FSR$_i^T$	0.0417***			
	(0.00858)			
FSR$_i^M$		0.00903	-0.0172	
		(0.0313)	(0.0339)	
FSR$_i^C$		0.0428***	0.0429***	
		(0.00874)	(0.00874)	
MA$_i$			0.0775**	0.0724**
			(0.0330)	(0.0312)
OI$_i$				0.0635***
				(0.0114)
Socio Demographics	Yes	Yes	Yes	Yes
Family Characteristics	Yes	Yes	Yes	Yes
Health problems	Yes	Yes	Yes	Yes
Non Cognitive Skills	Yes	Yes	Yes	Yes
Assets	Yes	Yes	Yes	Yes
Personal History	Yes	Yes	Yes	Yes
Health Risk Factors	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes
Observations	12,259	12,259	12,259	12,259

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The estimate results are presented in Table 8. The sign and the significance of the effects on psychological distress in the Probit estimations are consistent with those of the previous models. Focusing then on the size of the effects, total financial service ratio increases the probability of having high psychological distress in 4.17%. [22] As

[22]Females exhibit a probability of having having high psychological distress 8.9% larger than

a benchmark, the effect of having a close relative recently passed away increases the probability of depression in 13% (column 3 in Table 8).

We observe that the increase in the probability of high psychological distress associated with a change from $OI_i = 0$ to $OI_i = 1$ is above 6%. Moreover, the impact of having mortgage arrears on depression is 7%. These are very large effects, as they amount to half of the impact of having had a close relative that has recently passed away.

4 Identifying a causal effect on depression: Instrumental Variables and Bi-probit Estimation

Identifying the causal effect of over indebtedness on depression is not straightforward given the possibility of reverse causality or a spurious correlation. Our identification strategy is based on instrumental variables that capture differences in the geographic supply of consumer credit. Later, as a robustness exercise, we use an entirely independent method, a bivariate probit model as in Bridges and Disney (2010). Both approaches have different identifying assumptions and, overall, the results obtained are remarkably consistent.

4.1 Instrumental Variables

We use a set of instruments that take advantage of the geographic variation of retail chain stores across municipalities, provinces and regions at the time of the survey. In our sample, 88.4% of the group of over indebted individuals have a standing credit with retailers, and this form of credit represents 60% of consumer credit. This suggests that geographic access to retail chain stores is a good measure of access to non-banking credit providers.[23] The key assumption for identification is that the location of credit could be linked to average socio economic characteristics of the area, but is not correlated with those of each individual, particularly with his psychological distress.

In December of 2009 there were 11 large retail chains with national geographic coverage in Chile and a total of 482 retail stores throughout the country. These chains concentrate 61% of the sales of durable goods, issue more than 77% of credit cards and supply more than 40% of the non-banking credit held by households. The country's territorial administrative division consists of 15 regions, each region is divided into provinces with a total of 53 provinces, and each province is subdivided

males. The large size of the coefficients of unemployment and inactivity (close to 5%) indicates that labor status also matters for psychological distress. On the other hand, children under 1 year old seems to decrease depressiveness in 7%, while having children above 5 years old seem to increase that probability in 2%.

[23] It is also possible that the location of commercial centers is correlated with banks, an thus with access to bank credit as well.

into municipalities with a total of 345 municipalities. Only 12% of the country's population live in rural areas. Using official data from the retail stores industry, we were able to construct an exhaustive list of the stores with their respective locations. Table 10 shows the geographic variation of stores located in each area. Using this information, for each individual in the sample, we generated two measures of access proximity to retail chain stores, A_i^{Mun} and A_i^{Prov}, that respectively designate the number of retail stores in the municipality and province where individual i lives. Maps that illustrate the geographic variation of these variables can be found in Appendix C.

The use of geographical credit access as an instrument requires us to account for the striking centralization of the country. The Metropolitan Region (MR) includes Santiago -the capital- and its immediate surroundings, and concentrates close to seven million inhabitants, nearly 40% of the population of the country in a relatively small area compared to other regions. It also concentrates most of the services, and 44% of the country's GDP. More closely related to the issue in hand, as seen in Table 10, 29% of the stores of the sample are in this region. Many of these stores are located either in centric areas of Santiago, in large regional malls or neighborhood malls. For illustration, at the end of 2009, Santiago had 11 large malls and each included at least one large retail store; these malls are located close to an urban transportation hub and the set covered most of the peripheral areas of the city. This means that almost anyone in Santiago had expedite access to a large retailer that offers credit. Hence, one should not expect the A_i^{Mun} and A_i^{Prov} variables defined above to be particularly informative about access within the MR: most individuals are proximate to multiple stores, and that probably puts them beyond an "access saturation point".[24] In contrast, at most one regional mall existed in other regions containing a city with 300,000 inhabitants or more, and transportation was considerably less developed. Indeed, as seen from Table 10, in our sample, the median number of stores in a province for individuals in the MR is 103 while the median in all other regions ranges from 4 to 22. Similarly, the average of this variable in the MR is 81.1, while the largest average for other regions is 20.3.

With this caveat in mind, let $\mathbb{1}_i^{out}$ be a dummy variable taking the value 1 if the individual i lives *outside* of the Metropolitan Region and 0 otherwise. Accordingly, the instruments for credit access in our main regressions are $Z_i^{Mun} = \mathbb{1}_i^{out} \times A_i^{Mun}$ and $Z_i^{Prov} = \mathbb{1}_i^{out} \times A_i^{Prov}$. Thus, the instruments should capture geographical variation in access to credit for individuals in regions other than the Metropolitan Region (maps showing the geographical variation are in Figures 4 and 5 in Appendix C).

[24]In practice, we expect physical access to stores offering non-banking credit to be an increasing and concave function of these variables.

Table 10: Retail Stores Offering Credit Access by Region

Geographic Region	Population	Retail Stores	% Retail Stores	A^{Prov} Mean	A^{Prov} Median	A^{Prov} SD	A^{Mun} Mean	A^{Mun} Median	A^{Mun} SD
I	238,950	12	2.5	12.0	12	0.0	10.5	11	2.2
II	493,984	27	5.6	10.4	14	5.0	9.8	13	4.7
III	254,336	13	2.7	6.0	8	3.1	5.6	8	3.7
IV	603,210	29	6.0	16.2	20	6.3	6.8	8	4.7
V	1,539,852	61	12.7	20.3	10	13.7	6.2	6	4.4
VI	780,627	22	4.6	12.0	16	5.0	4.9	2	5.6
VII	908,097	37	7.7	11.5	11	1.2	5.0	3	4.4
VIII	1,865,650	50	10.4	16.8	22	5.8	4.4	1	5.8
IX	869,535	27	5.6	13.8	22	8.5	4.9	0	6.0
X	716,739	29	6.0	9.2	9	4.9	5.7	1	6.3
XI	91,492	6	1.2	3.1	4	1.0	3.1	4	1.0
XII	150,696	9	1.9	8.0	8	0.0	8.0	8	0.0
MR	6,061,185	140	29.0	81.1	103	40.0	4.8	2	7.2
XIV	356,396	12	2.5	7.8	9	2.4	6.1	8	3.4
XV	189,644	8	1.7	8.0	8	0.0	8.0	8	0.0
Total	15,120,393	482	100	38.3	16	40.7	5.4	4	6.0

Source: Author's own calculation

Note: A^{Prov} and A^{Mun} correspond to the number of retail stores at provincial and municipality level respectively.

We use these instruments to estimate the first stage of the 2SLS implementation of the IV:

$$\begin{aligned} OI_i &= X_i'\beta \quad +\alpha_1 A_i^{Mun} + \alpha_2 A_i^{Prov} + \alpha_3 A_i^{Mun} \times A_i^{Prov} \\ &\qquad\qquad +\alpha_4 Z_i^{Mun} + \alpha_5 Z_i^{Prov} + \alpha_6 Z_i^{Mun} \times Z_i^{Prov} + R_i'\gamma + \eta_i, \end{aligned} \tag{5}$$

where OI_i is the over indebtedness index used previously, X_i is the vector of controls, R_i is a vector of regional dummies, and η_i is the error term.

Importantly, we observe that the location decisions of retail stores are driven by urban density, demographic, socioeconomic and commercial variables -access to services, transportation, space availability and price. For example, in Chile, the location of malls and large retail stores is explicitly aimed to attract an expected amount of revenue per year, and the models used to project these amounts are based precisely on these type of variables aggregated at the municipal level (Galetovic et al., 2009). Thus, conditional on the large list of demographic and socioeconomic control variables and regional dummies we consider, we believe that the instruments we propose are uncorrelated with the individual depression error term, as required by the IV exclusion restriction.

The first stage of the IV estimation is interesting on its own merit. The F-test yields a value of 16.07, making us confident that the instruments are not weak

Table 11: First Stage Instrumental Variables Estimation: Probability of Being Over Indebted - OLS

Dependent Variable: Over Indebted (OI_i)					
Socio Demographics		*Health problems*		**Had Foster parents**	0.0325
Female	0.0155*	**Has a chronic disease**	0.0318***		(0.0221)
	(0.00799)		(0.00863)	**Fatherless**	0.0159
Age	0.00341**	**Has cancer**	0.0294		(0.0154)
	(0.00142)		(0.0254)	*Health risk factors*	
Squared age	-4.17e-05***	**Has been inpatient in last 2 years**	0.0150	**Obesity**	0.0320***
	(1.25e-05)		(0.0113)		(0.00915)
Income Quintile I	0.0644***	**Has newborn**	0.00400	**Smokes**	0.0124
	(0.0146)		(0.0318)		(0.00829)
Income Quintile II	0.0522***	**Relative diagnosed with depression**	0.0118	**Drinks alcohol**	0.0275***
	(0.0129)		(0.0140)		(0.00805)
Income Quintile III	0.0359***	**Has been diagnosed with depression**	0.0313**	*Instruments*	
	(0.0119)		(0.0128)	A_i^{Mun}	-0.00112
Income Quintile IV	0.0222**	*Non cognitive skills*			(0.00307)
	(0.0112)	**Emotional Stability**	-0.00387	A_i^{Prov}	0.000332
Years of Schooling	0.00778***		(0.00363)		(0.000223)
	(0.00105)	**Agreeableness**	0.00895**	$A_i^{Mun} \cdot A_i^{Prov}$	-5.99e-06
Unemployed	-0.00713		(0.00392)		(3.09e-05)
	(0.0137)	**Openness to Experience**	0.00244	Z_i^{Mun}	0.0150***
Inactive	-0.0318***		(0.00306)		(0.00373)
	(0.00955)	**Extraversion**	0.00543	Z_i^{Prov}	0.00653***
Family Characteristics			(0.00344)		(0.000965)
Married	0.0458***	**Conscientiousness**	0.00402	$Z_i^{Mun} \cdot Z_i^{Prov}$	-0.000716***
	(0.0102)		(0.00369)		(0.000128)
Separated	0.0242*	*Assets*		**Constant**	-0.191***
	(0.0140)	**Car owner**	0.0380***		(0.0699)
Widower	0.00424		(0.00938)		
	(0.0151)	**Owns machinery**	-0.0161	**Regional Dummies**	YES
Has no children	-0.0181*		(0.0149)		
	(0.00933)	**Holds financial assets**	-0.00884	**Observations**	12,259
Has under 1 year old children	-0.0110		(0.00848)	**R-squared**	0.058
	(0.0213)	**Home owner**	-0.00290		
Has children between 2 and 4 years old	0.0113		(0.00856)		
	(0.0148)	**Relative Income**	-0.0594***		
Has children between 5 and 13 years old	0.0195**		(0.00807)		
	(0.00972)	*Personal History*			
Has children between 14 and 18 years old	0.00861	**Family member recently passed away**	0.00322		
	(0.00955)		(0.0205)		

(Stock and Yogo, 2002). Gender (being female) has a positive significant effect on the probability of being over indebted and age is associated with a positive, concave and significant effect. Individuals in lower income quintiles exhibit larger probabilities of being over indebted. However, inactivity is associated with a lower probability of being over indebted. Couples and separated individuals seem to be more likely to be over indebted. Chronic diseases and a diagnosis with depression are associated with higher over indebtedness probabilities; so is car ownership. Considering health risk factors, both obesity and alcohol drinking are associated with a higher probability of over indebtedness.

The second stage of the 2SLS implementation of the IV estimation is similar to our main equation (2), using the results of the first stage. That is,

$$d_i = X_i'\beta + \delta \hat{f}_i + R_i'\gamma + \varepsilon_i. \tag{6}$$

where $\hat{f}_i$ is the predicted value of the financial stress indicator from the first stage.

The results of the second stage of the IV estimation are summarized in Table 12. The main result is that we obtain a positive and significant coefficient for over indebtedness. The point estimate is 2.77, the size of the effect is rather large, it is nearly seven times larger than the non-instrumented estimate (Table 13). This is likely due to the fact that instrumental variables capture a local effect. This local effect is driven by those individuals that are actually affected by the instrument, in this case, those who are exposed to more access to credit and increase their indebtedness because of that. Finally, it is also worth mentioning that most of the coefficients related to individual characteristics and other controls remain fairly unchanged with the IV implementation (Table 12). These results strongly support a causal link from over indebtedness to depression.

4.2 Robustness Exercise Using Bivariate Probit Estimation

The IV estimates just presented imply a statistically significant effect of over indebtedness on the depression index and yield a point estimate coefficient that is considerably larger than the one obtained without correcting for endogeneity. As just pointed out, this is not surprising given local effect captured by the IV estimation. Nevertheless, as a robustness exercise, we implement an alternative identification method and estimate a recursive bivariate probit model (see Greene and Hensher, 2010). The Bivariate Probit estimation uses the binary depression measure D_i and the binary index of over indebtedness OI_i defined in the previous section. As before, the threshold to determine over indebtedness is endogenously chosen to maximize

Table 12: Second Stage Instrumental Variables estimation

Dependent Variable: Depression Index (d_i)					
$\widehat{OI_i}$	2.774***	**Has under 1 year old children**	-0.367***	**Conscientiousness**	-0.00112
	(0.674)		(0.117)		(0.0234)
Socio Demographics		**Has children between 2 and 4 years old**	-0.0523	*Assets*	
Female	0.580***		(0.0834)	**Car owner**	-0.395***
	(0.0514)	**Has children between 5 and 13 years old**	0.0841		(0.0586)
Age	0.0230**		(0.0572)	**Owns machinery**	0.144
	(0.0102)	**Has children between 14 and 18 years old**	0.175***		(0.0985)
Squared age	-0.000281***		(0.0551)	**Holds financial assets**	0.00399
	(9.61e-05)	*Health problems*			(0.0500)
Income Quintile I	0.137	**Has a chronic disease**	0.423***	**Home owner**	-0.0964*
	(0.0966)		(0.0576)		(0.0513)
Income Quintile II	0.140*	**Has cancer**	0.219	**Relative Income**	0.234***
	(0.0844)		(0.150)		(0.0660)
Income Quintile III	0.0317	**Has been inpatient in last 2 years**	0.386***	*Personal History*	
	(0.0761)		(0.0705)	**Had Foster parents**	0.185
Income Quintile IV	0.0634	**Has newborn**	0.456***		(0.135)
	(0.0698)		(0.173)	**Fatherless**	-0.0938
Years of Schooling	-0.0779***	**Relative diagnosed with depression**	0.407***		(0.0956)
	(0.00881)		(0.0808)	*Health risk factors*	
Unemployed	0.368***	**Has been diagnosed with depression**	1.773***	**Obesity**	0.0925
	(0.0832)		(0.0714)		(0.0587)
Inactive	0.376***	**Family member recently passed away**	0.742***	**Smokes**	0.326***
	(0.0645)		(0.146)		(0.0495)
Family Characteristics		*Non cognitive skills*		**Drinks alcohol**	-0.0842
Married	-0.339***	**Emotional Stability**	-0.169***		(0.0515)
	(0.0710)		(0.0216)	**Constant**	3.111***
Separated	0.205**	**Agreeableness**	0.131***		(0.394)
	(0.0912)		(0.0251)		
Widower	0.101	**Openness to Experience**	-0.0516***	**Regional Dummies**	YES
	(0.112)		(0.0193)		
Has no children	-0.0366	**Extraversion**	-0.167***	**Observations**	12,259
	(0.0629)		(0.0218)	**F-test, weak Ident**	16.07

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: OLS estimates for the effect of Over Indebtedness on the Depression Index

Dependent variable	**Depression Index (d_i)**	
	OLS	2nd stage IV
	(1)	(2)
$\hat{OI}_i$	0.379***	2.774***
	(0.0506)	(0.674)
Socio Demographics	Yes	Yes
Family Characteristics	Yes	Yes
Health problems	Yes	Yes
Non Cognitive Skills	Yes	Yes
Assets	Yes	Yes
Personal History	Yes	Yes
Health Risk Factors	Yes	Yes
Regional Dummies	Yes	Yes
Observations	12,259	12,259
R-squared	0.222	
Hansen J test		0.0188
F-test, weak Ident		16.07

the likelihood, so that $\overline{FRS^C} = 0.34$. The problem is set up as a system of linear equations of unobserved underlying latent variables D_i^* and OI_i^*:

$$D_i^* = X_{1i}'\beta_1 + \delta OI_i + \varepsilon_{1i} \quad (7)$$

$$OI_i^* = X_{1i}'\beta_2 + \varepsilon_{2i} \quad (8)$$

where only the binary variables D_i and OI_i are observed. In this system, ε_{1i} and ε_{2i} are assumed to be jointly normal distributed with zero mean, variance equal to 1, and correlation parameter ρ. As Wilde (2000) points out, the existence of sufficient variation in the regressors is sufficient to obtain identification, even if the sets of regressors in each equation are the same. That is, no exclusion restrictions are needed (see also Bridges and Disney, 2010 for a similar application).

The estimation of the marginal effects of the second stage of the bivariate probit is presented in column 2 of Table 14.[25] We use the instruments introduced previously to overidentify the bivariate probit estimation (column 3). The last row shows the significant coefficient of correlation between equations (ρ), which is consistent with the endogeneity presumption. As a comparison baseline, column 1 reproduces the results of the simple probit model presented in the previous section (Table 9). The sign and the significance of the coefficients in the bivariate probit estimations are consistent with those obtained in the IV model: the point estimate is much larger than the one obtained without correcting for endogeneity in the simple probit model.

[25]For the case of bivariate probit with instruments, the first stage coefficients are presented in Table 19 in the Appendix D.

Table 14: Recursive Bivariate Probit estimates for the effect of Over Indebtedness on the Depression Binary Indicator

Dependent variable	**Depression binary Indicator (D_i)**		
	Probit	Bivariate Probit W/O Instruments	Bivariate Probit W/ Instruments
	(1)	(2)	(3)
$\hat{OI}_i$	0.0636***	0.316***	0.339***
	(0.0114)	(0.0755)	(0.0632)
Socio Demographics	Yes	Yes	Yes
Family Characteristics	Yes	Yes	Yes
Health problems	Yes	Yes	Yes
Non Cognitive Skills	Yes	Yes	Yes
Assets	Yes	Yes	Yes
Personal History	Yes	Yes	Yes
Health Risk Factors	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes
Observations	12,259	12,259	12,259
ρ		-0.409***	-0.454***
		(0.126)	(0.109)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In sum, our robustness exercise confirms a significant positive impact of indebtedness and over indebtedness on psychological distress. These results suggest that there is a causal effect and that the magnitudes of the coefficients are robust for two independent identification strategies.

5 Sad Debtors

In this section we explore the role of self-control and cognitive skills on over indebtedness and depression. A central contribution of the psychology and economics literature has been to provide theoretical and empirical foundations on the limits of self-control and cognitive resources in economic decision-making (Schelling, 1984; Akerlof, 1991; Laibson, 1997). In the context of household financial decisions, there is a floury of research suggesting that individuals may over consume and over borrow due to self-regulation problems or overconfidence. More generally, debt decisions could be associated with mistakes that can potentially harm an individual's well-being.[26] The evidence we present below sheds light on the costs of "impulsive debt" on psychological well-being.

[26]For example, recent research suggests that pay-day-loan debts are likely associated either with self control problems or miscalculations Skiba and Tobacman (2009) and that these debtors invest less in health and education, and exhibit poorer work performance (Melzer, 2011; Carrel and Zinman, 2013).

Let θ_i measure an individual trait that we later identify either with impulsivity (self-control problems) or cognitive ability. We write $f_i = f(X_i, \theta_i)$ to represent the fact that over indebtedness -an endogenous behavior- is a function of θ_i and other individual characteristics captured by the vetcor X_i. At the same time, it seems safe to assume that well-being and, in particular, psychological well-being, depends at least on endogenous decisions (e.g. consumption, savings, debt, health investments, among others) individual characteristics and exogenous circumstances. Then, we can write our depression index as $d_i = \Gamma(f(X_i, \theta_i), X_i, \theta_i)$. This implies that self-control can affect depression directly, or indirectly, via debt choices $f(X_i, \theta_i)$. In this framework, the overall impact of an increase of θ_i on our depression measure can be decomposed as the sum of a direct and an indirect effect. For exposition, if we assume that all variables are continuous, we have that

$$\frac{\mathrm{d}d}{\mathrm{d}\theta} = \underbrace{\frac{\partial \Gamma}{\partial \theta}}_{\text{Direct Effect}} + \underbrace{\frac{\partial \Gamma}{\partial f}\frac{\partial f}{\partial \theta}}_{\text{Indirect Effect}} . \tag{9}$$

If θ_i measures impulsivity, we would expect $\frac{\partial f}{\partial \theta} > 0$. That is, more impulsivity -less self-regulation- is associated with larger over indebtedness. In the case of cognitive abilities, the sign of $\frac{\partial f}{\partial \theta}$ is less obvious. Higher cognitive skills could be associated with more awareness of the use of credit instruments, more information gathering and processing, or more consciousness about the potential consequences of over indebtedness. These might lead to either higher or lower credit demand. However, if more cognitive skills are associated with less mistakes, one might expect that, if people with more cognitive resources choose higher over indebtedness, the overall effect on depression need not be positive. The indirect effect via debt might be compensated by the direct effect. For example, if the over indebtedness of an individual with higher cognitive resources is less likely to be suboptimal, it seems plausible that it might be less likely to trigger more depression.

We estimate $\frac{\partial f}{\partial \theta}$ using a linear regression like the one used in the first stage of our IV procedure presented in the previous section, including measures of impulsivity and numeracy skills as explanatory variables of over indebtedness. On the other hand, to estimate $\frac{\partial \Gamma}{\partial \theta}$ and $\frac{\partial \Gamma}{\partial f}$ we use a linear model like the second stage of our IV estimation, now adding again self-control and cognitive ability as explanatory variables for depression.

We provide measures of self-control problems that exploit a set of questions included in the SPS survey related to behaviors that are typically associated with self-regulation problems and addictions (Gruber and Köszegi, 2001; Bernheim and Rangel, 2004). The questions ask individuals about their drinking, smoking and gambling habits.[27] We use a dummy variable for each of these habits: *Gambler* is equal to 1 if the individual reports at least one gambling activity and 0 if not; *Smoker* is equal to 1 if the individual smokes and 0, otherwise; and *Drinker* is analogously defined.[28] In our sample, 25% of the individuals are gamblers, 31% are smokers and 39% are drinkers.

Since smoking and drinking can affect health directly, for robustness, we use two measures of self-control problems. The first one is simply the gambling indicator. The second one is an index that combines the impact of gambling, smoking and drinking. Specifically, we define $Impulsivity = Drinker + Gambleer + Smoker$, with values $\in$ {0, 1, 2 and 3}.[29] As shown in Table 15, there is a strong correlation between smoking and drinking, but the correlation between these habits and gambling is rather weak.

Table 15: Correlation of measures of self-control problems

	Gambler	Smoker	Drinker
Smoker	0.016		
Drinker	0.063	0.264	
Impulsivity	0.530	0.672	0.716

The survey also includes a few basic numeracy questions in a financial literacy module. The two questions we used to construct our measure of numeracy skills are the following: *If the likelihood of getting a disease is 10%, how many people out of 1,000 would get the disease?*; and *If 5 people have the lottery winning numbers, and the prize is 2,000,000 pesos, how much would each one receive?* We construct an ordinal variable, *Numeracy Score*, indicating whether the respondent answered correctly zero, one or both questions. The share of the sample with zero correct answers is 42%; 27% have one correct answer; and 31% have both answers correct. The correlation between having the first and the second question correct is 0.46. Clearly, a successful answer to these questions could depend on the level of education, socioeconomic status or other individual variables. To isolate a relative

[27]The SPS questionnaire asks: *Do you smoke?*, and then *How many cigarettes do you smoke on average in a month?* Individuals are also requested to answer *Do you consume alcoholic drinks such as beer, wine, distilled liquor, or other liquor? How many days per week each?* To measure gambling behavior, the questionnaire asks *Do you participate in any of the following gambling? Horse racing; casino; lottery; slot machines; others; and how many times per month/week/year?*

[28]We also tried other definitions that made use of intensity information such as frequency of gambling and obtained very similar results. [These estimations are available upon request].

[29]We are aware that the impulsivity index may confound self-control information with direct health effects associated to drinking and smoking, so that this should be considered when interpreting our results.

numeracy ability indicator, we regress *Numeracy Score* on the vector of individual characteristics X_i and define the *Numeracy Skills* variable as the residual. That is, *Numeracy Skills* index is the part of the numeracy score that is not explained by the large set of individual controls that we have included. We believe that this measure is more closely associated with innate abilities.[30]

With these self-control and numeracy skills indicators, we obtain estimates of the indirect effects on depression (Table 16). We find that gambling, self-control problems, and numeracy skills all have significant positive effect on over indebtedness. An individual identified as gambler increases his probability of being over indebted by 2.15% (column 1). In parallel, our impulsivity index indicates that an additional self-control problem (either gambling, drinking or smoking), increases the probability of being over indebted by 2.01% (column 2). Finally, our results indicate that larger numeracy skills would increase the probability of being over indebted by 3.19% (column 3).

Table 16: Heterogeneous effects

Dependent variable:	**Over Indebted** (OI_i)			**Depression Index** (d_i)		
	(1)	(2)	(3)	(4)	(5)	(6)
Gambler	0.0215***			-0.0340		
	(0.00829)			(0.0529)		
Impulsivity		0.0201***			0.0762**	
		(0.00435)			(0.0300)	
Numeracy Skills			0.0319***			-0.200***
			(0.00474)			(0.0351)
Socio Demographic	Yes	Yes	Yes	Yes	Yes	Yes
Family Characteristic	Yes	Yes	Yes	Yes	Yes	Yes
Health problems	Yes	Yes	Yes	Yes	Yes	Yes
Non Cognitive Skills	Yes	Yes	Yes	Yes	Yes	Yes
Assets	Yes	Yes	Yes	Yes	Yes	Yes
Personal History	Yes	Yes	Yes	Yes	Yes	Yes
Health Risk Factors	Yes	Yes	Yes	Yes	Yes	Yes
Over Indebted	Yes	Yes	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,259	12,259	12,259	12,259	12,259	12,259

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In line with equation (9), to compute the total effect of the personal traits on our depression index we obtain estimates of the direct effects ($\frac{\partial \Gamma}{\partial \theta}$). The results show that being a gambler has no significant direct effect on the depression index (column 4 in Table 16). On the other hand, self-control problems index has a positive significant coefficient of 0.076 (column 5), suggesting that self-control proxies

[30]This methodology follows Carranza and Hojman (2013).

such as smoking and drinking may directly affect on psychological well-being. We observe that numeracy skills also have a negative significant coefficient of -0.20 (column 6). Thus, self control problems (if anything) contribute to higher depression and numeracy skills lower it. As mentioned earlier, possible interpretations of the negative contribution of numeracy skills to depression are that these skills might help to better overcome psychological distress or anticipate stressful situations.

With these results in hand, we compute the indirect effect of being a gambler on the depression index at 0.0611, with a *bootstrap* standard error of 0.028, which indicates it is highly significant.[31] This is a measure of the psychological cost associated to impulsive indebtedness. Since the direct effect of being a gambler is not statistically significant, we considered the overall effect as equal to the indirect effect.[32] Recalling the standard deviation of the depression index is 2.4, this effect corresponds to 2.5% of a standard deviation. We believe this is a large effect when compared to the death of a close relative, which implies an increase of 32% of a standard deviation of the index. In parallel, the impulsivity index has an overall effect of 0.133 (with a bootstrap standard error equal to 0.023), being as big as 5.5% of a standard deviation. Again, this is an important effect that supports that self-control problems may have an important effect on depression through a direct and indirect channel. Finally, the total effect of numeracy skills is estimated at -0.11 as the negative direct effect dominates the positive indirect effect of over indebtedness (the bootstrap standard error is equal to 0.026).

6 Conclusions

This paper finds robust causal evidence of the effect of over indebtedness on different measures of depression. The effect is mainly driven by consumer debt rather than mortgage debt. The impact of over indebtedness on depression is large, the psychological cost of non-mortgage debt burden is comparable to half of the effect associated to the loss of a family member. Depression is the leading cause of disability in the world and is associated with major individual well-being and economic costs. In Chile, it is the second cause of years of life lost due to premature death and disability, and the fourth most expensive to treat illness.

Depression implies costs in lost earnings, in demands on the health service and in prescribing drugs to tackle the problem. In England, for example, it is thought to represent a staggering £11 billion annually.[33] In the United States, Peng et al. (2013) estimated that the annual aggregate productivity loses due to depression-induced absenteeism range from 700 million to 1.4 billion in 2009 USD. Our results

[31] We compute bootstrap standard errors using 1,000 replications.

[32] Nevertheless, when including the direct effect in the computation of the bootstrap standard errors, the variance increased significantly enough to make the overall effect non-signficant.

[33] UK House of Commons (2011).

support the importance of identifying policies to improve different types of credit choices by individuals to avoid the psychological distress.

In our data, the effect of debt burden is stronger in the population with self-regulation problems. While these findings suggest that impulsivity and forecasting abilities could play a role in explaining "sad debt", in line with the predictions in the psychology and economics literature, further research is required to assess the relative importance of psychological biases in mediating the impact of debt on depression. More knowledge of these issues would better inform which policies might be more effective in reducing the negative psychological costs of excessive liquidity at high interest rates. In particular, some places like Oregon have recently enacted laws to limit credit access with questionable results as it could lead individuals to acquire similar amounts of credit at high prices and against the law (Zinman, 2010). In contrast, other interventions such providing better information to consumers on the real costs of a loan might lead to lower over-borrowing and depression rates (Hastings and Mitchell, 2011). This is an exciting agenda for future research.

References

Akerlof, G. A. (1991). Procrastination and obedience. *The American Economic Review*, 81(2):pp. 1–19.

Angeletos, G.-M., Laibson, D., Repetto, A., Tobacman, J., and Weinberg, S. (2001). The hyperbolic consumption model: Calibration, simulation, and empirical evaluation. *The Journal of Economic Perspectives*, 15(3):pp. 47–68.

Bernheim, B. D. and Rangel, A. (2004). Addiction and cue-triggered decision processes. *The American Economic Review*, 94(5):pp. 1558–1590.

Bernheim, B. D. and Rangel, A. (2009). Beyond revealed preference: Choice-theoretic foundations for behavioral welfare economics. *The Quarterly Journal of Economics*, 124(1):51–104.

Bertrand, M. and Morse, A. (2011). Information disclosure, cognitive biases, and payday borrowing. *Journal of Finance*, 66(6):1865–1893.

Bridges, S. and Disney, R. (2010). Debt and depression. *Journal of Health Economics*, 29(3):388 – 403.

Bromet, E., Andrade, L., Hwang, I., Sampson, N., Alonso, J., de Girolamo, G., de Graaf, R., Demyttenaere, K., Hu, C., Iwata, N., Karam, A., Kaur, J., Kostyuchenko, S., Lepine, J.-P., Levinson, D., Matschinger, H., Mora, M., Browne, M., Posada-Villa, J., Viana, M., Williams, D., and Kessler, R. (2011). Cross-national epidemiology of dsm-iv major depressive episode. *BMC Medicine*, 9(1):90.

Brown, S., Taylor, K., and Price, S. W. (2005). Debt and distress: Evaluating the psychological cost of credit. *Journal of Economic Psychology*, 26(5):642 – 663.

Campbell, J. Y., Jackson, H. E., Madrian, B. C., and Tufano, P. (2011). Consumer financial protection. *The Journal of Economic Perspectives*, 25(1):91–113.

Carranza, R. and Hojman, D. (2013). Cognitive skills and equality of opportunities. Mimeo, in preparation, University of Chile.

Carrel, S. E. and Zinman, J. (2013). Payday loan access and military personnel performance. Working papers, UC Davis, Department of Economics.

Carroll, C. D. (1997). Buffer-stock saving and the life cycle/permanent income hypothesis. *The Quarterly Journal of Economics*, 112(1):1–55.

Disney, R., Bridges, S., and Gathergood, J. (2008). Drivers of over-idebtedness. Report to the department for business, enterprise and regulatory reform, University of Nottingham.

Drentea, P. (2000). Age, debt, and anxiety. *Journal of Health and Social Behavior*, 41(4):437 – 450.

Drentea, P. and Lavrakas, P. J. (2000). Over the limit: the association among health, race and debt. *Social Science and Medicine*, 50(4):517 – 529.

Dynan, K. E. (2009). Changing household financial opportunities and economic security. *Journal of Economic Perspectives*, 23(4):49–68.

Galetovic, A., Poduje, I., and Sanhueza, R. (2009). Malles en santiago: De centros comerciales a centros urbanos. *Estudios Públicos*, 114.

Gathergood, J. (2012). Debt and depression: Causal links and social norm effects*. *The Economic Journal*, 122(563):1094–1114.

Gosling, S. D., Rentfrow, P. J., and Jr., W. B. S. (2003). A very brief measure of the big-five personality domains. *Journal of Research in Personality*, 37(6):504 – 528.

Green, J. and Hojman, D. (2009). Choice, rationality and welfare measurement. Working Paper Series rwp07-054, Harvard University, John F. Kennedy School of Government.

Greene, W. H. and Hensher, D. A. (2010). *Modeling Ordered Choices*. Cambridge Books. Cambridge University Press.

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

Gruber, J. and Köszegi, B. (2001). Is addiction "rational" theory and evidence. *The Quarterly Journal of Economics*, 116(4):1261–1303.

Hastings, J. S. and Mitchell, O. S. (2011). How financial literacy and impatience shape retirement wealth and investment behaviors. NBER Working Papers 16740, National Bureau of Economic Research, Inc.

Heckman, J. J. (2011). Integrating personality psychology into economics. NBER Working Papers 17378, National Bureau of Economic Research, Inc.

IMF (2006). Global financial stability report. Technical report, International Monetary Found.

IMF (2013). Brazil: Technical note on consumer credit growth and household financial stress. Country Report No. 13/149, International Monetary Found.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics*, 112(2):443–478.

Laibson, D. (2001). A cue-theory of consumption. *The Quarterly Journal of Economics*, 116(1):pp. 81–119.

Laibson, D., Repetto, A., and Tobacman, J. (2003). Wealth accumulation, credit card borrowing, and consuption-income comovement. Documentos de Trabajo 166, Centro de Economía Aplicada, Universidad de Chile.

Laibson, D., Repetto, A., and Tobacman, J. (2007). Estimating discount functions with consumption choices over the lifecycle. NBER Working Papers 13314, National Bureau of Economic Research, Inc.

Melzer, B. T. (2011). The real costs of credit access: Evidence from the payday lending market*. *The Quarterly Journal of Economics*, 126(1):517–555.

Peng, L., Meyerhoefer, C. D., and Zuvekas, S. H. (2013). The effect of depression on labor market outcomes. Working Paper 19451, National Bureau of Economic Research.

Piccinelli, M. and Wilkinson, G. (2000). Gender differences in depression: Critical review. *The British Journal of Psychiatry*, 177(6):486–492.

Reading, R. and Reynolds, S. (2001). Debt, social disadvantage and maternal depression. *Social Science and Medicine*, 53(4):441 – 453.

Ruiz-Tagle, J., García, L., and Miranda, A. (2013). Proceso de endeudamiento y sobre endeudamiento de los hogares en chile. Working Papers Central Bank of Chile 703, Central Bank of Chile.

Schelling, T. C. (1984). Self-command in practice, in policy, and in a theory of rational choice. *The American Economic Review*, 74(2):pp. 1–11.

Scholz, J. K. and Seshadri, A. (2009). The assets and liabilities held by low income families. In Blank, R. M. and Barr, M. S., editors, *Insufficient Funds: Savings, Assets, Credit, and Banking Among Low-Income Households*. Russell Sage Foundation, New York.

Simon, G. E., VonKorff, M., Piccinelli, M., Fullerton, C., and Ormel, J. (1999). An international study of the relation between somatic symptoms and depression. *New England Journal of Medicine*, 341(18):1329–1335. PMID: 10536124.

Skiba, P. M. and Tobacman, J. (2008). Payday loans, uncertainty and discounting: Explaining patterns of borrowing, repayment, and default. Vanderbilt Law and Economics Research Paper 08-33, Harvard University, John F. Kennedy School of Government.

Skiba, P. M. and Tobacman, J. (2009). Do payday loans cause bankruptcy? Vanderbilt Law and Economics Research Paper 11-13, Harvard University, John F. Kennedy School of Government.

Steffick, D. E. (2000). Documentation of affective functioning measures in the health and retirement study. HRS/AHEAD Documentation Report 05, Survey Research Center, University of Michigan.

Stock, J. H. and Yogo, M. (2002). Testing for weak instruments in linear iv regression. Working Paper 284, National Bureau of Economic Research.

Thaler, R. and Benartzi, S. (2004). Save more tomorrow: Using behavioral economics to increase employee saving. Natural Field Experiments 00337, The Field Experiments Website.

Thaler, R. H. (1993). *Advances in Behavioral Finance*. Russell Sage Foundation, New York.

Thaler, R. H. (2005). *Advances in Behavioral Finance II*. Princeton University Press, New Jersey.

White, M. J. (2007). Bankruptcy reform and credit cards. *Journal of Economic Perspectives*, 21(4):175–200.

Wilde, J. (2000). Identification of multiple equation probit models with endogenous dummy regressors. *Economics Letters*, 69(3):309 – 312.

Zimmerman, F. J. and Katon, W. (2005). Socioeconomic status, depression disparities, and financial strain: what lies behind the income-depression relationship? *Health Economics*, 14(12):1197–1215.

Zinman, J. (2010). Restricting consumer credit access: Household survey evidence on effects around the oregon rate cap. *Journal of Banking and Finance*, 34(3):546 – 556.

Appendix A CES-D Short Questionnaire

The table below shows the questions from the CES-D short form and the coding used to construct the dummy variables (d_{ij}) to generate the Psychological Distress Index (d_i).

Table 17: Center for Epidemiological Studies Depression Scale (CES-D) Short Form (8 questions)

	d_{ij}	
	Yes	No
Have you felt depressed?	1	0
Have you felt that everything you do is an effort?	1	0
Have you felt that your sleep is restless?	1	0
Have you felt alone?	1	0
Have you felt happy?	0	1
Have you felt that you enjoy your life?	0	1
Have you felt sad?	1	0
Have you felt you could not get going?	1	0

Appendix B Financial Service Ratio

B.1 Monthly Payments Data

The table below shows the interest rates used to calculate de monthly payments of the FSR measures (see footnote 16 in the main text).

Table 18: Interest Rates and Residual Periods for Financial Service Computation

Type of debt in SPS	Anual interest rate (December 2009)	Residual Periods (in months)
Bank credit cards	42.7%	18
Bank overdrafts	20.43%	3
Department stores loans (less than 90 days)	50.9%	1.5
Department stores loans (90 days to 1 year)	50.9%	7.5
Department stores loans (more than 1 year)	50.9%	30
Bank consumption loans (less than 1 year)	42.7%	18
Bank consumption loans (more than 1 year)	17.2%	50
Finance company consumption loans	51%	18
Motorvehicle loans	44.3%	52
Social credit	18.3%	50
Educational loans	5%	96

Source: Central Bank of Chile and Superintendecy of Banks and Financial Institutions.

B.2 Grid Search for FSR^c threshold to define Over Indebtedness (OI_i)

The graphs below illustrate the results of the estimated effects of over indebtedness on the depression measures for different thresholds of the consumer financial service ratio ($\overline{FSR^C}$) used to define over indebtedness. The graphs present the results of the estimates using OLS, Ordered Probit, and Probit, respectively. The central fact is that, regardless of the $\overline{FSR^C}$ value considered, confidence intervals do not include zero.

Figure 1: OLS Estimated Effects of Over Indebtedness on the Depression Index

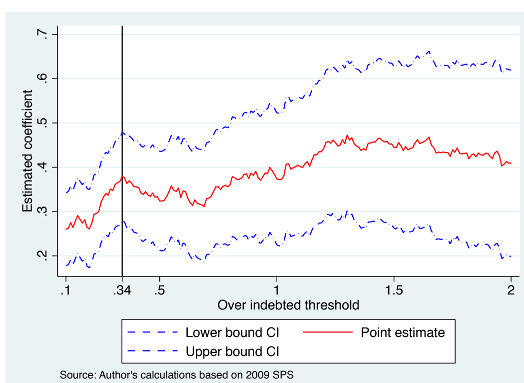
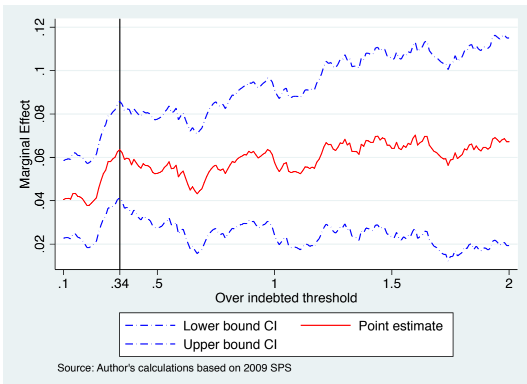


Figure 2: Ordered Probit Estimated Effects of Over Indebtedness on the Depression Index (coefficients reported)

Figure 3: Marginal effects of Probit estimates of the effect of Total Financial Service Ratio on the Depression Binary Index



Appendix C Access to Retail Stores

Figure 4: Geographical Variation of the number of retail stores by municipality (A_i^{mun})

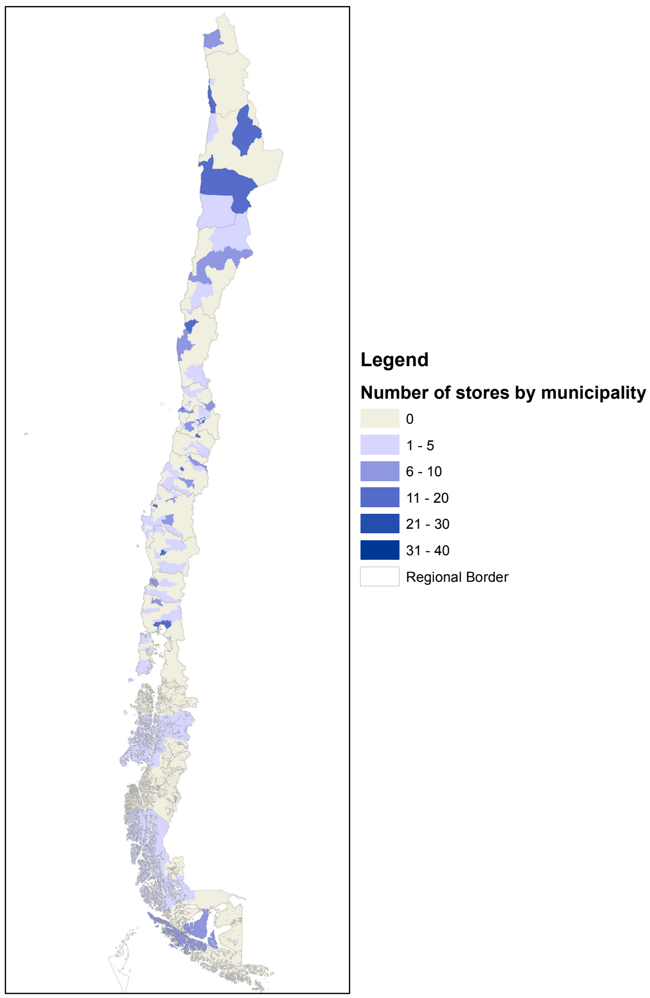
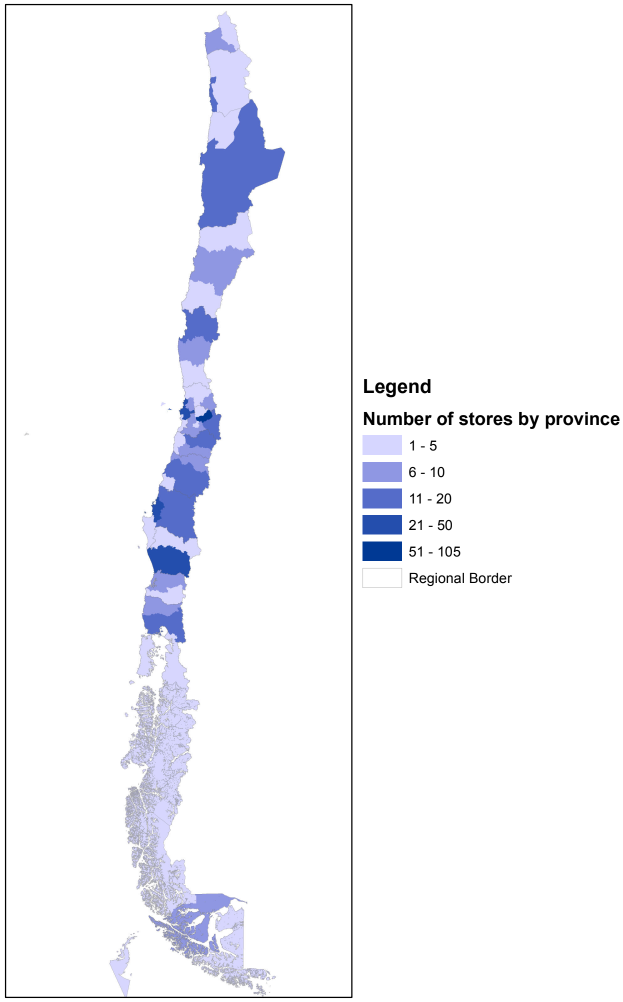


Figure 5: Geographical Variation of the number of retail stores by province (A_i^{prov})



Appendix D Bivariate Probit Estimation

In the main text, Table 14 shows the Biprobit estimation of the effect of over indebtedness on the Depression Binary Index. The table below shows the estimation of the probability of being over indebted (OI_i) as a function of the instruments used for the bivariate estimation.

Table 19: First Stage Bivariate Probit estimation

Female	0.0638*	**Has children between 14 and 18 years old**	0.0125	**Relative Income**	-0.257***
	(0.0326)		(0.0349)		(0.0360)
Income Quintile I	0.260***	**Has a chronic disease**	0.143***	**Had Foster parents**	0.128
	(0.0592)		(0.0355)		(0.0834)
Income Quintile II	0.210***	**Has cancer**	0.128	**Fatherless**	0.0740
	(0.0529)		(0.0968)		(0.0628)
Income Quintile III	0.146***	**Has been inpatient in last 2 years**	0.0525	**Obesity**	0.137***
	(0.0499)		(0.0450)		(0.0344)
Income Quintile IV	0.0867*	**Has newborn**	-0.00623	**Smokes**	0.0362
	(0.0469)		(0.110)		(0.0311)
Age	0.0261***	**Relative diagnosed with depression**	0.0638	**Drinks alcohol**	0.109***
	(0.00753)		(0.0542)		(0.0313)
Squared age	-0.000318***	**Has been diagnosed with depresion**	0.110**	A_i^{mun}	-0.00484
	(7.36e-05)		(0.0488)		(0.0117)
Years of Schooling	0.0328***	**Family member recently passed away**	0.0756	A_i^{prov}	0.000925
	(0.00439)		(0.110)		(0.000876)
Unemployed	-0.0396	**Emotional Stability**	-0.0140	$A_i^{mun} \cdot A_i^{prov}$	-2.10e-05
	(0.0508)		(0.0144)		(0.000118)
Inactive	-0.139***	**Agreeableness**	0.0408**	Z_i^{mun}	0.0800***
	(0.0401)		(0.0162)		(0.0151)
Married	0.196***	**Openness to Experience**	0.0107	Z_i^{prov}	0.0308***
	(0.0438)		(0.0125)		(0.00381)
Separated	0.0879	**Extraversion**	0.0224	$Z_i^{mun} \cdot Z_i^{prov}$	-0.00374***
	(0.0577)		(0.0138)		(0.000520)
Widower	-0.0333	**Conscientiousness**	0.0199	**Constant**	-2.881***
	(0.0881)		(0.0154)		(0.290)
Has no children	-0.104**	**Car owner**	0.147***	**Regional Dummies**	YES
	(0.0444)		(0.0347)		
Has under 1 year old children	-0.0466	**Owns machinery**	-0.0891	**Observations**	12,259
	(0.0769)		(0.0729)		
Has children between 2 and 4 years old	0.0168	**Holds financial assets**	-0.0270		
	(0.0519)		(0.0329)		
Has children between 5 and 13 years old	0.0428	**Home owner**	-0.00600		
	(0.0356)		(0.0336)		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1