Edinburgh School of Economics

Discussion Paper Series

Number 193

Evolution of Consumption Volatility for the Liquidity Constrained Households over 1983 to 2004

Olga Gorbachev
Edinburgh University

Keshav Dogra
Columbia University

Date
November 2009

Published by
School of Economics
University of Edinburgh
30 -31 Buccleuch Place
Edinburgh EH8 9JT
+44 (0)131 650 8361
http://edin.ac/16ja6A6

THE UNIVERSITY *of* EDINBURGH

Evolution of Consumption Volatility for the Liquidity Constrained Households over 1983 to 2004.

Olga Gorbachev*and Keshav Dogra†

November 15, 2009

Abstract

We study whether the increased income uncertainty in the US over the last quarter-century had a negative impact on household welfare by looking at variability of household consumption growth. We are particularly interested in understanding the effect of greater uncertainty on the liquidity constrained households. We study the evolution of liquidity constraints in the US in the Panel Study of Income Dynamics, greatly extending Jappelli et al. [1998] methodology on how to construct such measures using information from the Survey of Consumer Finances. We find that although household indebtedness increased substantially, reflecting greater availability of credit, there was no decline in the proportion of liquidity constrained households between 1983 and 2007. Applying methodology developed in Gorbachev [2009], we find that the evolution of consumption volatility for the liquidity constrained households increased by economically and statistically more than for the unconstrained households. This increase was lower than that of family income volatility for these groups. Nevertheless, the welfare cost to society is substantial: we estimate that an average household would be willing to sacrifice 2.35 percent of nondurable consumption per year to lower consumption risk to its 1984 levels.

*School of Economics, University of Edinburgh, Edinburgh, UK, corresponding author, email olga.gorbachev@ed.ac.uk

†Department of Economics, Columbia University, New York, NY USA.

1 Introduction

In times of great uncertainty, it is important to understand whether vulnerable individuals can cope. Negative shocks to income may not necessarily translate into welfare losses, even under incomplete markets, if people can find ways to smooth consumption by borrowing at bad times and paying back at good times. This is because, ultimately, it is consumption that matters for individuals (Friedman [1957]). Thus, in theory, while individual income became less certain,[1] instability of household consumption may have remained unchanged - provided that the households had access to consumption-smoothing tools, such as savings, credit markets, welfare programs and other insurance mechanisms.

This paper makes several contributions. First is methodological. Since, to our knowledge, there is no panel data set that provides information on consumption, income, wealth, and liquidity constraints, we combine information from several datasets. We document the evolution of liquidity constraints in the US between 1983 and 2007 based on the Survey of Consumer Finances (SCF), providing methodology on how to construct such measures in the Panel Study of Income Dynamics (PSID). In contrast to Jappelli et al. [1998],[2] we allow for changes in credit supply over time by using the SCF data from different years. As the result, the probability of being liquidity constrained may be different in different years, even for households with identical characteristics. To our knowledge this is the first such study. We find that although household indebtedness increased substantially, there is no clear decline in the proportion of liquidity constrained households in this period. Our PSID estimates of liquidity constraints are lower than that in the SCF. Whereas in the SCF on average 1 in 5 households are denied credit, in the PSID we compute that 3 in 20 are constrained. Nevertheless, the estimate picks up correctly the trend in the constraints over the 1983-2004 period. After 1995, credit constraints relaxed for better off households - those in the upper income quantiles, and those with more than 12 years of education. By contrast, for poorer households, and those with less education, the probability of being denied credit remained the same or even increased after 1998, and the percentage of such households without a credit card also increased. Finally, according to all indicators, poorer households, single parents and nonwhites, particularly those with

[1] See for example Moffitt and Gottschalk [1994, 1998, 2002], Gottschalk and Moffitt [2009], Dynarski and Gruber [1997], Haider [2001], Hacker [2006], Dynan et al. [2007], Keys [2008], Shin and Solon [2008], Jensen and Shore [2008].

[2] To our knowledge Jappelli et al. [1998] was the first to construct liquidity constraints in the PSID using SCF data and to study their evolution and impact on consumption smoothing.

12 or less years of education, are still the most likely to be constrained, and there is no evidence that liquidity constraints slackened for these groups.

Second, we assess the development of income shocks for liquidity constrained and unconstrained households. We distinguish the evolution of total family income variability from that of total labor income variability, as family income includes public and private transfers, labor, business and asset income from all working adults. We find that family income volatility increased by 43 percent between 1983 and 2004, while total labor volatility did not change. This divergence of trends can be attributed to a substantial increase in business and asset income volatility. The biggest increase in total family income volatility was experienced by households on welfare and nonwhite households with low education (less than 13 years). Family income volatility increased by 71 percent (or 16ppts.) for these households between 1983 and 2004, whereas it went up by half as much (or 8ppts.) for non welfare recipients and white households. Increased income variability contributed to the increased demand for debt and thus to the tightening of the liquidity constraints in the market of great financial liberalization.

Third, we apply methodology developed in Gorbachev [2009] to document the evolution of consumption volatility for the liquidity constrained and unconstrained households, and to study the role played by the changes in liquidity constraints on transmission of income shocks. We find that consumption volatility also increased over this sample in line with income volatility but by a smaller percentage. Rising income volatility and tightening liquidity constraints, led to a higher increase in consumption volatility for liquidity constrained households. We found that all liquidity constrained households, regardless of their other characteristics, experienced a similar increase in volatility of food consumption, though this increase was significantly lower than that of volatility of family income for these groups. The increase in volatility of consumption for liquidity constrained households supports the claims that transitory shocks to income in the US increased over this time period.

Since food consumption is well known to have low income elasticity, (see for example, Bunkers and Cochrane [1957]), the results presented in this study are a lower bound of what might have actually happened to volatility of total nondurable consumption. Blundell et al. [2008] estimate a demand equation for food as a function of relative prices, as well as nondurable expenditure and a host of demographic and socioeconomic characteristics of the household. The elasticity of food consumption with respect to nondurable consumption is 0.85 and statistically significant. Thus a 1 percent change in nondurable consumption will lead to a 0.85 percent change in food expenditure. Therefore, a 1 percent increase in volatility of food consumption will translate into a $1.38 = 1/(0.85)^2$ percent increase in volatility of nondurable consumption. This again is an underestimate if we consider that the elasticity changes over time and that this change appears to be positive.

As greater income uncertainty may not necessarily translate into welfare losses, having a good measure of the volatility of household consumption is thus fundamental to assessing whether, and to what extent, welfare was affected by increased income shocks.[3] Gorbachev [2009] developed such a measure. After accounting for predictable variation arising from movements in real interest rates, family composition and structure, changes in demographics, income shocks, measurement errors, and nonseparability of preferences, and using data from the Panel Study of Income Dynamics (PSID) and the Consumer Expenditure Survey (CES), Gorbachev showed that volatility of household expenditure on food, and on nondurables in general, in the US increased by 20 percent between 1970 and 2004 for *liquidity unconstrained* households. This increase was especially pronounced for nonwhite households with no more than 12 years of education; in contrast, households with more than 12 years of education saw a significantly smaller increase in volatility, irrespective of race.

Since these findings were based on a liquidity unconstrained sample of households, identified on the basis of their wealth holdings, Gorbachev [2009] could not evaluate the extend to which liquidity constrained households were adversely affected by the increased income uncertainty. As liquidity constrained households are typically poorer households, single parents and nonwhites, especially those with 12 or less years of education, the findings on increased consumption volatility of unconstrained households are insufficient for a proper welfare analysis. If one also keeps in mind the negative externalities for society that arise out of poverty and discontent, such as for example increased crime, a study of the welfare of liquidity constrained households becomes essential.

[3] A word of caution is in order here: we are not studying changes in *inequality* of consumption, which concerns itself with the widening of the distribution of consumption levels. Instead, we are interested in examining changes in *variability* of consumption growth rates, as a measure of volatility of consumption. Changes in volatility of consumption enter welfare calculations directly, whereas changes in inequality do not necessarily affect social welfare unless one makes normative claims.

It is reasonable to believe that since liquidity unconstrained households experienced a significant increase in volatility, liquidity constrained households would have experienced an even larger increase, as these households, by definition, were unable to borrow to smooth out the shocks. However, without direct measures of liquidity constraints, it is problematic to make statements on the evolution of consumption risk for liquidity constrained households as the changes in the unpredictable shocks to consumption could be due either to changes in liquidity constraints affecting households' ability to achieve their desired consumption, or to shocks directly affecting households' desired consumption (for example, shocks to permanent income). Differences in the origins of variability are thus important for our welfare analysis.

Volatility for liquidity constrained households might not have increased by more than that of unconstrained households, as these households might have had opportunities to smooth consumption through receipt of public transfers. In addition, there are strong a priori grounds for expecting that liquidity constraints relaxed over the period under consideration, and information on wealth holdings might not have been enough to pick up on this trend. Increased use of credit scoring, risk-based pricing and product differentiation allowed household debt to nearly triple in real terms, and facilitated a subprime lending boom, particularly in the mortgage market, which explicitly targeted traditionally excluded households. However, according to recent work by Dogra [2009], who uses data from the Survey of Consumer Finances, the proportion of households unable to borrow as much as they would like actually slightly increased over the 1983-2007 period. We find that rising income volatility and tightening liquidity constraints, led to a higher increase in consumption volatility for liquidity constrained households. All liquidity constrained households, regardless of their other characteristics, experienced a similar increase in volatility of food consumption, though this increase was significantly lower than that of volatility of family income for these groups.

The rest of the paper is organized into three parts. Part II provides a brief review of the literature on liquidity constraints; quickly describes the SCF data and presents estimates of evolution of liquidity constraints and debt over time; presents and estimates a model relating liquidity constraints to household characteristics, and discusses the assumptions necessary to invert the SCF liquidity measures into the PSID within the standard consumption model; and presents results on the evolution of liquidity constraints in the PSID sample. Part III presents the evolution of income volatility for liquidity constrained and unconstrained households for all the subcategories of total family income, total labor, business and asset income, and public and private transfers; and discusses these trends. Part IV constructs volatility of household consumption for the liquidity constrained and unconstrained households; documents its evolution; and discusses the role changes in liquidity constraints played in transmission of income shocks for these households. Part V concludes.

2 Liquidity Constraints

Consumption is more sensitive to current income if consumers are liquidity constrained: that is, they cannot borrow as much as they would like, subject to their intertemporal budget constraint, and therefore cannot completely smooth consumption over time. This possibility led several authors to test for the presence of liquidity constraints. Zeldes [1989] was one of the first to use information on wealth in the PSID to split the sample into constrained and unconstrained households, and found that liquidity constraints were binding for low wealth households.[4] However, the sample splitting approach is not ideal as a method for accurately identifying which households are liquidity constrained. For example, Runkle [1991], using a similar approach, does not find evidence of liquidity constraints.

Another approach to identifying liquidity constrained households is to use direct information on loan rejections or on consumer reactions to changes in their borrowing limit. Gross and Souleles [2002], using data on credit card accounts to identify liquidity constrained households, find that the 'marginal propensity to consume out of liquidity' is on average 10-14%, and for bankcard accounts with balances above 90% of their credit limits, it is almost 50%. Attanasio and Kyriazidou [2008], use micro data on car loans, document that consumers as a whole are more responsive to loan maturity than interest rates, especially low-income consumers. Similarly, W. Adams and J.Levin [2009] find evidence of liquidity constraints in the auto sales market: demand is highly responsive to changes in the minimum down-payment required, and is 50% higher during tax rebate season. However, these studies by their nature do not investigate whether the proportion of households facing binding liquidity constraints has changed over time.

Many authors have used the Survey of Consumer Finances in order to investigate liquidity

[4]In particular, Zeldes [1989] found that, for low wealth households, consumption growth responded to changes in current income.

constraints. As well as detailed information on households' assets and liabilities, the survey contains direct information on whether households face binding credit constraints. Jappelli [1990] was the first to use direct information on credit constraints, available in the 1983 Survey of Consumer Finances, to determine what proportion of US households were liquidity constrained. He also determined what factors influence whether a household is constrained, by estimating a logit model relating the probability of being constrained to the characteristics of borrowers and lenders.

More relevant to our paper is the work by Fissel and Jappelli [1990]. They study whether the fraction of households that are liquidity constrained has changed over time. They estimate a logit model following Jappelli [1990] using the SCF 1983 data, and then use the estimated coefficients to impute the probability of being constrained in a sample from the PSID (1969-1982) (which contains the same explanatory variables, but no direct information on liquidity constraints). However, a limitation of this approach is that it assumes that the relationship between the probability of being constrained and the characteristics of borrowers and lenders does not change over time.

We estimate the probability of being liquidity constrained using a probit model. We start with a simple specification used by Jappelli et al. [1998], and improve on it by estimating the probability of being constrained separately for each year that the SCF data is available. Thus, unlike Jappelli et al. [1998] we allow for changes in credit supply over time by using the SCF data from each available year (1983, 1989, 1992, 1995, 1998, 2001, 2004, and 2007), so that the probability of being liquidity constrained may be different in different years, even for households with identical characteristics. We use these estimates to obtain a time-varying measure of liquidity constraints. We then use variables common to the PSID and the SCF to invert these estimates and compute liquidity constraints for the PSID households for 1983 to 2004 period.

2.1 Data

2.1.1 Survey of Consumer Finances

The 1983, 1989, 1992, 1995, 1998, 2001, 2004 and 2007 Surveys of Consumer Finances (SCF), sponsored by the Board of Governors of the Federal Reserve System, are cross-sectional surveys of the balance sheet, pension, income, and other demographic characteristics of U.S. families.

The SCF collects data from two samples: a standard multistage area-probability sample selected from the 48 contiguous US states, and a list sample designed to disproportionately sample wealthy families. For example, 3,007 of the 4,522 interviews for the 2004 SCF were from the area probability sample, and 1,515 were from the list sample. Except in 1983, the SCF public-use dataset does not identify which households come from which sample, therefore the total sample is not representative of US households. The SCF provides a set of probability weights which account for the sample design, and also for differential patterns of non-response among families with different characteristics (B. Bucks and Moore [2006]).

Econometricians and statisticians dispute whether sample weights should be used in regression (see Deaton [1997]). Using sample weights will make the estimates look like those that would be estimated using a representative panel. If the estimated model is viewed as a structural relationship, however, these estimates are not meaningful. If the model's parameters differ across strata of the population, even weighted estimates are inconsistent for the true, heterogeneous population parameters; if they do not, unweighted regression is consistent and efficient. If regression is seen as a tool to describe the population, however, sample weights should be used. Since we only estimate a reduced-form model, we use the sample weights in all regressions, as well as when calculating summary statistics, unless otherwise stated.

Over 1989-2007, the SCF uses a multiple imputation method to account for missing data. For each piece of missing data, the SCF provides 5, possibly different, responses (referred to as "implicates"), resulting in a data set with 5 times the actual number of households. Lindamood et al. (2007) report that using only one implicate may bias results; ideally, all implicates should be used according to the "repeated-imputation inference" method. However, since using all 5 implicates renders the standard errors automatically calculated by Stata invalid, we average across all five implicates.

The core sample consists of heads of households (both female and male) who are not students and are not retired. We keep households whose head is at least 25 years old but less than 65. Table 1 provides summary statistics for our the SCF sample, including the summary statistics for the constrained and the unconstrained households based on the denied credit variable discussed below.

2.1.2 Panel Study of Income Dynamics

The PSID is the only cross-sectional time-series survey that collects data on household consumption.[5] Consumption data in the PSID are limited to food and shelter. We compute all the consumption volatility measures on food consumption calculated as a sum of food consumed at home plus away from home plus food stamps received. Our utility specification will allow for the non-separability of food consumption from other nondurable consumption goods in the utility function. Since food consumption is well known to have low income elasticity, (see for example, Bunkers and Cochrane [1957]), the results presented in this study are a lower bound of what might have actually happened to volatility of total nondurable consumption.

The core PSID sample contains data from 1968 to 2005, and consists of heads of households (both female and male) who are not students and are not retired. We keep households whose head is at least 25 years old but less than 65. We drop all the households that belonged to the Latino or Immigrant samples, and those that were drawn from the Survey of Economic Opportunity (SEO). Households that report negative or zero food consumption levels (that is a sum of food at home plus away from home plus food stamps) are also eliminated. In order to minimize effects of outliers on the results, we follow the literature by dropping households who report more than 500 percent change in family income or food consumption over a one year period as well as those whose income or consumption fall by more than 100 percent.

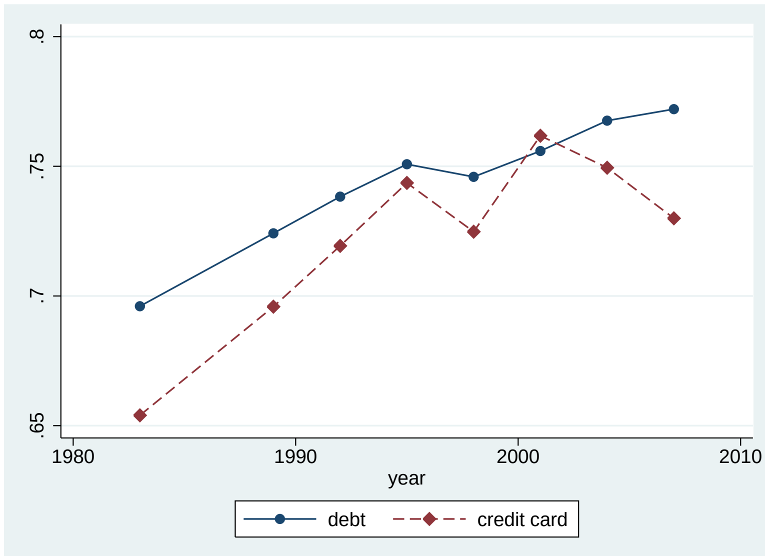
The most important issue to note regarding the data is that it became biennial after 1997. We construct a hypothetical biennial sample to study the evolution of consumption volatility up to 2004. Since income and consumption data is collected for previous year, the biennial sample has data for all *even* years from 1970 to 2004. In fact, it is the limitations in consumption data that render the sample length so short. Food consumption data is available for years 1968 to 1972, 1974

[5]The Consumer Expenditure Survey (CEX) collects a more comprehensive inventory of consumption data, but its structure as a repeated cross-section makes it impossible to construct individual volatility measures that track volatility for the same household over periods of time longer than one year. Current work on inequality utilizes CEX data by constructing synthetic cohorts. This strategy is inappropriate here as our main concern is to provide a measure of temporal volatility for each household. Synthetic cohort techniques would require aggregation within cohorts, which in itself introduces a lot of data smoothing, and is exactly what we want to avoid. It is unclear whether this extra information will bring more benefit than cost, as it will introduce extra model uncertainty. Thus, interpretation of results on evolution of residuals squared might not be as clear cut as they are now.

to 1986, 1989 to 1996 and biennial thereafter. Since we are computing biennial growth rates, we have one data point for 1970 and one for 1972, then 1976 to 1986, 1992 to 2004. Income data has no gaps and is available from 1968 to 2004. Because the SCF data begins in 1983, and the PSID data we have ends in 2004, our sample starts from 1983 and ends in 2004.

2.2 Evolution of Liquidity Constraints Over Time

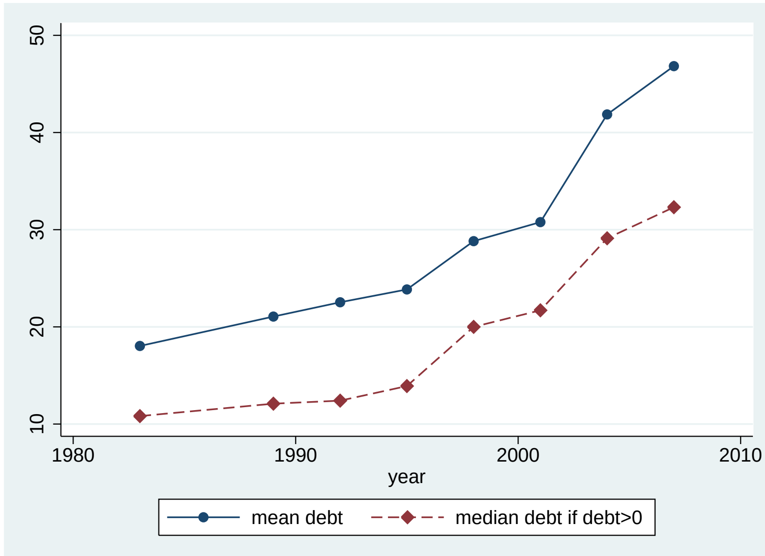
Figure 1: Percentage of households with debt or credit card.



Source: Survey of Consumer Finances.

US household debt has undergone an extraordinary expansion over the past three decades. As Figure 1 illustrates, between 1983 and 2007, the percentage of households holding some debt went from 70% to 77%. Credit card ownership also expanded over this period. The percentage of households owning a credit card increased from 65% in 1983 to a peak of 76% in 2001, before falling slightly to 73% in 2007. The increase in credit card ownership was particularly marked among the poorest 20% of households, rising from 26% to 42% between 1983 and 2007. The composition of credit card holders changed to include more traditionally excluded households: 21% of card holders were nonwhite in 2007, compared to only 12% in 1983; 9% were single parents in 2007, compared to 6% in 1983. Card holders also tended to come from a lower income quintile in 2007. Black and Morgan [1999] and Bird et al. [1999] argue that between 1983 and 1995, credit card access expanded to include riskier and poorer borrowers; these results confirm that the expansion was maintained after 1995. Although credit card debt only accounts for 3% of total debt, it increased by 270% over this period.

Figure 2: Increase in average debt, in 1983 dollars



Source: Survey of Consumer Finances.

Figure 2 shows that the mean real debt for all households increased by 170%, from \$17,000 to \$47,000 (in 1983 dollars), between 1983 and 2007. This is largely an expansion of mortgage debt: 70% of debt is secured against the household's primary residence, and mortgage debt accounts for 80% of the increase in average debt between 1983 and 2007. However, average non-mortgage debt nearly doubled, increasing from \$7,700 to \$13,200 in real terms (two thirds of this increase concerns debt secured against other residential property).[6] For those households with some debt, the median amount of debt held increased from \$11,000 in 1983 to \$33,000 in 2007 (in 1983 dollars).

The literature attributes this expansion of credit to changes in the supply of credit. Legislation, starting with the Monetary Control Act of 1980 and the Garn-St. Germain Act of 1982, increased the competitiveness of consumer lending (see Campbell and Hercowitz [2009]). Innovations in the credit market not only reduced costs in general, but also expanded access to traditionally excluded consumers. The increased use of statistical credit scores since the mid-1990s (the 1970s in the case

[6] See Figure 8 in the Appendix and Dogra [2009] for a detailed analysis of these facts.

of credit cards) may have facilitated lending to consumers whose credit quality would otherwise be hard to discern (e.g. first-time buyers). Increased product differentiation has allowed lenders to mitigate adverse selection problems, and to accommodate the needs of consumers with low current income: in particular, mortgages with lower required down-payments have allowed low wealth consumers to become homeowners (see Doms and Krainer [2007]). Finally, increased use of risk-based pricing has allowed the expansion of subprime lending in the mortgage, auto loan and credit card markets, which explicitly targets less creditworthy households (see Belsky and Essene [2008]).

Figure 3: Proportion of liquidity constrained households

Note: solid line indicates the average proportion of liquidity constrained households based on denied credit measure; dashed lines provide 95% confidence intervals.

Given these trends, and the expansion of debt and access to credit described above, we might expect liquidity constraints to have relaxed over this period, particularly for traditionally constrained groups such as low income and ethnic minority families. However, an increase in debt does not imply that more consumers can obtain as much as they desire. If, for example, consumers' demand for debt has increased in line with the supply of credit, the stock of consumer liabilities might increase, while the proportion of households unable to borrow as much as they desire remains the same, or increases. This is in fact what we observe.

Figure 3 demonstrates that there is no clear decline in the proportion of liquidity constrained households between 1983 and 2007. If anything, the proportion of households denied credit tends to increase, rising by 8 percentage points between 1983 and 1995, then remaining roughly constant until 2007. As expected, the proportion denied credit is slightly counter-cyclical, showing its largest increases in 1992 (after the 1990-1991 recession) and 2004 (after the 2001 recession). (The proportion of households with assets less than two months' income also shows a marked rise and then decline around the 1990-1991 recession.) The increase in loan rejections is most marked for single parents and whites with 12 years or less education, and for the poorest 40% of households: all these groups show a sustained increase in loan rejections across the whole period. For whites with more than 12 years of education, by contrast, the increase in loan rejections is reversed after 1995, falling from a peak of 21% in 1995 to 15% in 2007. Among the richest 60% of households, the proportion denied credit shows a similar decline after 1995 or 1998,(see Figures 9, 10, and 11 in the Appendix).

Another indicator of availability of credit is credit card holdings. We find that while the proportion without a credit card or line of credit trends downwards between 1989 and 2001, falling by 5 percentage points, it shows no clear trend over the period as a whole. The increase in credit card ownership, especially between 1989 and 2001, is particularly marked among poorer households. Among households in the lowest income quintile, the percentage with out a credit card or line of credit fell from 66% to 45% between 1989 and 2001. However, this expansion of credit appears to have reversed for poorer households after 2001: the proportion without a credit card increases by 10 percentage points for both the lowest and the second lowest quantiles. The increase in loan rejections over this period also appears to be highest for poorer households: the proportion denied credit rises by 9 percentage points for the lowest quintile, and by 6 percentage points for the second lowest.

Finally, according to all indicators, availability of a line of credit and credit card holdings, poorer households, single parents and nonwhites, particularly those with 12 or less years of education, are the most likely to be constrained, as we would expect. There is no evidence that liquidity constraints slackened for these groups in particular.

In general, there is no clear decline in the proportion of liquidity constrained households between 1983 and 2007. It appears that credit constraints tightened for all households until the mid-90s

- despite a significant expansion of credit card ownership, especially among the poorest 20% of households. After 1995 and 1998, credit constraints appear to have relaxed for better off households - those in the upper income quantiles, and those with more than 12 years of education. By contrast, for poorer households, and those with less education, the probability of being denied credit remained the same or even increased after 1998, and the percentage of such households without a credit card also increased.

2.3 Estimating Constraints in the PSID

We construct an indicator of liquidity constraints within the SCF sample, following Jappelli et al. [1998], based on the following questions asked by the SCF:

1. "In the past five years, has a particular lender or creditor turned down any request you (or your [husband/wife]) made for credit, or not given you as much credit as you applied for?"
2. "Were you later able to obtain the full amount you (or your husband/wife) requested by reapplying to the same institution or by applying elsewhere?"
3. "Was there any time in the past five years that you (or your [husband/wife]) thought of applying for credit at a particular place, but changed your mind because you thought you might be turned down?"

Following Jappelli [1990] and Duca and Rosenthal [1994], we count a household as liquidity constrained if either it had a request for credit turned down and it was not able to obtain the full amount by reapplying or applying elsewhere, or if it was discouraged from applying because it though it would be turned down. To estimate the probability of being denied credit, we use information on:

> a spline function for age, dummies for a nonwhite respondent or female head of household, marital status (married/ widow/ divorced) and being a single parent, 6 dummies for education, 2 dummies for the number of adults, 3 dummies for the number of kids; dummies for self-employment, receiving welfare payments, unemployment, having any positive asset income; dummies for occupation; log household disposable income, its square, and its cube; annual hours worked; the log of (household mortgage +1) and its

square, log (annual mortgage payment+1) and its square, log (asset income+1) and its square, log (house value+1) and its square, interactions between education and unemployment and between race and number of children, having positive asset income and being a single parent.

Table 2 presents our estimation results on the SCF data. Since the first-stage model is only a reduced-form expression which does not distinguish factors affecting the demand and supply of credit, the estimated coefficients presented in Table 2 do not have a straightforward interpretation: here we are more concerned with accurately predicting the probability of being constrained in the PSID. Nonetheless, the results obtained broadly accord with economic theory and the results of previous studies. Single parents and nonwhite, working heads of household with low education are more likely to be constrained. Individuals with only a high school degree were significantly more likely to be constrained than those with a college degree, whereas those with more than 16 years of education were much less likely to be constrained. Higher family income decreases the probability of being constrained. This concurs with previous studies (although it is not obvious a priori, because our model does not distinguish transitory income, which should unambiguously decrease the probability of being constrained, and permanent income, which has an ambiguous effect).

To check the robustness of the results to use of the survey weights, we estimate the model both with and without survey weights. We also check for stability of coefficients and show that most important variables (in terms of economic importance) vary over time. For details see Table 3. Accordingly, the first-stage coefficients from these regressions, depending on the test results, are allowed to vary over time or are fixed to be time invariant, are then used to impute the probability of being liquidity constrained for households in the PSID sample. For each year of the PSID observations, we impute the probability of being constrained using the coefficients estimated using the nearest subsequent year of the SCF data.

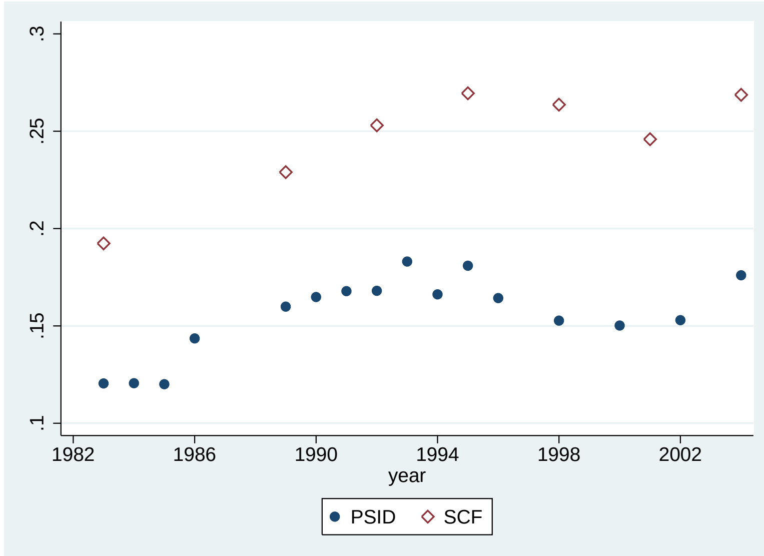
One problem we encounter is the scarcity of appropriate explanatory variables common to both the PSID and the SCF samples. Jappelli et al. [1998] state that the variables used to predict the probability of being constrained in the first stage regression should include all dependent variables in the second stage regression. If variables which affect the probability of being liquidity constrained, and enter the Euler equation estimated in the second stage, are omitted from the first stage regression, then the second stage parameter estimates will be inconsistent. In particular, the probability of being constrained may be different for households with different rates of time preference (because less patient households will demand more consumption today, have a higher desired debt, and be more likely to be constrained). The discount factor is accounted for in the second stage estimation by the household fixed effect, but is not accounted for in the first stage SCF regression, as the SCF is not a panel. This is potentially a serious problem, as the fixed effect will pick up some variation in the dependent variable that should be attributed to liquidity constraints, and the second stage parameter estimates will be inconsistent. We remedy the above problem, by proxying fixed effects with several household specific variables that do not change over time, such as race, education, sex, birth cohort. We also include interactions of these with time varying variables in order to account for correlations between for example discount factors and liquidity constraints.

A related issue is that, in order to use, say, data relating to 1989 to predict the probability of being constrained in 1988, 1987 or 1986, we need to control for aggregate shocks. We would expect the probability of being constrained to be much higher in recessions. (This problem is mitigated to some extent by the fact that the SCF asks whether households were constrained in the last 5 years, which may average out cyclical fluctuations to some extent). We address this problem by including region specific variables, such as the unemployment rate, in the first stage regressions. Although changes in the national unemployment rate would be picked up by the constant term, we can exploit variation in regional unemployment rates to control for region specific aggregate shocks.

Finally, the measures of liquidity constraints used in the SCF are less than ideal. Whereas we require an estimate of whether a household is currently constrained, based on its current characteristics, the denied credit indicator only reports whether a household has ever been constrained in the past 5 years. It might also appear that this indicator overestimates the proportion of constrained households, since some individuals may apply for multiple loans, be rejected for some, but still be able to obtain as much credit as they desire. However, as described above, we exclude such households by counting as unconstrained those households who reported that they were later able to obtain the full amount of credit they desired by reapplying or borrowing elsewhere.

Figure 4 compares estimated constraints in the PSID to actual constraints in the SCF. Two-sample estimation depends on the assumption that both samples are drawn from the same population. As Table 4 shows, the SCF and the PSID samples are broadly similar, although there

Figure 4: Mean Estimated Probabilities in the SCF and the PSID for Denied Credit Constraint



Source: Survey of the Consumer Finances and the Panel Study of Income Dynamics.

are some differences, which may explain why the average SCF household is about 5 percentage points more likely to be constrained. The SCF sample has more welfare recipients and households headed by self-employed or nonwhite individuals than the PSID sample: this makes the average SCF household more likely to be constrained according to our estimated model. The average PSID household also has more asset income and higher mortgage payments than the average SCF household, which decreases the probability of being constrained. As long as the relationship between the probability of being constrained and the explanatory variables is the same in both samples, these differences do not imply that the estimate of this probability is inaccurate. The estimated percentage of constrained households in the PSID and the actual percentage of constrained households in the SCF also display the same trend, which further suggests that our estimates are accurate.

3 Evolution of Income Shocks

The above findings indicate that credit constraints tightened for all households until the mid-90s - despite a significant expansion of credit card ownership, especially among the poorest 20% of households, and that for poorer households, and those with less education, the probability of being denied credit remained the same or even increased after 1998. As the first step towards understanding whether and/or how the welfare of vulnerable households was affected in the last 25 years, we look at the evolution of income volatility. We assume for simplicity, (and due to lack of more complete data), that the sole relevant source of uncertainty faced by the consumer is family income uncertainty. As in Blundell et al. [2008], we assume that the income process for each household h is:

$$ln(Y_{h,a,t}) = Z'_{h,a,t}\vartheta_t + P_{h,a,t} + \nu_{h,a,t} \tag{1}$$

where a and t index age and time respectively, Y is real income, and Z is a set of income characteristics observable and anticipated by consumers, that is allowed to change over time. In individual labor income models, these regressors are usually proxied by age, age squared, dummy variables for education, occupation and industry categories, and interactions between age, age squared and education, sex and race indicators, cohort dummies, time dummies (to control for aggregate shocks), and interaction terms. Since in the present case we are interested in the family income process, we redefine these parameters as those pertaining to the head of household, and include additional parameters, such as head's marital status, number of hours worked by head and his partner, and the number of children in the household.

Equation (1) decomposes the remainder of income into a permanent component $P_{h,a,t}$ and a transitory or mean-reverting component, $\nu_{h,a,t}$. By writing $Y_{h,a,t}$ rather than $Y_{h,t}$ we emphasize the importance of cohort effects in the evolution of earnings over the life-cycle.

For consistency with previous empirical studies[7], we assume that the permanent component $P_{h,a,t}$ follows a martingale process of the form:

$$P_{h,a,t} = P_{h,a,t-1} + \varsigma_{h,a,t} \tag{2}$$

where $\varsigma_{h,a,t}$ is serially uncorrelated, and the transitory component $\nu_{h,a,t}$ that follows an MA(q) process. It follows that unexplained income growth can be computed from:

$$\Delta ln(Y_{h,a,t}) = \Delta \widehat{ln(Y_{h,a,t})} + \varsigma_{h,a,t} + \Delta\nu_{h,a,t} \tag{3}$$

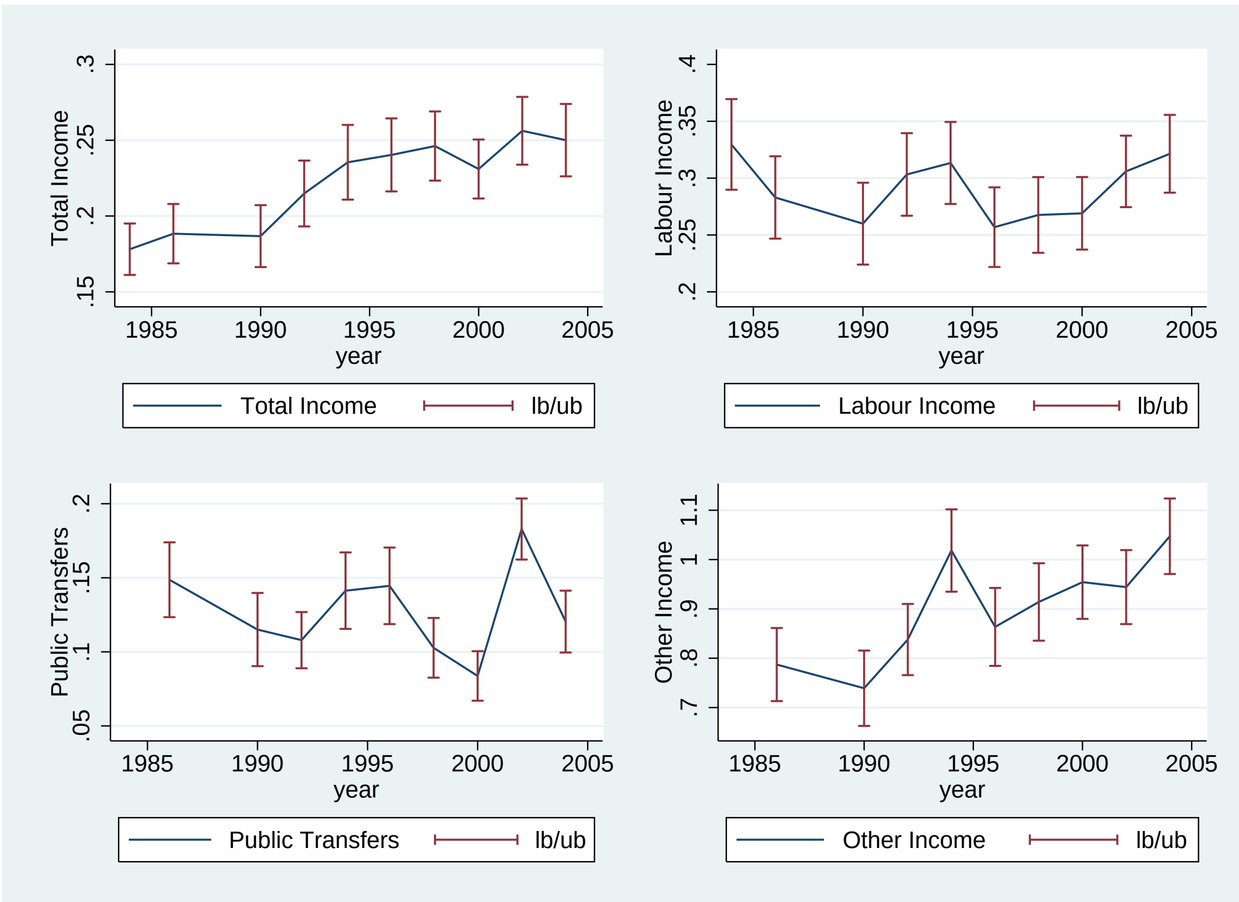
[7]This is a standard model of the income process, see for example MaCurdy [1982], Hall and Mishkin [1982], Abowd and Card [1986], Moffitt and Gottschalk [1994]; or Banks et al. [2001] and Meghir and Pistaferri [2004] for more recent studies.

The volatility of income will be measure as a square of the unexplained income growth component, which is composed of household specific shocks to permanent and transitory income.

$$\sigma^2_{h,a,t} = \Big(\varsigma_{h,a,t} + \Delta\nu_{h,a,t}\Big)^2 = \Big(\Delta ln(Y_{h,a,t}) - \Delta \widehat{ln(Y_{h,a,t})}\Big)^2 \tag{4}$$

The volatility of income, $\sigma^2_{h,a,t}$, is thus composed of household specific shocks to permanent and transitory family income.

Figure 5: Mean Volatility of Income Shocks, 1984 to 2004.



By now it is well documented that volatility of *individual* male earnings increased substantially from the 1970s to early 1980s, was stable in the 1980s to early 1990s, and began to increase again since the mid 1990s.[8] Volatility of *family* income, both its permanent and transitory components,

[8]See for example, Moffitt and Gottschalk [1994, 1998, 2002], **?**, Dynarski and Gruber [1997], Haider [2001], Hacker [2006], Dynan et al. [2007], Keys [2008], Shin and Solon [2008], Jensen and Shore [2008].

also increased substantially since 1970s.[9]

Figure 5 illustrates volatility of family income versus that of total labor income, income from public transfers, and other income, for our biennial sample. As mentioned, this measure of volatility does not distinguish between permanent and transitory shocks to income. Additionally, since the sample is biennial, volatility presented here, is a smoothed out version of annual volatility series.[10] Total labor income is the sum of labor income of all working adults in the household. Family income is the sum of total labor income, plus public and private transfer payments, plus business and asset income.[11] Income from public transfers includes AFDC/TANF and Food Stamps programs, income from SSI and SS benefits, unemployment and workmen compensation benefits. Other income is the difference between family income, labor income and income from public transfers. It is evident from the graphs that volatility of family income is lower than that of labor income, as we would expect given that family income includes public and private transfers, though other income (which is primarily business and asset income) is much more volatile, and its volatility increased dramatically over the sample period.

Tables 5 to 8 provide results on the differences in the trends in income volatility by different categories. As Table 5 illustrates, total labor income volatility increased between 1984 and 2004. This was also true for single parents. On the other hand, labor income volatility actually fell for married households and for households with less than 13 years of education.

Unlike labor income, family income volatility, increased significantly, rising by 43 percent (or 8ppts.) over 1984-2004 period. This difference is a result of a much higher increase in volatility of other income (as can be seen from Table 8). Households on welfare and nonwhite households with low education (less than 13 years) experienced the largest increase in volatility of household family income. Family income volatility increased by 71 percent (or 16ppts.) for these households between 1984 and 2004, whereas it went up by 8ppts. for non welfare recipients and white households. Thus, race and education played an important role in evolution of income volatility. The association between welfare payments and volatility of family income should be read with caution as here we are describing correlations rather than causal relationships. It is reasonable to assume that

[9] See for example Dynan et al. [2007], Keys [2008], Shin and Solon [2008], Jensen and Shore [2008], and Gorbachev [2009].

[10] Volatility computed on annual growth rates behaves in the same way as described by the already cited studies.

[11] Business income is a sum of rental, room and board income, self-employment, farm income and other activities.

households that experienced high volatility of family income turned to public transfers to smooth consumption; of course, not all such households would have received public transfers. It is also worth pointing out that increase in income shocks could have on contributed to the increased demand for credit and thus to the tightening of the liquidity constraint during our sample period.

4 Welfare Implications of Increased Income Volatility and Tighter Liquidity Constraints.

4.1 A Consumption Model

In the absence of perfect insurance, households are unable to insure against income shocks, with the consequence that an increase in unanticipated risk would directly increase volatility of consumption especially if households have limited ability to smooth out these shocks. Since families desire to smooth consumption, such an increase in volatility would have a negative impact on welfare, other things being equal. Thus, it is critical to study changes in variability of household consumption.

Consumption growth varies with preferences or demographics, the risk free interest rate, anticipated income shocks, cash-on-hand relative to future wealth, and idiosyncratic risk. To see this, consider a typical Euler equation.

$$E_t \left[\frac{U'(C_{h,t+1}; \theta_{h,t+1})(1 + r_{h,t+1})}{U'(C_{h,t}; \theta_{h,t})(1 + \delta_h)} \right] (1 + \lambda_{h,t+1}) = 1 \tag{5}$$

where h stands for household and t for time; $C_{h,t}$ is real consumption of family h in period t; $\theta_{h,t}$ are family $h's$ tastes; δ_h is its rate of time preference and is assumed to be household specific but time invariant; E_t is the expectation operator, conditional on information available at time t; $r_{h,t+1}$ is the ex post real return on risk free asset held by family h between periods t and $t+1$; $\lambda_{h,t+1}$ is the extra utility that would result from borrowing an extra dollar, consuming it, and reducing consumption the next period accordingly to repay the debt. If $\lambda_{h,t+1} > 0$, the liquidity constraint is binding and the family cannot borrow, and thus will have to consume out of current assets.

In order to allow for precautionary savings and nonseparability of preferences between consumption of food and other nondurables,[12] and to be able to take the model to the data, we assume

[12] As pointed out by example Attanasio and Weber [1995], Meghir and Weber [1996], Banks et al. [1997] it is important to control for nonseparability of food consumption relative to consumption of other goods.

that the utility function takes the constant relative risk aversion form, such that

$$U(O_{h,t}, F_{h,t}; \theta_{h,t}) = e^{\theta_{h,t}} \left[\frac{O_{h,t}^{\alpha} F_{h,t}^{\beta}}{1-\gamma} \right]^{1-\gamma} \tag{6}$$

where $F_{h,t}$ is food consumption and $O_{h,t}$ is consumption of other nondurable goods, such that $p_t^F F_{h,t} + p_t^O O_{h,t} = C_{h,t}$; α and β are share parameters measuring the importance of consumption of other nondurable goods relative to food and visa versa; and γ controls the degree of relative risk aversion.[13]

The above Euler equations with respect to food consumption:

$$E_t \left[\frac{p_t^F U_F(O_{h,t+1}, F_{h,t+1}; \theta_{h,t+1})(1 + r_{h,t+1})}{p_{t+1}^F U_F(O_{h,t}, F_{h,t}; \theta_{h,t})(1 + \delta_h)} \right] (1 + \lambda_{h,t+1}) = 1 \tag{7}$$

Using functional form for the utility function, and 2nd order Taylor approximation of the above Euler equation,[14] we can show that the growth rate of household food consumption, $\Delta ln(F_{h,t+1})$, is a function of anticipated changes in demographics or preferences $\Delta\theta_{h,t+1}$ and risk free interest rate $ln(1 + r_{h,t+1})$, the shadow price of borrowing an extra dollar $ln(1 + \lambda_{h,t+1})$, personal discount rate $ln(1 + \delta_h)$, on changes in food prices, Δlnp_{t+1}^F, on price differential between inflation in food and other nondurables, $\Delta lnp_{t+1}^O - \Delta lnp_{t+1}^F$, on precautionary saving motive, $V_t \epsilon_{h,t+1}$, and on idiosyncratic shocks to consumption growth, $\varsigma_{h,t+1}$.

[13]The coefficient of relative risk aversion with this utility specification is given by $\frac{-FU_{FF}}{U_F} = 1 - \beta(1-\gamma)$. Intertemporal elasticity of substitution for food consumption is pinned down by $\frac{1}{\beta(1-\gamma)-1}$. The assumption of the iso-elastic form for the utility function means that, in a world without uncertainty, an increase in lifetime wealth will lead to a proportionate increase in consumption. This form also assumes that utility is time additive.

[14]Attanasio and Low [2004] show that a log-linearized Euler equation for consumption yields consistent estimates of the preference parameters when utility is isoelastic and a sample covers a long time period. The requirement on the length of the panel is imposed in order to tackle estimation problems that arise due to the presence of liquidity constraints.

$$\begin{aligned}
\Delta lnF_{h,t+1} &= \frac{1}{1-(1-\gamma)(\alpha+\beta)}\Big[\Delta\theta_{h,t+1} + ln(1+r_{h,t+1}) + ln(1+\lambda_{h,t+1}) + ln(1+\delta_h)\Big] \\
&- \frac{1}{1-(1-\gamma)(\alpha+\beta)}\Big[\Delta lnp^F_{t+1} + \alpha(1-\gamma)(\Delta lnp^O_{t+1} - \Delta lnp^F_{t+1})\Big] + z_{h,t+1} \qquad (8)
\end{aligned}$$

where

$$\begin{aligned}
z_{h,t+1} &= \frac{\alpha(1-\gamma)-1}{(1-\beta(1-\gamma))(1-(1-\gamma)(\alpha+\beta))}\Big[\varsigma^F_{h,t+1} - \frac{V_t\epsilon^F_{h,t+1}}{2}\Big] \\
&- \frac{\beta\alpha(1-\gamma)^2}{(1-\beta(1-\gamma))(1-(1-\gamma)(\alpha+\beta))}\Big[\varsigma^O_{h,t+1} + \frac{V_t\epsilon^O_{h,t+1}}{2}\Big] \\
&= \varsigma_{h,t+1} - \frac{V_t\epsilon_{h,t+1}}{2}
\end{aligned}$$

The estimation strategy allows for household fixed effects to account for household specific discount factors. We include our estimate of the liquidity constraints, Pr(denied credit) as a regressor to control for the shadow price of borrowing an extra dollar, $ln(1+\lambda_{h,t+1})$. Since this variable was estimated based on direct information on constraints from the SCF data, it indicates the probability of a household being constrained in the last 5 years, rather than a probability of being constrained between period t and $t+1$. We also control for the possibility that labor decisions are not separable from the marginal utility of consumption by including the change in the total number of hours worked by the head of the household and by their partner.[15]

To address endogeneity that arises due to presence of second and higher-order terms in the residual, it is typical to estimate the model using as instruments information known at time t.[16] Since the instrument set includes lagged terms of all the parameters in the Euler equation, it violates strict exogeneity assumptions required by the IV estimator. Additionally, as pointed out by Nickell [1981] estimated coefficients under within estimator together with predetermined regressors will give biased and inconsistent results. One more problem we encounter is the limited temporal size of our sample. In fact, on average we have only 5 periods per households, with 10 being the maximum. Thus, our sample is short and highly unbalanced.

To get consistent estimates, we use forward orthogonal deviations transform in order to purge our data from fixed effects proposed by Arellano and Bover [1995]. We use orthogonal transfor-

[15] The inclusion of the information on the labor supply decision is important for the identification purposes, see Attanasio [1999].

[16] See Attanasio and Low [2004] for a detailed discussion of issues involved in estimating log linearized Euler equations.

mation instead of first differences, as forward transform reduces the loss of observations when the data is highly unbalanced. Instead of subtracting the previous observation from the contemporaneous one, forward transform subtracts the average of all future available observations of a variable. Thus it minimizes data loss, and since lagged observations don't enter the formula, they become valid instruments. We perform a two-step AB-GMM estimation that allows for heteroskedasticity and intragroup correlation. We also make the Windmeijer finite-sample correction to the reported standard errors in two-step estimation, without which those standard errors tend to be severely downward biased. Too many instruments will not compromise the coefficient estimates but will weaken the Sargan/Hansen test of overidentifying restrictions. In addition, too many instrument can overfit endogenous variables.[17] We limit the number of instruments to one lag, in order to reduce the potential efficiency loss this type of GMM estimators could suffer. We use second lag of the explanatory variables, plus marginal tax rate, as our instruments. Since probability of being constrained refers to a 5 year period, between $t-3$ and $t+1$, to instrument for liquidity constraints, we use information on probability of being denied credit from $t-4$ and information on race of the household, and whether a household is a welfare recipient.

Table 9 reports our coefficient estimates. Columns (1) to (2) provide estimates using pooled OLS, (3) to (4) using LSDV and finally columns (5) to (7) the Arellano and Bover [1995] estimator. The AB-GMM estimator is *consistent*, but it is not in general unbiased, as in finite samples the instruments are not in general perfectly uncorrelated with the endogenous components of the instrumented regressors. Column (5) provides a AB-GMM estimator that does not control for liquidity constraints or for nonseparabilities of preferences. Column (6) allows for nonseparabilities of preferences. Column (7) is our preferred estimation as it controls for probability of being denied credit. Column (8) includes both nonseparabilities and liquidity constraints. Our estimate of intertemporal elasticity of substitution (IES) is consistent with other studies and is estimated to be around 1.[18] As can be seen from the table, all the necessary tests for the consistency of our estimation are passed. Specifically, we fail to reject the null for both the Sargan test (p-value=0.569) and the Hansen test (p-value=0.198) of overidentification restrictions.

[17] See for example Roodman [2009] on the problems too many instruments could cause this type of GMM estimator.

[18] See for example Attanasio and Weber [1995], Attanasio [1999], and Attanasio and Low [2004].

4.2 Evolution of Consumption Risk

To compute volatility of household consumption, we first predict residuals from the above Euler equation (8):

$$\begin{aligned}
\widehat{z_{h,t+1}} &= \Delta lnF_{h,t+1} - \Big[\frac{1}{1-(1-\widehat{\gamma})(\widehat{\alpha}+\widehat{\beta})}\Big[\Delta\theta_{h,t+1} + ln(1+r_{h,t+1}) + ln(1+\lambda_{h,t+1})\Big] \\
&- \frac{1}{1-(1-\widehat{\gamma})(\widehat{\alpha}+\widehat{\beta})}\Big[\Delta lnp^F_{t+1} + \widehat{\alpha}(1-\widehat{\gamma})(\Delta lnp^O_{t+1} - \Delta lnp^F_{t+1})\Big]\Big] \qquad (9)
\end{aligned}$$

We then subtract out household fixed effects κ_h, thus subtracting out household specific discount factors that are not directly computed by AB-GMM estimator, and time fixed effects τ_t, to center our estimator. We construct consumption volatility parameter as the square of the residual minus $\kappa_h + \tau_t$, such that:

$$\begin{aligned}
\widehat{\kappa_h} &= \frac{1}{T_h}\sum_{t=1}^{T_h}\widehat{z_{h,t+1}} \qquad (10) \\
\widehat{e_{h,t+1}} &= \widehat{z_{h,t+1}} - \widehat{\kappa_h} \\
\widehat{\tau}_t &= \frac{1}{H_t}\sum_{h=1}^{H_t}\widehat{e_{h,t+1}} \qquad (11) \\
\widehat{\varsigma_{h,t+1}}^2 &= (\widehat{e_{h,t}} - \widehat{\tau}_t)^2 \qquad (12)
\end{aligned}$$

We run pooled OLS regression on a time trend to study whether volatility of consumption, $\widehat{\varsigma_{h,t+1}}^2$, changed over this time period.

$$\widehat{\varsigma^2_{h,t+1}} = \beta_0 + \beta_1 t + \omega_{h,t+1} \qquad (13)$$

where β_0 reflects the average variance of the measurement error, which we assumed to be stationary and household specific. If the constant is well estimated, we can then analyze volatility changes in addition to its levels.

Ultimately we are interested in analyzing how the increase in income volatility affected household welfare. Thus, looking at the volatility of food consumption is not enough, since volatility of food consumption is a lower bound of the volatility of nondurable consumption. This statement is true if the relationship between food and nondurable consumption can be approximated by a linear function, and since food consumption has a lower income elasticity than that elasticity for total nondurable consumption, its volatility will also be lower.

Blundell et al. [2008], use Consumer Expenditure Survey, which has detailed information on all consumption goods, and estimate demand for food as a function of nondurable expenditure, relative prices, and a host of demographic and socioeconomic characteristics of the household. They model food expenditure and total expenditure as jointly endogenous and allow this relationship to change over time. Under monotonicity (normality) of food demand, this function can be inverted to obtain a measure of nondurable consumption in the PSID. They find that the elasticity of food expenditure with respect to nondurable expenditure does change over time (testing for joint significance of time varying coefficients, they get p-value=0.06), but they find that none of the time coefficients are individually significant. They estimate budget elasticity at 0.85. Thus, 1 percent change in nondurable expenditure, will lead to a 0.85 percent change in expenditure on food. Translating this into volatility terms, we get that 1 percent increase in volatility of food consumption means a $1/(0.85)^2 = 1.38$ percent increase in nondurable consumption volatility. If we also account for a fact that the elasticity changes over time, and that the change appears to be positive, this number would be even larger.

Figure 6: Change in Mean Volatility with respect to 1984.

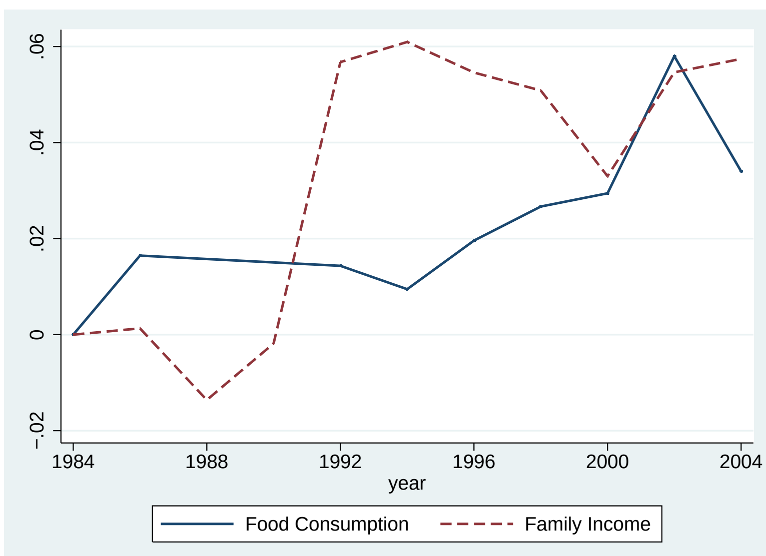


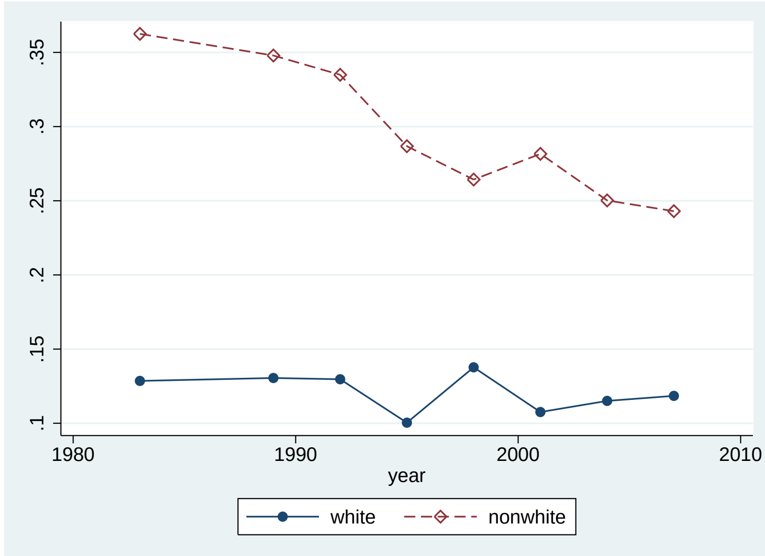
Figure 6 illustrates that household volatility of food consumption was, as we would expect, lower than that of family income volatility, and that it increased over the 1984 - 2004 period. Comparing

Tables 6 and 10, we see that the trend in volatility of consumption is positive and statistically significant, though it is slightly lower than the trend in volatility of family income. Unlike family income volatility, consumption volatility for single parents and welfare recipients (those receiving AFDC/TANF and/or Food Stamps benefits) did not change, although it remained at very high levels, at 23 percent for welfare recipients, vs. 14 for non recipients; and at 16 percent for single parents vs. 12 for married households. Thus, public transfers seemed to have played an important role in mitigating income shocks for some households. Nevertheless, recent work by Moffitt and Scholz [2009] find that very poor single parent and two-parent households experienced declines in public expenditures, driven largely by lower recipient rates, benefit receipts, or both in the AFDC/TANF and Food Stamps programs. Their study documents that there was a redistribution of income from the very poor to near-poor and nonpoor households, as the later group experienced an increase in benefits over 1984 to 2004 time period. Thus, although volatility did not increase for the already disadvantaged groups, the fact that it did not fall indicates that there is scope for government intervention.

On average, education did not play an important role, as volatility of consumption increased in the same way for both well and poorly educated households, i.e. those with more than 12 years of education vs. those with less education. On the other hand, race was much more significant, as on average, nonwhite households experienced an economically and statistically higher increase in volatility of consumption than white households, 35 percent (or 6ppts.) vs. 34 percent (or 4ppts), respectively. In addition, we document that nonwhite households with no more than a high school diploma experienced a much higher increase in volatility of consumption than white households with the same level of education, 49 percent (or 7ppts.) vs. 32 percent (or 3ppts.), respectively. Well educated households saw an increase in volatility that was the same across racial groups, rising by 5ppts.

These differences might be explained by the availability of credit and other smoothing opportunities available to different types of households. In fact, it is not surprising that nonwhite households were less able to smooth out shocks to income as nonwhite households are typically households with low asset holdings that are also more likely to be liquidity constrained. Figure 7 shows that, using the SCF data, in 2004, 25 percent of nonwhite households had net assets lower than 2 months of income, in comparison to 35 percent in 1983. Thus, even though the holdings of

Figure 7: Percent of Households with net assets less than two months of income.



Source: Survey of Consumer Finances.

net assets increased even for nonwhite households, the share with low net assets remained significantly higher than that for white households, for whom this percentage remained constant at 10 percent over this period. Nonwhite households are also much more likely to be denied credit, and as Figure 9 in the Appendix illustrates, this probability did not improve much over the period.

4.3 Constrained and Unconstrained Households

Next we analyze what role, if any, was played by liquidity constraints. Tables 6 and 11 illustrate that liquidity constraints played an important role in propagating shocks to income. Volatility of household consumption was significantly higher for households that had a higher probability of being denied credit, these households experienced a 42 percent (or 5ppts) increase in volatility of consumption, vs. 32 percent (or 3ppts) felt by unconstrained households. This increase was statistically smaller than the increase in income volatility for these groups. Volatility of family income increased by 52 percent (or 11ppts) for constrained and by 42 percent (or 6ppts) for liquidity unconstrained households. Public transfers played an important role in helping constrained households to smooth income shocks, conditional on the household being a recipient. We estimate that if a household was liquidity constrained in a previous period ($Pr(DeniedCredit)_{t-1}$), it received on average, 2,400 dollars (in 1983 terms) of public transfers in period t. On the other hand, liquidity constrained households that were not recipients of welfare benefits, experienced a significant increase in volatility of consumption. This finding indicates that transitory shocks to income increased substantially over the period.[19]

Poorly educated constrained households experienced a significant increase in consumption volatility of 42 percent, whereas for unconstrained households with the same level of education, consumption volatility remained unchanged. This observation again contrasts with the trends in family income volatility. Family income volatility for constrained poorly educated households went up by 52 percent, and by 42 percent for unconstrained households. On the other hand, family income volatility increased by much more for well educated households, it went up by 82 percent for constrained and by 62 percent for the unconstrained households. Food consumption volatility also went up for these households, though there was no statistical difference between constrained and unconstrained households, for both types volatility increased by 47 percent.

Nonwhite households, whether constrained or not, did not experience an increase in volatility of household consumption, though volatility for those households remained very high at 19 percent for constrained and 16 percent for unconstrained households. Family income volatility disaggregated by race also did not show a differential trend, though it did increased by 41 percent. Unfortunately, we do not have enough observations to have a meaningful further disaggregation of data.

5 Conclusions

Despite the extraordinary increase in US household debt over the past quarter-century, consumers are no less likely to be denied credit in 2007 than they were in 1983. Financial sector innovations such as credit scoring and risk-based pricing have surely increased borrowing limits for at least some consumers, and may have contributed to the near-tripling of household debt, but they have not prevented around 1 in 5 households from being denied credit. One explanation for this apparent paradox is that the demand for debt has increased in line with the supply, due to historically low

[19] Finding supported by large research literature that disaggregates income volatility into transitory and permanent components and finds that both increased over the period. See for example, See for example Moffitt and Gottschalk [1994, 1998, 2002], Gottschalk and Moffitt [2009], Dynarski and Gruber [1997], Haider [2001], Hacker [2006], Dynan et al. [2007], Keys [2008], Shin and Solon [2008], Jensen and Shore [2008].

real interest rates, increasing house prices and increased income volatility.

We estimate income volatility for family, labor, public transfers, and other income categories. We find that total labor income volatility was high but did not increase over the period. On the other hand, volatility of family income increased substantially, rising by 43 percent between 1984 and 2004. The biggest increase in family income volatility was experienced by households that were welfare recipients and nonwhites with poor education. Like family income volatility, volatility of household consumption also increased, rising by 34 percent between 1984 and 2004. The increase was particularly high for nonwhite households, particularly those with low education. On the other hand, welfare recipients did not see an increase in consumption volatility.

Liquidity constraints also played an important role in household's lives. We find that already disadvantaged households were unable to smooth out shocks to their income. Given a typical consumption model, this increase in volatility of consumption has an obvious welfare cost, as it comes not from the choices made by the households, but from inability of households to smooth consumption. Using the simplest back of the envelope calculation, we find that an average household would be willing to sacrifice 2.35 percent of their annual nondurable consumption to reduce consumption risk back to where it was in 1984. We use a simple formula derived from Lucas [1987], where the cost of business cycle can be approximated by $\mu = \frac{1}{2}\gamma\sigma_c^2$. Volatility of household food consumption was 0.114 in 1984 and went up to 0.148 by 2004, and our estimate of relative risk aversion $\gamma = 1$. Thus, the cost is 1.7 percent of household food consumption per year. Since, the elasticity of food expenditure with respect to expenditure on nondurables is 0.85, consumers would be willing to sacrifice 2.35 percent of annual nondurable consumption to lower risk to its 1984 level. In 2004, according to National Income and Product Accounts, total personal consumption expenditure was 8,285 billion dollars, thus, households were willing to sacrifice 195 billion dollars to lower consumption risk. Given that the elasticity changes over time, and that the change appears to be positive, this is a conservative estimate of the actual price. This is a substantial cost to society; to put it in current economic terms: the American Recovery and Reinvestment Act package enacted in February 2009 pledged 787 billion dollars to "jump-start the economy and to reduce the loss of jobs".

Given the shear scale of the problem, this is a hugely important and understudied question that deserves greater attention from the academic community.

References

John Abowd and David Card. "On the covariance structure of earnings and hours changes". *NBER Working Paper*, 1832, Feb. 1986.

M. Arellano and O. Bover. "Another look at the instrumental variables estimation of errorcomponents models". *Journal of Econometrics*, 1995.

Orazio Attanasio. *Handbook of Macroeconomics*, volume 1, chapter "Consumption", pages 741–812. Elsevier Science B.V., 1999.

Orazio Attanasio and Hamish Low. "Estimating Euler equations". *Review of Economic Dynamics*, 7:406–435, 2004.

Orazio Attanasio and Guglielmo Weber. "Is consumption growth consistent with intertemporal optimization? Evidence from the Consumer Expenditure Survey. *Journal of Political Economy*, 103(6), Dec. 1995.

P. Goldberg Attanasio, O. and E. Kyriazidou. "Credit constraints in the market for consumer durables: Evidence from micro data on car loans". *International Economic Review*, 49(2), 2008.

A. Kennickell B. Bucks and K. Moore. "Recent changes in family finances: Evidence from the 2001 and 2004 Surveys of Consumer Finances". *Federal Reserve Bulletin*, 2006.

James Banks, Richard Blundell, and Arthur Lewbel. "Quadratic Engel curves and consumer demand.". *The Review of Economics and Statistics*, LXXIX(4):527–539, Nov. 1997.

James Banks, Richard Blundell, and Agar Brugiavini. "Risk pooling, precautionary saving and consumption growth". *Review of Economic Studies*, 68:757–779, 2001.

E. Belsky and R. Essene. "Consumer and mortgage credit at a crossroads: Preserving expanded access while informing choices and protecting consumers". Joint Center for Housing Studies, Harvard University, Working Paper, 2008.

Richard Blundell, Luigi Pistaferri, and Ian Preston. "Consumption Inequality and Partial Insurance". *American Economic Review*, 98(5), 2008.

E. W. Bunkers and Willard W. Cochrane. "On the income elasticity of food services". *The Review of Economics and Statistics*, 39(2):211–217, May 1957.

J. Campbell and Z. Hercowitz. "Welfare implications of the transition into high household debt". *Journal of Monetary Economics*, 56(1):1–16, 2009.

Angus Deaton. *The Analysis of Household Surveys. A Microeconometric Approach to Development Policy.* John Hopkins University Press, Baltimore, 1997.

Keshav Dogra. "Evolution of liquidity constraints for US households, 1983-2007: evidence from the Survey of Consumer Finances". Master's thesis, School of Economics, University of Edinburgh, July 2009.

M. Doms and J. Krainer. "Innovations in mortgage markets and increased spending on housing". *Federal Reserve Bank of San Francisco*, WP 2007-05, 2007.

J. Duca and S. Rosenthal. "Borrowing constraints and access to owner-occupied housing". *Regional Science and Urban Economics*, 24(3):301–322, 1994.

Karen Dynan, Douglas Elmendorf, and Daniel Sichel. "The Evolution of Household Income Volatility". *Board of Governors of the Federal Reserve System, Finance and Economics Discussion Series*, (61), 2007.

Susan Dynarski and Johathan Gruber. “Can families smooth variable earnings?”. *Brookings Papers on Economic Activity*, 1, 1997.

G. Fissel and Tullio Jappelli. “Do Liquidity Constraints Vary over Time? Evidence from Survey and Panel Data: Note”. *Journal of Money, Credit and Banking*, 22(2), 1990.

Milton Friedman. *A Theory of the Consumption Function*. Princeton University Press, 1957.

Olga Gorbachev. “Did Household Consumption Become More Volatile?”. *Revise and Resubmit at American Economic Review*, 2009.

Peter Gottschalk and Robert Moffitt. “The rising instability of U.S. earnings”. *Journal of Economic Perspectives*, 23(4), 2009.

D. Gross and N. Souleles. “Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data”. *Quarterly Journal of Economics*, 117(1), 2002.

Jacob Hacker. *The Great Risk Shift: The Assault on American Jobs, Families Health Care, and Retirement – And How You Can Fight Back*. Oxford University Press, Oct. 2006.

Steven Haider. “earnings instability adn earnings inequality of males in the United States: 1967-1991”. *Journal of Labour Economics*, pages 799–836, Oct. 2001.

Robert Hall and Frederic Mishkin. “The sensitivity of consumption to transitory income: estimates from panel data on households”. *Econometrica*, 50(2): 461–482, Mar. 1982.

Tullio Jappelli. “Who is credit constrained in the U. S. economy?”. *Quarterly Journal of Economics*, 105 (1), 1990.

Tullio Jappelli, Jörn-Steffen Pischke, and Nicholas S. Souleles. “Testing for liquidity constraints in Euler equations with complementary data sources”. *The Review of Economics and Statistics*, 80(2):251–262, May 1998.

Shane T. Jensen and Stephen H. Shore. “Changes in the Distribution of Income Volatility”. 2008.

Benjamin Keys. *Income Volatility and Food Assistance in the United States*, chapter “Trends in Income and Consumption Volatility, 1970-2000”. Upjohn Institute for Employment Research, 2008.

Robert Lucas. *Models of Business Cycle*. Oxford: Basil Blackwell, 1987.

Thomas E. MaCurdy. “The use of time-series processes to model the error structure of earnings in a longitudinal data-analysis”. *Journal of Econometrics*, 18(1):83–114, 1982.

Costas Meghir and Luigi Pistaferri. “Income variance dynamics and heterogeneity”. *Econometrica*, 72(1): 1–32, Jan. 2004.

Costas Meghir and Guglielmo Weber. “Intertermporal Nonseparability or Borrowing Restrictions? A Disaggregate Analysis using a U.S. Consumption Panel”. *Econometrica*, 64(5), Sept. 1996.

Robert Moffitt and Peter Gottschalk. “The growth of earnings instability in the US labor market”. *Brookings Papers on Economic Activity*, 2:217–72, 1994.

Robert Moffitt and Peter Gottschalk. “Trends in the variances of permanent and transitory earnings in the US and their relation to earnings mobility”. *Boston College Working Paper*, 444, Nov. 1998.

Robert Moffitt and Peter Gottschalk. “Trends in the transitory variance of earnings in the US”. *The Economic Journal*, 112: C68–C73, Mar. 2002.

Robert A. Moffitt and John K. Scholz. "Trends in the level and distribution of income support". *NBER Working Paper Series*, 15488, 2009.

S. Nickell. "Biases in dynamic models with fixed effects". *Econometrica*, 49(6), 1981.

David Malin Roodman. "A note on the theme of too many instruments". *Oxford Bulletin of Economics and Statistics*, 71(1):135–158, 2009.

David Runkle. "Liquidity constraints and the permanent-income hypothesis". *Journal of Monetary Economics*, 27:73–98, 1991.

Donggyun Shin and Gary Solon. "Trends in Men's Earnings Volatility: What Does the Panel Study of Income Dynamics Show?". *NBER Working Paper Series*, (W14075), Jun. 2008.

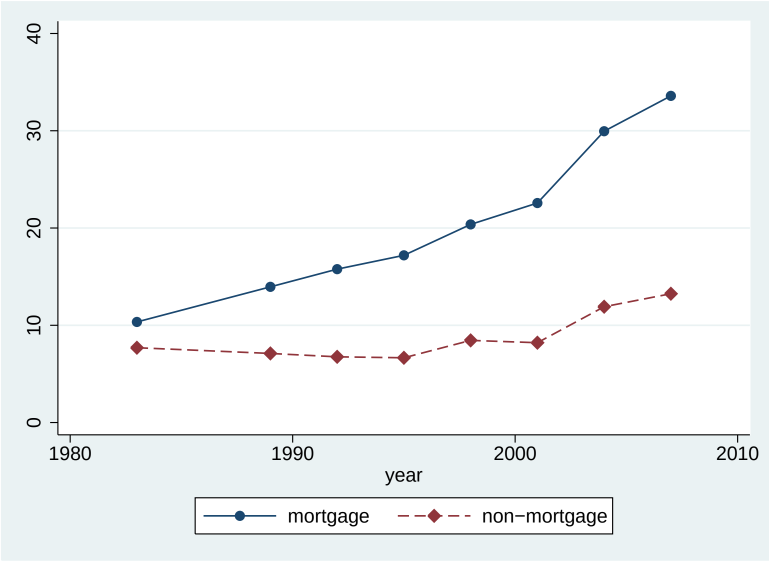
L. Einav W. Adams and J.Levin. "Liquidity constraints and imperfect information in subprime lending". *American Economic Review*, 99(1), 2009.

Stephen Zeldes. "Consumption and liquidity constraints: An empirical investigation". *Journal of Political Economy*, 97(2):305–346, 1989.

6 Appendix

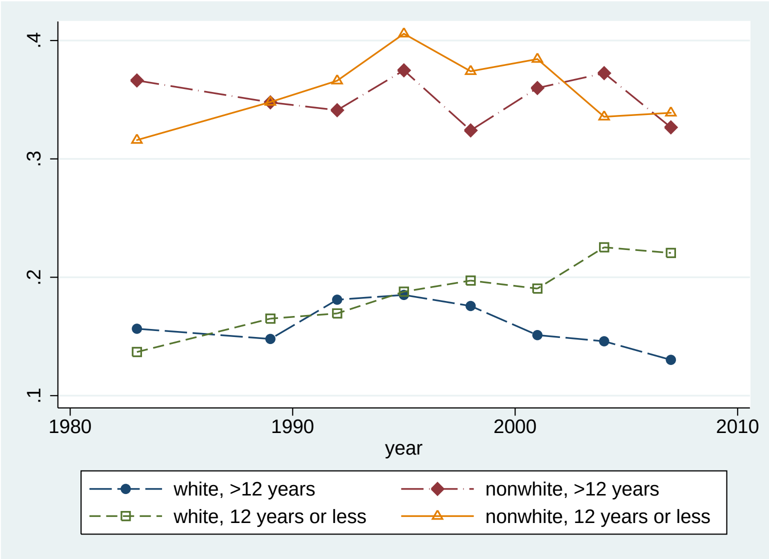
6.1 Supplementary Figures

Figure 8: Average mortgage vs. non-mortgage debt, in 1983 dollars



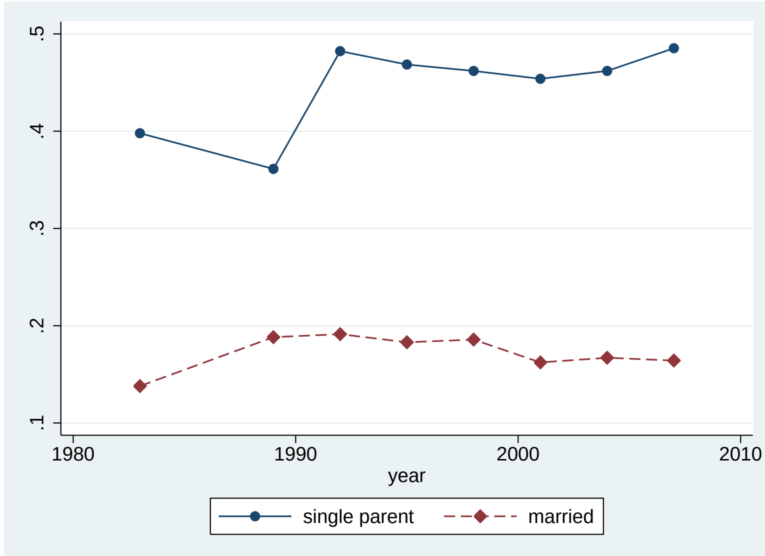
Source: Survey of Consumer Finances.

Figure 9: Proportion of constrained household, by demographic group



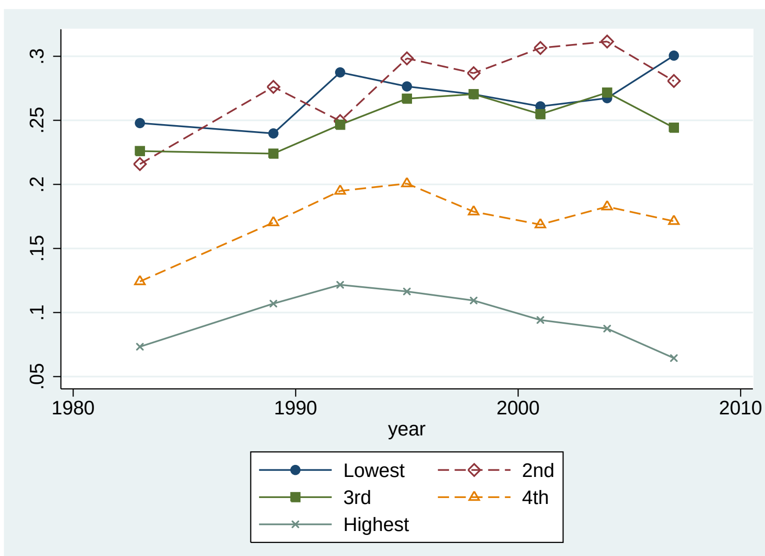
Source: Survey of Consumer Finances.

Figure 10: Proportion of constrained household, by marital status



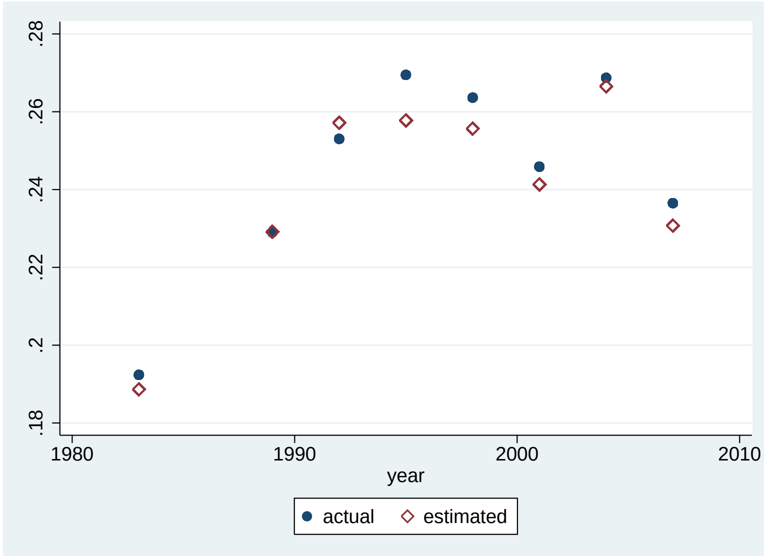
Source: Survey of Consumer Finances.

Figure 11: Proportion of constrained household, by income quintile



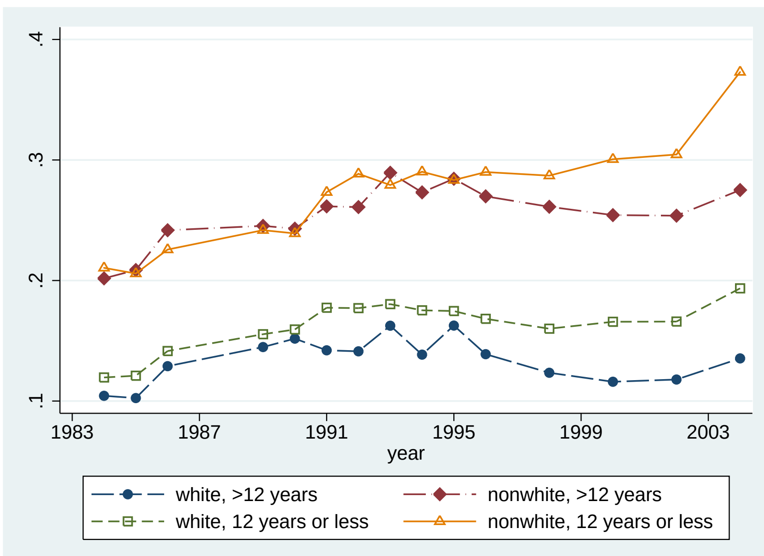
Source: Survey of Consumer Finances.

Figure 12: Estimated vs. Actual Probability of Being Denied Credit in SCF Data



Source: Survey of Consumer Finances.

Figure 13: Proportion of constrained household, by demographic group in PSID



Source: Panel Study of Income Dynamics.

Table 1: Summary statistics for SCF data

	1983			1989			1992			1995		
	All	C	UC	All	C	UC	All	C	UC	All	C	UC
Age	46.8	36.0	49.2	47.9	38.2	50.5	48.5	39.4	51.0	48.5	39.0	51.3
Education	12.3	12.4	12.2	12.5	12.3	12.6	12.9	12.8	13.0	12.9	12.7	13.0
% female	26.3	34.5	24.6	28.1	31.3	27.3	27.7	30.2	27.1	28.9	32.5	27.8
% married	60.6	47.1	63.5	58.2	54.1	59.3	57.6	50.1	59.6	52.6	41.4	56.0
% nonwhite	17.7	32.7	14.4	25.2	42.2	20.8	24.7	39.7	20.5	22.4	37.9	17.8
Family size	2.7	2.8	2.7	2.7	3.1	2.6	2.6	2.9	2.5	2.6	2.9	2.5
% homeowners	63.4	33.9	69.8	64.9	44.1	70.2	65.9	45.4	71.7	66.3	46.8	72.3
# credit cards	3.3	1.7	3.6	4.0	2.7	4.3	3.7	2.6	4.0	4.0	2.5	4.4
Family income	26,969	18,275	28,840	31,693	21,172	34,158	27,823	19,829	30,079	27,434	18,622	30,044
Assets	193,424	68,449	219,785	174,822	68,255	201,902	157,794	72,396	181,846	164,318	62,274	194,839
Net worth	120,206	36,877	137,670	153,762	50,382	180,012	135,262	54,613	158,014	140,465	43,408	169,482
Debt	18,037	14,661	18,644	21,060	17,873	21,890	22,532	17,783	23,832	23,853	18,866	25,357
% with debt	69.6	74.5	68.5	72.4	83.9	69.5	73.8	84.9	70.7	75.1	83.5	72.5
% unemployed	5.6	11.8	4.3	3.1	6.6	2.3	4.1	6.2	3.5	2.8	6.1	1.8
# observations	4,103	647	3,449	3,143	469	2,672	3,906	720	3,179	4,299	789	3,506

	1998			2001			2004			2007		
	All	C	UC	All	C	UC	All	C	UC	All	C	UC
Age	48.7	38.9	51.6	49.0	39.5	51.6	49.5	40.3	52.2	50.0	40.8	52.5
Education	13.1	12.8	13.1	13.1	12.7	13.2	13.3	12.7	13.4	13.3	12.7	13.5
% female	28.0	31.8	26.9	26.8	34.2	24.7	28.0	34.8	26.1	27.6	35.0	25.7
% married	52.3	43.4	54.9	53.1	39.7	56.9	50.8	37.9	54.6	51.1	39.5	54.3
% nonwhite	22.3	35.4	18.5	23.8	41.0	19.0	26.4	41.3	22.0	26.1	40.8	22.1
Family size	2.6	3.0	2.5	2.6	2.9	2.5	2.6	2.9	2.5	2.6	2.9	2.5
% homeowners	67.0	44.4	73.5	68.3	42.3	75.5	70.0	48.0	76.4	69.4	48.2	75.2
# credit cards	3.5	2.6	3.8	3.3	2.4	3.6	3.3	2.4	3.6	3.2	1.9	3.6
Family income	31,004	21,242	33,754	36,679	20,687	41,152	35,138	20,539	39,338	38,960	20,914	43,858
Assets	203,801	77,653	239,056	256,709	66,222	309,870	279,972	80,724	337,548	315,307	92,674	375,800
Net worth	174,979	53,866	208,802	225,929	44,071	276,666	238,110	50,238	292,427	268,474	58,151	325,568
Debt	28,822	23,788	30,254	30,781	22,151	33,204	41,863	30,486	45,120	46,833	34,522	50,231
% with debt	74.6	84.3	71.8	75.6	83.4	73.4	76.8	82.3	75.1	77.2	83.1	75.6
% unemployed	3.1	5.3	2.4	2.4	3.8	2.0	2.8	5.4	2.0	3.1	5.7	2.4
# observations	4,305	800	3,498	4,442	789	3,649	4,519	850	3,663	4,418	733	3,679

All refers to the whole sample, C refers to constrained households, U refers to unconstrained households. All means are calculated using the survey weights. All values are in 1983 US dollars.

Table 2: Estimating Probability of Being Denied Credit on 1983 sample, with survey weights

Dependent Variable	Coef.	Std. Err.	P>|t|	Dependent Variable	Coef.	Std. Err.	P>|t|
age	0.18	0.11	0.09	nonwhite*unemployed	7.10	1.41	0.00
age2	0.00	0.00	0.14	nonwhite*keephouse	6.63	1.41	0.00
1930<year of birth<1936	-1.17	0.73	0.11	nonwhite*homeowner	0.59	0.19	0.00
1935<year of birth<1941	-1.19	0.65	0.07	adults==2	-0.17	0.11	0.13
1945<year of birth<1951	-0.90	0.51	0.08	eduHS	7.35	0.74	0.00
1950<year of birth<1956	0.18	0.39	0.65	edHS*working	-7.65	0.55	0.00
Single Parent	0.24	0.13	0.07	edHS*unemp	-6.22	0.62	0.00
female	-4.14	0.83	0.00	edCol	0.25	0.78	0.75
female*edHS	5.24	0.27	0.00	edColp	-5.71	0.50	0.00
female*edCol	4.88	0.28	0.00	edColp*(1930<yb<1936)	-1.26	0.72	0.08
female*edColp	5.52	0.36	0.00	edColp*(1946>yb>1940)	-1.36	0.60	0.02
female*widow	-0.63	0.31	0.04	edCol*(1950<yb<1956)	-0.53	0.38	0.16
female*(kids>=3)	-0.24	0.30	0.42	edColp*(1950<yb<1956)	-1.07	0.57	0.06
female*(yb<1926)	-0.11	0.51	0.83	welfare*(1941>yb>1935)	-1.85	0.72	0.01
female*nonwhite*coh1	0.08	0.91	0.93	welfare*(1946>yb>1940)	-1.14	0.64	0.08
female*(1931>yb>1925)	-1.14	0.45	0.01	unemployed*(kids==1)	-0.50	0.35	0.15
female*nonwhite*(1941>yb>1935)	1.30	0.84	0.12	unemployed*(1946>yb>1940)	-1.11	0.71	0.12
female*(1946>yb>1940)	-0.59	0.37	0.12	unemployed*(1950<yb<1956)	-1.27	0.69	0.06
female*(1950<yb<1956)	-0.66	0.35	0.06	ln(family income)	-6.71	6.27	0.29
nonwhite	-7.36	1.50	0.00	asset income	0.76	0.35	0.03
nonwhite*ednoHS	1.05	0.39	0.01	ln(asset income)^2	0.02	0.01	0.11
nonwhite*edHS	-0.55	0.24	0.02	ln(house value)	0.15	0.08	0.06
nonwhite*edCollege	0.90	0.39	0.02	ln(house value)^2	-0.02	0.01	0.01
nonwhite*working	6.85	1.39	0.00	technical industry	0.28	0.11	0.01
				service industry	0.43	0.14	0.00
Number of observations	2,370			constant	13.03	19.23	0.50
Population size	52,225,138						
F(138,2232)							

Note: the table provide information only on statistically significant variables to minimize the number of variables presented, a full table for all the years is available upon request.

Table 3: P-values for a test of the null hypothesis that the coefficients on the selected variable are constant over time.

Variable	Model 1	Model 2	Variable	Model 1	Model 2
Age	0.16	0.15	Log asset income	0.85	0.83
Age^2	0.3	0.29	(Log asset income)^2	0.81	0.72
Female	0.33	0.21	Any asset income?	0.66	0.65
Nonwhite	0.9	0.83	Annual rent pay’ts	0.29	
# adults	0.91	0.88	Mortgage pay’t	0	
# children	0.96	0.95	(Mortgage pay’t)^2	0	
Single parent	0.48	0.44	Managers/profess.	0.7	0.8
Married	0.54	0.46	Technical, sales, admin	0.12	0.08
Some HS	0.11	0.1	Service	0.68	0.66
Completed HS	0.8	0.72	Precision production, craft, repair	0.44	0.41
Some college	0.67	0.46	Operators, fabricators	0.49	0.45
College degree	0.38	0.21	Farmers	0.27	0.25
Graduate degree	0.62	0.64	Checking account?	0.66	0.68
Business income	0.19	0.21	Borrow for vacation?	0.9	0.93
Receive welfare	0.93	0.94	Borrow for income cut?	0.27	0.22
# credit cards	0.02		Borrow for fur coat?	0.2	0.28
Wealth x10^{-5}	0.05		Borrow for car?	0.56	0.64
Homeowner	0.29		Borrow for education?	0.42	0.49
House value x10^{-}	0.01		Loan problems	0	0
Debt x10^{-5}	0		Owned home >5yrs?	0.26	0.19
Mortgage x10^{-5}	0.42		Expect inheritance	0.15	0.14
Log income	0.4	0.24	Constant	0.4	0.23
(Log income)^2	0.41	0.26			

Table 4. Summary Statistics: SCF vs. PSID samples.

	Age		% female		% nonwhite		Education		% on welfare		% unemployed		% with business income		Family income	
	SCF	PSID	SCF	PSID	SCF	PSID	SCF	PSID	SCF	PSID	SCF	PSID	SCF	PSID	SCF	PSID
1983	41.36	39.74	0.22	0.16	0.18	0.09	12.87	13.51	0.09	0.05	0.07	0.04	0.17	0.13	31,502	33,899
1989	41.34	39.30	0.22	0.18	0.25	0.11	13.18	13.34	0.08	0.04	0.04	0.03	0.14	0.09	37,625	30,381
1992	41.54	40.68	0.22	0.16	0.26	0.10	13.53	13.74	0.07	0.03	0.06	0.04	0.14	0.07	33,734	38,759
1995	41.65	40.31	0.24	0.20	0.24	0.11	13.48	13.36	0.09	0.04	0.03	0.03	0.14	0.01	32,540	30,202
1998	42.13	42.60	0.21	0.17	0.24	0.11	13.51	13.77	0.05	0.02	0.04	0.02	0.14	0.02	37,148	42,222
2000		42.95		0.17		0.10		13.76		0.02		0.03		0.02		44,041
2001	42.85		0.23		0.25		13.61		0.04		0.03		0.11		43,601	
2002		43.33		0.17		0.11		13.71		0.03		0.04		0.10		41,140
2004	43.27	44.55	0.23	0.15	0.28	0.10	13.69	13.74	0.06	0.04	0.04	0.03	0.12	0.10	42,000	43,598

Table. 5 Volatility of Labour Income, biennial sample, 1984-2004

	all		single parents		married		other		on welfare		not on welfare	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Year/1000	-1.005	0.603	-1.413	0.391	-1.838*	-2.239	1.293	5.106	12.716	15.653	-0.683	0.377
	(0.965)	(1.819)	(5.638)	(6.008)	(1.091)	(2.352)	(2.179)	(3.253)	(9.195)	(9.629)	(0.928)	(1.761)
Unconstrained*year/1000		-1.799		-16.442		2.127		-10.888***		-16.946		-1.050
		(2.081)		(17.183)		(2.583)		(4.134)		(27.241)		(2.021)
Unconstrained		3.414		32.646		-4.396		21.544***		33.888		1.951
		(4.151)		(34.330)		(5.151)		(8.248)		(54.312)		(4.031)
Constant	2.301	-0.802	3.286	-0.298	3.937*	4.839	-2.241	-9.767	-24.231	-30.106	1.639	-0.388
	(1.926)	(3.628)	(11.251)	(11.989)	(2.177)	(4.691)	(4.346)	(6.487)	(18.337)	(19.200)	(1.851)	(3.513)
Observations	19177	19177	898	898	14208	14208	4071	4071	442	442	18735	18735
R-squared	0.000	0.013	0.000	0.004	0.000	0.010	0.000	0.015	0.004	0.007	0.000	0.009

	Education<13		Education>12		Nonwhite		White		Nonwhite, Edu<13		Nonwhite, Edu>12		White, Edu<13		White, Edu>12	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Year/1000	-3.068*	-3.625	1.249	4.971**	-0.012	0.891	-1.094	0.383	2.660	4.417	0.370	-0.239	-3.710**	-5.601*	1.022	5.040*
	(1.644)	(2.774)	(1.132)	(2.314)	(3.951)	(4.821)	(0.980)	(1.948)	(5.941)	(7.043)	(4.794)	(6.135)	(1.668)	(2.956)	(1.186)	(2.580)
Unconstrained*year/1000		0.935		-4.780*		-3.470		-1.519		-9.917		3.785		3.098		-4.916*
		(3.308)		(2.598)		(7.361)		(2.203)		(11.972)		(7.197)		(3.472)		(2.858)
Unconstrained		-2.071		9.402*		6.683		2.875		19.517		-7.766		-6.361		9.687*
		(6.600)		(5.180)		(14.691)		(4.394)		(23.883)		(14.357)		(6.929)		(5.697)
Constant	6.470**	7.691	-2.241	-9.577**	0.461	-1.289	2.463	-0.385	-4.802	-8.252	-0.380	0.887	7.730**	11.607**	-1.796	-9.729*
	(3.280)	(5.534)	(2.257)	(4.613)	(7.884)	(9.621)	(1.956)	(3.885)	(11.852)	(14.051)	(9.567)	(12.240)	(3.327)	(5.898)	(2.366)	(5.142)
Observations	8290	8290	10887	10887	1820	1820	17357	17357	1015	1015	767	767	7275	7275	9777	9777
R-squared	0.001	0.015	0.000	0.009	0.000	0.011	0.000	0.010	0.000	0.011	0.000	0.011	0.001	0.013	0.000	0.007

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

Note: We define household in year t as being unconstrained if its probability of being denied credit is below the average probability of being denied credit in that particular year.

Table. 6 Volatility of Family Income, biennial sample, 1984-2004

	all		single parents		married		other		on welfare		not on welfare	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Year/1000	3.933***	5.679***	1.680	2.328	3.645***	5.143***	4.530***	4.787**	8.746**	10.106**	3.993***	5.464***
	(0.590)	(1.025)	(3.174)	(3.394)	(0.618)	(1.179)	(1.578)	(2.253)	(4.154)	(4.502)	(0.585)	(1.028)
Unconstrained*year/1000		-2.584**		-6.244		-1.661		-2.370		-16.001*		-2.124*
		(1.212)		(7.174)		(1.356)		(2.970)		(9.487)		(1.213)
Unconstrained		5.057**		12.396		3.246		4.630		31.817*		4.158*
		(2.416)		(14.318)		(2.702)		(5.923)		(18.912)		(2.419)
Constant	-7.622***	-11.049***	-3.001	-4.289	-7.080***	-10.024***	-8.737***	-9.207**	-16.901**	-19.606**	-7.753***	-10.639***
	(1.176)	(2.042)	(6.330)	(6.769)	(1.232)	(2.348)	(3.147)	(4.493)	(8.278)	(8.973)	(1.167)	(2.048)
Observations	21874	21874	1181	1181	15922	15922	4771	4771	730	730	21144	21144
R-squared	0.002	0.011	0.000	0.001	0.003	0.007	0.002	0.008	0.006	0.009	0.002	0.009

	Education<13		Education>12		Nonwhite		White		Nonwhite, Edu<13		Nonwhite, Edu>12		White, Edu<13		White, Edu>12	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Year/1000	3.218***	4.116***	4.798***	7.352***	3.812*	5.146**	3.902***	5.718***	8.143**	10.727***	-0.459	-1.425	2.437**	2.208	5.005***	8.963***
	(0.953)	(1.438)	(0.745)	(1.471)	(2.086)	(2.419)	(0.612)	(1.128)	(3.168)	(3.549)	(2.403)	(2.870)	(0.980)	(1.535)	(0.794)	(1.727)
Unconstrained*year/1000		-1.928		-3.408**		-5.465		-2.487*		-14.381*		4.929		0.303		-5.200***
		(1.884)		(1.631)		(4.606)		(1.302)		(7.311)		(4.565)		(1.967)		(1.862)
Unconstrained		3.748		6.708**		10.793		4.869*		28.542*		-9.904		-0.689		10.283***
		(3.756)		(3.250)		(9.194)		(2.594)		(14.589)		(9.112)		(3.921)		(3.710)
Constant	-6.169***	-7.913***	-9.368***	-14.406***	-7.319*	-9.957**	-7.567***	-11.132***	-15.926**	-21.054***	1.162	3.106	-4.623**	-4.118	-9.787***	-17.621***
	(1.899)	(2.866)	(1.484)	(2.931)	(4.159)	(4.821)	(1.220)	(2.249)	(6.312)	(7.069)	(4.796)	(5.729)	(1.954)	(3.060)	(1.581)	(3.441)
Observations	9595	9595	12279	12279	2255	2255	19619	19619	1278	1278	920	920	8317	8317	10910	10910
R-squared	0.001	0.010	0.004	0.011	0.002	0.008	0.002	0.010	0.007	0.019	0.000	0.004	0.001	0.007	0.004	0.012

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: We define household in year t as being unconstrained if its probability of being denied credit is below the average probability of being denied credit in that particular year.

Table. 7 Volatility of Public Transfer Income, biennial sample, 1984-2004

	all		single parents		married		other		on welfare		not on welfare	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Year/1000	-0.046	1.349	-6.838	-6.210	-0.716	0.480	3.464**	3.891	0.207	-2.478	0.781	2.517**
	(0.737)	(1.435)	(6.432)	(6.795)	(0.755)	(1.515)	(1.587)	(2.669)	(5.534)	(6.481)	(0.580)	(1.238)
Unconstrained*year/1000		-1.729		-6.662		-0.867		-2.726		6.858		-2.384*
		(1.598)		(18.838)		(1.687)		(3.198)		(11.692)		(1.341)
Unconstrained		3.344		13.255		1.657		5.366		-13.684		4.680*
		(3.189)		(37.638)		(3.366)		(6.384)		(23.319)		(2.676)
Constant	0.220	-2.500	14.007	12.757	1.526	-0.809	-6.742**	-7.559	0.294	5.652	-1.473	-4.888**
	(1.471)	(2.864)	(12.844)	(13.568)	(1.508)	(3.022)	(3.168)	(5.330)	(11.040)	(12.935)	(1.159)	(2.470)
Observations	15996	15996	811	811	11658	11658	3527	3527	1054	1054	14942	14942
R-squared	0.000	0.012	0.002	0.002	0.000	0.007	0.001	0.007	0.000	0.000	0.000	0.012

	Education<13		Education>12		Nonwhite		White		Nonwhite, Edu<13		Nonwhite, Edu>12		White, Edu<13		White, Edu>12	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Year/1000	-1.661	0.437	1.700**	2.382	1.524	2.788	-0.278	0.735	2.610	4.404	2.768	2.961	-2.315	-0.849	1.419*	1.723
	(1.431)	(2.409)	(0.717)	(1.541)	(3.102)	(3.739)	(0.740)	(1.524)	(4.797)	(5.671)	(3.153)	(3.636)	(1.462)	(2.596)	(0.744)	(1.721)
Unconstrained*year/1000		-3.957		-0.492		-4.344		-1.091		-11.585		1.165		-2.473		0.115
		(2.819)		(1.693)		(5.979)		(1.677)		(8.332)		(7.358)		(2.992)		(1.858)
Unconstrained		7.777		0.904		8.531		2.091		22.917		-2.401		4.848		-0.298
		(5.628)		(3.377)		(11.941)		(3.347)		(16.643)		(14.689)		(5.973)		(3.706)
Constant	3.495	-0.629	-3.304**	-4.612	-2.789	-5.283	0.668	-1.297	-4.891	-8.434	-5.367	-5.735	4.778	1.902	-2.750*	-3.309
	(2.857)	(4.808)	(1.431)	(3.075)	(6.193)	(7.463)	(1.476)	(3.043)	(9.575)	(11.318)	(6.292)	(7.255)	(2.919)	(5.184)	(1.485)	(3.433)
Observations	6599	6599	9397	9397	1616	1616	14380	14380	910	910	672	672	5689	5689	8412	8412
R-squared	0.000	0.011	0.001	0.010	0.000	0.008	0.000	0.009	0.000	0.011	0.001	0.006	0.001	0.007	0.000	0.008

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

Note: We define household in year t as being unconstrained if its probability of being denied credit is below the average probability of being denied credit in that particular year.

Table. 8 Volatility of Family Income minus Labour Income minus Public Transfers, biennial sample, 1984-2004

	all		single parents		married		other		on welfare		not on welfare	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Year/1000	13.573***	14.559***	13.236*	12.878*	15.477***	16.293***	7.309	8.305	11.773*	21.818**	14.067***	13.246***
	(2.430)	(3.717)	(7.156)	(7.638)	(2.893)	(5.074)	(5.300)	(7.646)	(6.503)	(8.645)	(2.599)	(4.053)
Unconstrained*year/1000		-2.310		0.371		-3.336		0.022		-21.695*		0.643
		(4.829)		(21.150)		(6.111)		(10.581)		(12.892)		(5.182)
Unconstrained		4.789		-0.678		6.857		0.030		43.419*		-1.087
		(9.636)		(42.203)		(12.192)		(21.124)		(25.727)		(10.341)
Constant	-26.188***	-28.267***	-25.685*	-24.977	-29.970***	-31.734***	-13.702	-15.727	-22.519*	-42.624**	-27.186***	-25.673***
	(4.850)	(7.416)	(14.273)	(15.233)	(5.773)	(10.119)	(10.581)	(15.270)	(12.976)	(17.244)	(5.187)	(8.088)
Observations	10838	10838	611	611	7927	7927	2300	2300	1418	1418	9420	9420
R-squared	0.003	0.007	0.004	0.004	0.004	0.008	0.001	0.002	0.002	0.006	0.003	0.008

	Education<13		Education>12		Nonwhite		White		Nonwhite, Edu<13		Nonwhite, Edu>12		White, Edu<13		White, Edu>12	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Year/1000	11.337***	20.520***	14.301***	7.955	11.477	14.334*	13.807***	14.607***	3.878	12.212	20.172	17.669	12.430***	23.040***	14.037***	3.577
	(3.589)	(4.811)	(3.295)	(5.702)	(8.066)	(8.241)	(2.548)	(4.165)	(10.117)	(9.206)	(13.512)	(15.686)	(3.840)	(5.616)	(3.440)	(6.071)
Unconstrained*year/1000		-16.653**		8.444		-18.007		-1.865		-43.994		6.392		-17.492**		13.462*
		(7.034)		(6.845)		(23.467)		(5.190)		(35.250)		(29.506)		(7.608)		(7.204)
Unconstrained		33.401**		-16.694		36.267		3.898		88.178		-12.611		35.061**		-26.678*
		(14.036)		(13.661)		(46.872)		(10.357)		(70.398)		(58.919)		(15.179)		(14.377)
Constant	-21.798***	-40.215***	-27.588***	-15.031	-22.042	-27.809*	-26.651***	-28.366***	-6.954	-23.656	-39.283	-34.321	-23.973***	-45.238***	-27.061***	-6.322
	(7.161)	(9.596)	(6.577)	(11.378)	(16.098)	(16.440)	(5.085)	(8.311)	(20.190)	(18.364)	(26.969)	(31.296)	(7.662)	(11.202)	(6.866)	(12.115)
Observations	4611	4611	6227	6227	1048	1048	9790	9790	587	587	443	443	4024	4024	5612	5612
R-squared	0.002	0.008	0.003	0.007	0.002	0.011	0.003	0.007	0.000	0.018	0.006	0.008	0.003	0.007	0.003	0.008

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: We define household in year t as being unconstrained if its probability of being denied credit is below the average probability of being denied credit in that particular year.

Table 9. Euler Equation Estimation

VARIABLES	(1) OLS	(2) OLS	(3) LSDV	(4) LSDV	(5) AB_GMM	(6) AB_GMM	(7) AB_GMM	(8) AB_GMM
Age	-0.000	-0.001	-0.002	-0.009	0.001	-0.116**	0.003	-0.116*
	(0.002)	(0.002)	(0.004)	(0.008)	(0.002)	(0.049)	(0.002)	(0.066)
Real Interest Rate	0.092	-0.160	-0.021	0.059	1.759***	3.378***	1.823***	3.737***
	(0.152)	(0.175)	(0.221)	(0.242)	(0.534)	(1.096)	(0.668)	(1.438)
Change in Number of Adults	0.162***	0.161***	0.159***	0.158***	0.151***	0.152***	0.148**	0.148**
	(0.009)	(0.009)	(0.010)	(0.010)	(0.054)	(0.054)	(0.057)	(0.058)
Change in Number of Kids	0.121***	0.120***	0.119***	0.119***	0.093	0.136	0.207	0.211
	(0.008)	(0.008)	(0.010)	(0.010)	(0.131)	(0.124)	(0.172)	(0.171)
Change in Marital Status	-0.025***	-0.024***	-0.025**	-0.023**	-0.045	-0.053	-0.043	-0.057
	(0.009)	(0.009)	(0.011)	(0.011)	(0.042)	(0.042)	(0.047)	(0.049)
Change in Hours Worked, Wife	0.005***	0.005***	0.005**	0.005**	0.004	0.004	0.004	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.008)	(0.008)	(0.008)	(0.008)
Change in Hours Worked, Head	0.013**	0.013**	0.010	0.009	-0.027	-0.028	-0.012	-0.017
	(0.006)	(0.006)	(0.008)	(0.008)	(0.038)	(0.038)	(0.041)	(0.041)
Precautionary Savings	-0.001	0.004	0.015	0.016	-0.139*	-0.126	-0.167**	-0.170**
	(0.010)	(0.009)	(0.015)	(0.015)	(0.084)	(0.081)	(0.083)	(0.082)
Price Differential		-0.045***		0.173		3.353**		0.445
		(0.016)		(0.182)		(1.394)		(0.430)
Pr(Denied Credit)		-0.145***		-0.232**			0.982**	3.397*
		(0.034)		(0.091)			(0.447)	(1.883)
Constant	0.052	0.337***	0.116	-0.419				
	(0.042)	(0.087)	(0.085)	(0.624)				
Observations	20808	20808	20808	20808	16652	16652	16652	16652
R-squared	0.053	0.054	0.176	0.177				
Number of clusters	4120	4120	4120	4120	3582	3582	3582	3582
Arrelano-Bond test for AR(1)					-25.25	-25.27	-24.22	-24.07
Pr>z					0	0	0	0
Arrelano-Bond test for AR(2)					6.837	6.734	6.330	6.381
Pr>z					0	0	0	0
Arrelano-Bond test for AR(3)					-0.691	-0.728	-0.374	-0.560
Pr>z					0.489	0.466	0.709	0.575
Sargan test of overid					21.38	30.90	15.85	19.07
df					20	22	12	13
Prob>chi2					0.375	0.0982	0.569	0.121
Hansen test of overid					14.45	21.97	10.54	13.36
df					20	22	12	13
Prob>chi2					0.807	0.461	0.198	0.421
Number of Instruments					31	34	24	26
F-stat					7.543	6.387	6.840	5.963
Prob>F					0	0	0	0
Avg num obs					4.649	4.649	4.649	4.649
max num obs					10	10	10	10

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

Table 10. Volatility of Food Consumption, biennial sample, 1984-2004

	all		single parents		married		other		on welfare		not on welfare	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Year/1000	1.979***	2.648***	1.889	2.296	1.379***	1.591**	3.417***	2.749**	1.441	2.187	2.073***	2.760***
	(0.395)	(0.638)	(1.708)	(1.765)	(0.437)	(0.790)	(0.943)	(1.293)	(3.494)	(3.906)	(0.392)	(0.620)
Unconstrained*year/1000		-0.930		-5.146		-0.159		1.029		-6.472		-0.966
		(0.785)		(6.867)		(0.924)		(1.875)		(7.158)		(0.771)
Unconstrained		1.826		10.284		0.303		-2.083		12.878		1.901
		(1.565)		(13.703)		(1.841)		(3.736)		(14.255)		(1.537)
Constant	-3.810***	-5.127***	-3.609	-4.421	-2.630***	-3.042*	-6.627***	-5.280**	-2.647	-4.133	-4.001***	-5.355***
	(0.788)	(1.271)	(3.405)	(3.518)	(0.871)	(1.575)	(1.879)	(2.580)	(6.960)	(7.782)	(0.781)	(1.236)
Observations	17261	17261	826	826	12816	12816	3619	3619	387	387	16874	16874
R-squared	0.002	0.005	0.002	0.003	0.001	0.002	0.004	0.006	0.001	0.002	0.002	0.005

	Education<13		Education>12		Nonwhite		White		Nonwhite, Edu<13		Nonwhite, Edu>12		White, Edu<13		White, Edu>12	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Year/1000	1.848***	2.590***	2.143***	2.714***	2.640*	2.450	1.910***	2.626***	3.498*	4.092*	2.504	1.118	1.660**	2.231**	2.312***	3.040***
	(0.642)	(0.980)	(0.498)	(0.819)	(1.472)	(1.671)	(0.409)	(0.688)	(2.000)	(2.459)	(2.295)	(2.294)	(0.677)	(1.058)	(0.526)	(0.930)
Unconstrained*year/1000		-1.321		-0.654		0.962		-0.973		-2.930		5.585		-0.944		-0.865
		(1.243)		(0.997)		(3.447)		(0.825)		(3.379)		(5.962)		(1.318)		(1.091)
Unconstrained		2.609		1.274		-1.950		1.918		5.804		-11.165		1.862		1.702
		(2.477)		(1.988)		(6.867)		(1.644)		(6.740)		(11.873)		(2.627)		(2.173)
Constant	-3.542***	-5.008**	-4.143***	-5.261***	-5.087*	-4.700	-3.677***	-5.090***	-6.796*	-7.973	-4.812	-2.041	-3.172**	-4.300**	-4.482***	-5.917***
	(1.279)	(1.952)	(0.994)	(1.632)	(2.935)	(3.333)	(0.815)	(1.371)	(3.986)	(4.900)	(4.574)	(4.577)	(1.349)	(2.109)	(1.049)	(1.852)
Observations	7223	7223	10038	10038	1602	1602	15659	15659	869	869	700	700	6354	6354	9010	9010
R-squared	0.002	0.004	0.003	0.005	0.003	0.004	0.002	0.004	0.005	0.007	0.002	0.005	0.001	0.003	0.003	0.005

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

Note: We define household in year t as being unconstrained if its probability of being denied credit is below the average probability of being denied credit in that particular year.

Table 11. Volatility of Food Consumption: constrained vs. unconstrained households, biennial sample, 1984-2004

	all		single parents		maried		nonwhite		white		on welfare		not on welfare	
VARIABLES	C	UC	C	UC	C	UC	C	UC	C	UC	C	UC	C	UC
Year/1000	2.648***	1.718***	2.296	-2.851	1.379***	1.379***	2.450	3.412	2.626***	1.653***	2.187	-4.285	2.760***	1.794***
	(0.638)	(0.488)	(1.764)	(6.732)	(0.437)	(0.437)	(1.671)	(3.032)	(0.688)	(0.493)	(3.897)	(6.144)	(0.620)	(0.489)
Constant	-5.127***	-3.301***	-4.421	5.863	-2.630***	-2.630***	-4.700	-6.650	-5.090***	-3.172***	-4.133	8.745	-5.355***	-3.454***
	(1.271)	(0.972)	(3.514)	(13.433)	(0.871)	(0.871)	(3.332)	(6.038)	(1.371)	(0.982)	(7.765)	(12.233)	(1.236)	(0.974)
Observations	6772	10489	748	78	12816	12816	1245	357	5527	10132	335	52	6437	10437
R-squared	0.003	0.002	0.002	0.004	0.001	0.001	0.002	0.005	0.004	0.002	0.001	0.009	0.004	0.002

	Education<13		Education>12		Nonwhite, Edu<13		Nonwhite, Edu>12		White, Edu<13		White, Edu>12	
VARIABLES	C	UC	C	UC	C	UC	C	UC	C	UC	C	UC
Year/1000	2.590***	1.268	2.900***	2.323***	4.092*	1.162	1.118	6.702	2.231**	1.287	3.040***	2.174***
	(0.980)	(0.810)	(0.855)	(0.630)	(2.457)	(2.351)	(2.293)	(5.524)	(1.058)	(0.842)	(0.930)	(0.625)
Constant	-5.008**	-2.399	-5.631***	-4.510***	-7.973	-2.169	-2.041	-13.205	-4.300**	-2.438	-5.917***	-4.215***
	(1.952)	(1.615)	(1.703)	(1.256)	(4.896)	(4.695)	(4.573)	(10.999)	(2.109)	(1.679)	(1.852)	(1.246)
Observations	3373	3850	3270	6440	691	178	529	171	2682	3672	2741	6269
R-squared	0.003	0.001	0.005	0.003	0.005	0.001	0.001	0.011	0.002	0.001	0.005	0.003

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

Note: We define household in year t as being unconstrained if its probability of being denied credit is below the average probability of being denied credit in that particular year.