Consumption Volatility, Liquidity Constraints and Household Welfare*

Keshav Dogra[†] and Olga Gorbachev[‡]

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Abstract

We evaluate the impact of increased income uncertainty and financial liberalisation in the US on consumption volatility and household welfare. We estimate Euler equations and measure the volatility of unpredictable changes in consumption as the squared residuals. We directly control for liquidity constraints using SCF data on access to credit, and document that despite the increase in household debt between 1983 and 2007, there was no decline in the proportion of liquidity constrained households. Consumption volatility increased significantly over this period, especially for liquidity constrained households, indicating substantial welfare losses.

JEL D12, D91, E21, J15.

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The increase in family income volatility in the United States since the 1970s has been widely documented. Most recently, DeBacker et al. [2013] use a confidential panel of tax returns from the IRS to show that family income volatility increased

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

‡Department of Economics, Alfred Lerner School of Business and Economics, University of Delaware, Newark, DE, USA, corresponding author: email olgag@udel.edu.

between 1987 and 2009. This reinforces the finding in earlier studies (Dynan et al. [2012], Keys [2008], Gottschalk and Moffitt [2009], and Gorbachev [2011]), based on PSID data, that household income volatility increased between 1970 and 2006.[1] Whether this increase in income volatility affected household welfare, however, depends on whether it led to a comparable increase in consumption volatility. A priori, households may have been able to use credit markets to smooth consumption, despite increasingly volatile income shocks.

We estimate whether consumption volatility increased for US households between 1980 and 2004. Building on Gorbachev [2011]'s work, which uses an Euler equation approach to separate unpredictable changes in consumption from predictable changes stemming from observable taste shifters, interest rates, and life-cycle factors; we estimate consumption volatility as the square of the Euler equation residuals. Gorbachev [2011] addressed liquidity constraints only by estimating Euler equations on a sample of households with positive net worth, assuming that these households are unconstrained while those with zero or negative net worth are constrained.[2]

In this paper, we use direct information on household access to credit from the Survey of Consumer Finances (SCF) to identify the degree to which households are liquidity constrained, and predict the likelihood that individuals are constrained in our PSID sample. By using direct information about credit constraints, our approach improves on Gorbachev [2011] in three respects. First, it provides a more precise measure of liquidity constraints, since some positive net worth households may be liquidity constrained. Indeed, based on our SCF measure, 15 to 20 percent of positive net worth households are liquidity constrained. Second, it allows us to document how household access to credit changed over time, which is of independent interest. Third, it enables us to study how volatility of consumption evolved for the most vulnerable groups in society, liquidity constrained and wealth-poor households.

We find that consumption volatility increased by around 19 percent between 1980 and 2004, or by 3 volatility points for an average household, where as volatility of income went up by 14 volatility points, or 44 percent. Since unconstrained households can smooth temporary income shocks, this suggests that either a significant fraction of households were liquidity constrained, or that permanent income shocks became more volatile over this period, (or a combination of the two). In fact, consistent with

[1]This increase in *family* income volatility contrasts with recent evidence, based on confidential administrative data from Social Security Administration and IRS, that male earnings volatility remained constant or even decreased since the 1980s. See Dahl et al. [2008], Sabelhaus and Song [2009], Guvenen et al. [2012], and DeBacker et al. [2013].

[2]Since Euler equations for constrained households contain an additional term, the Lagrange multiplier on the borrowing constraint, it is necessary to either have an estimate of the Lagrange multiplier, or to drop liquidity constrained households.

our findings, a number of studies observe that the volatility of permanent shocks continued to increase into the 1990s.[3] Despite financial liberalisation and the near-tripling of household debt between 1983 and 2007, we find that the proportion of liquidity constrained households slightly *increased* during this period. In all years, poorer households and those headed by single parents, black or Hispanic individuals, or individuals with low education, were the most likely to be liquidity constrained. In fact, these gaps in access to credit (between rich and poor, white and black individuals, and so on) widened over time.

Households' inability to borrow and smooth consumption has a significant welfare cost. We find that the probability of being denied credit has an independent and strongly significant effect on consumption volatility beyond the effect of volatility of income. Consumption volatility was around 50 percent higher for the quarter of PSID households who were most likely to be constrained than for the quarter who were least likely to be constrained. Not surprisingly, households headed by black or Hispanic individuals, single parents or those with less than 13 years of education experienced the highest level of consumption volatility, and were the most likely to be liquidity constrained and to have very low wealth holdings.

Our work relates to a large theoretical and empirical literature on the response of household consumption to income shocks. The standard incomplete markets model predicts that consumption should move almost one-for-one with shocks to permanent income, while shocks to transitory income should have only small effects on consumption. A substantial empirical literature, surveyed by Jappelli and Pistaferri [2010] and Meghir and Pistaferri [2011], finds evidence against both predictions: consumption reacts too much to transitory shocks, and not enough to permanent shocks. Consequently, research has explored a variety of mechanisms which allow households to partially insure against both permanent and transitory shocks. In particular, there is some evidence that borrowing constraints prevent certain households from smoothing consumption in response to transitory shocks.[4] Moreover, according to Blundell et al. [2008], households' ability to insure against transitory shocks did not change between 1980 and 1993. Our goal is to add to these findings by examine how the partial insurance mechanisms available to households have allowed them to smooth consumption in the face of increasingly volatile income shocks (both permanent and transitory) between 1980 and 2004.

[3]Moffitt and Gottschalk [2011] and Jensen and Shore [2008] find that the volatility of permanent shocks to men's labour income increased since the mid 1970s; Keys [2008] finds that the variance of permanent shocks to family income (but not individual income) increased between the 1980s and 1990s.

[4]See for example Zeldes [1989a], Jappelli [1990], Blundell et al. [2008].

Our results are also relevant to the literature on consumption inequality: income volatility is an important factor contributing to income inequality, and the same partial insurance mechanisms affecting the mapping from income to consumption inequality also affect the mapping from income to consumption volatility. Most recently, Attanasio et al. [2013] using Consumer Expenditure Survey and PSID data find that consumption inequality increased by almost as much as income inequality in the US between 1980 and 2010.[5] This is consistent with our finding that consumption volatility significantly increased between 1980 and 2004.[6]

The rest of the paper is organised as follows. In Section I we present a consumption model and explain how we proxy for the effect of liquidity constraints and precautionary savings on the Euler equation. In Section II we discuss our estimation of consumption volatility and results. Section III concludes with estimates of the welfare cost of increased consumption volatility and unequal access to credit.

1 Consumption Model

In order to construct a measure of consumption volatility, we first estimate Euler equations, which give us an estimate of expected household consumption growth. We then compute unpredictable shocks to consumption as the difference between actual and expected consumption growth, the Euler equation residuals. We estimate consumption volatility as the square of these residuals. While the raw volatility of changes in household consumption would be easier to calculate, it is not an appropriate measure of welfare. Predictable changes in household consumption, (due, for example, to changes in household preferences) have different welfare implications from unpredictable changes in consumption, which arise due to households' inability to completely insure against shocks. An increase in the variance of predictable changes in consumption might not reduce household welfare, whereas an increase in the variance of unpredictable changes in consumption unambiguously reduces welfare, other things being equal.

We derive the household Euler equation from a relatively standard incomplete markets consumption model, building on Gorbachev [2011]. In particular, we allow for endogenous income and binding liquidity constraints.

[5] See also Aguiar and Bils [2011], Browning and Crossley [2009], Primiceri and vanRens [2009], Davis and Kahn [2008], Blundell et al. [2008], Krueger and Perri [2006] among many others.

[6] Evaluating the welfare cost of inequality depends on interpersonal comparisons of utility. Sen [1980] describes the difficulties this raises. The variance of unpredictable changes in consumption, however, has a direct welfare cost: risk-averse households would be willing to reduce their average consumption in return for a reduction in consumption volatility.

At time t, household h solves:

$$\max_{\{A_{h,s},C_{h,s},N^W_{h,s},N^H_{h,s}\}_{s=t}^T} \mathbb{E}_t \left\{ \sum_{s=t}^{T} e^{\delta_h(s-t)} \frac{\exp\{\eta_W N^W_{h,s} + \eta_H N^H_{h,s} + \theta' Z_{h,s} + \upsilon_{h,s}\} C_{h,s}^{1-\gamma}}{1-\gamma} \right\}$$
$$\text{s.t. } A_{h,s+1} = (1 + r_{h,s,s+1})A_{h,s} + w^W_{h,s}N^W_{h,s} + w^H_{h,s}N^H_{h,s} + Y_{h,s} - C_{h,s}$$
$$A_{h,s+1} \geq -L_{h,s}$$

where δ_h is the household-specific annual discount rate, $C_{h,t}$ non-durable consumption, and $1/\gamma$ the intertemporal elasticity of substitution. Our specification of preferences follows Attanasio [1999]: $N^W_{h,t}$ and $N^H_{h,t}$ are hours worked by the wife and husband respectively, $w^W_{h,t}, w^H_{h,t}$ are their respective real wages, $Z_{h,s}$ is a vector of other observable variables affecting preferences such as age, number of adults and children, marital status, and information on the household's housing status, and $\upsilon_{h,t}$ an unobservable preference shock.[7] $A_{h,t+1}$ are household assets at the end of period t, $r_{h,t,t+1}$ is the household-specific risk free interest rate on loans taken out between t and $t+1$, which depends on a household's marginal tax rate and on the local inflation rate; $Y_{h,t}$ is non-labour income; and $L_{h,t}$ is the household-specific and time-varying borrowing limit.

The PSID became biennial in 1997, so we have no data on annual changes in consumption after this date. To preserve the length of our sample, we consider two-year consumption growth rates. Throughout the paper, Δ denotes two-year changes in a variable: $\Delta X_t = X_t - X_{t-2}$. After taking first order conditions, rearranging terms and using the assumption that households have rational expectations, we can rewrite the Euler equation between periods $t-2$ and t as:

$$\mathbb{E}_{t-2}\left[(1 + r_{h,t})e^{\Delta\theta_{h,t} - 2\delta_h}\left(\frac{C_{h,t}}{C_{h,t-2}}\right)^{-\gamma}\right](1 + \lambda_{h,t-2}) = 1 \tag{1}$$

where for convenience, we define $\theta_{h,s} = \eta_W N^W_{h,s} + \eta_H N^H_{h,s} + \theta' Z_{h,s} + \upsilon_{h,s}$; $(1 + r_{h,t}) = (1 + r_{h,t-2,t-1})(1 + r_{h,t-1,t})$ is the ex post gross real interest rate on 2-year loans; and $\lambda_{h,t-2}$ is the Lagrange multiplier on the household's borrowing constraint, normalised

[7] Note that hours worked is an endogenous variable. In particular, households may change their labor supply as an insurance mechanism against unexpected income shocks (Blundell et al. [2012]). It is not necessary to model labor supply explicitly: the Euler equation for consumption is an equilibrium relationship that holds at the optimal values of $N^W_{h,t}, N^H_{h,t}$, however they are determined (Attanasio [1999]). We will control for the endogeneity of hours using instrumental variables, as we describe below.

by a constant that is known at time $t-2$.[8] For unconstrained households, $\lambda_{h,t-2} = 0$. Rational expectations implies that

$$(1 + r_{h,t})e^{\Delta\theta_{h,t}-2\delta_h} \left(\frac{C_{h,t}}{C_{h,t-2}}\right)^{-\gamma} (1 + \lambda_{h,t-2}) = 1 + e_{h,t} \tag{2}$$

where $e_{h,t}$ is an expectational error with $\mathbb{E}_{t-2}e_{h,t} = 0$. Taking logs of both sides and rearranging:

$$\Delta \ln C_{h,t} = \frac{1}{\gamma}[\ln(1 + r_{h,t}) - 2\delta_h + \Delta\theta_{h,t} + \ln(1 + \lambda_{h,t-2}) - \ln(1 + e_{h,t})] \tag{3}$$

Since $e_{h,t}$ has conditional mean zero, $\ln(1+e_{h,t})$ does not. Taking a Taylor expansion, we have

$$\ln(1 + e_{h,t}) = e_{h,t} - \frac{1}{2}e^2_{h,t} + R_{h,t} \tag{4}$$

where $R_{h,t}$ is a remainder containing third and higher order terms. We assume households never receive any news about third and higher order moments:[9] $R_{h,t} = R_h + e^R_{h,t}$, where $\mathbb{E}_{t-2}e^R_{h,t} = 0$. Let $\sigma^2_{h,t-2} = \mathbb{E}_{t-2}[e^2_{h,t}]$ be the year $t-2$ conditional variance of the year t expectational error, and let $\nu_{h,t} = \frac{1}{2}(e^2_{h,t} - \sigma^2_{h,t-2})$ be the household's expectational error concerning $e^2_{h,t}$, which has conditional mean zero. Substituting back into the Euler equation, we have:

$$\begin{aligned}\Delta \ln C_{h,t} &= \frac{1}{\gamma}\big[\ln(1 + r_{h,t}) - 2\delta_h + \Delta\theta_{h,t}\big] \\ &+ \frac{1}{\gamma}\big[\ln(1 + \lambda_{h,t-2}) + \frac{1}{2}\sigma^2_{h,t-2} - R_h - e^R_{h,t} + \nu_{h,t} - e_{h,t}\big]\end{aligned} \tag{5}$$

Because the PSID has data on food consumption, we need an Euler equation for food consumption, not total non-durable consumption. Following Blundell et al. [2008], we assume the demand for food consumption has the form

$$\ln F_{h,t} = \alpha_0 + \alpha_1 \ln p^F_t + \alpha_2 \ln p^O_t + \beta \ln C_{h,t} + \theta'_F Z_{h,t} + \iota_{h,t} \tag{6}$$

where p^F_t is the price of food, p^O_t is the price of other non-durables, $Z_{h,t}$ is the vector of demographic variables discussed above, and $\iota_{h,t}$ is an unobservable preference

[8] Following Zeldes [1989a],we define $\lambda_{h,t-2}$ by $\psi_{h,t-2} = \lambda_{h,t-2}\mathbb{E}_{t-2}\left\{\left((1 + r_{h,t})e^{-\delta_h}\right) e^{\theta_{h,t}}C^{-\gamma}_{h,t}\right\}$, where $\psi_{h,t-2}$ is the actual Lagrange multiplier on the borrowing constraint.

[9] This is a standard assumption, see for example Attanasio [1999].

shock.[10] If $\beta = 1$, this is a standard homothetic demand function. If $\beta \neq 1$, it is a log-linear approximation to an arbitrary non-homothetic demand system, and $\iota_{h,t}$ will also contain higher-order terms relating to the error in this approximation.[11] Our specification also allows for non-separability of preferences between consumption of food and other non-durables.[12] Taking two-year differences of this equation and substituting into equation (5), we obtain our estimating equation:

$$\begin{aligned} \Delta \ln F_{h,t} &= \frac{\beta}{\gamma}\big[\ln(1+r_{h,t}) - 2\delta_h\big] + \alpha_1 \Delta \ln p_t^F + \alpha_2 \Delta \ln p_t^O + \mu \Delta Z_{h,t} \\ &+ \frac{\beta}{\gamma}\big[\eta_W \Delta N_{h,t}^W + \eta_H \Delta N_{h,t}^H + \ln(1+\lambda_{h,t-2}) + \frac{1}{2}\sigma_{h,t-2}^2 - R_h\big] + \varsigma_{h,t} \end{aligned} \tag{7}$$

where $\mu = \frac{\beta}{\gamma}\theta + \theta_F$, and we combine the expectational errors and the two preference shocks into a single term:

$$\varsigma_{h,t} = \frac{\beta}{\gamma}(\nu_{h,t} - e_{h,t} - e_{h,t}^R + \Delta \upsilon_{h,t}) + \Delta \iota_{h,t} \tag{8}$$

Euler equations such as (7) are typically estimated using instrumental variables techniques. We discuss our estimation strategy in section II; here it suffices to say that we assume that $\mathbb{E}_{t-s}\varsigma_{h,t} = 0$, and use variables dated $t-4$ and earlier as our instruments. While the expectational errors which enter $\varsigma_{h,t}$ have mean zero conditional on year $t-2$ information, $\Delta \upsilon_{h,t}$ and $\Delta \iota_{h,t}$ will not, if $\upsilon_{h,t}$ and $\iota_{h,t}$ are i.i.d., but they will have mean zero conditional on year $t-4$ information. We consider *consumption volatility* to be the variance of household expectational errors, $\mathbb{E}_{t-2}[e_{h,t}^2]$. We will estimate volatility as the squared residuals, $\hat{\varsigma}_{h,t}^2$.

It is well known that consumption is measured with error. Following Alan et al. [2009], we assume measurement error is stationary and independent of all the regressors, including lagged values of the measurement error and expectations error,

[10] Unlike Blundell et al. [2008], we restrict β, the budget elasticity of food consumption, to be the same across all households.

[11] Crossley and Low [2011] show that the assumption of a constant intertemporal elasticity of substitution imposes strong restrictions on within-period demand. In particular, it rules out the demand system specified here unless $\beta = 1$. We consider it worthwhile to allow for more general preferences in (6), even though they can only be an approximation to the true demand system, since it is well known that food is a necessary good. All our results go through if we assume $\beta = 1$.

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

consumption levels and interest rates.[13] Since the residual $\varsigma_{h,t}$ also contains this measurement error, our measure of consumption volatility, $\hat{\varsigma}^2_{h,t}$, will mis-measure the *level* of the variance of household expectational errors. However, as long as the variance of measurement error and the variance of preference shocks are constant over time, we can accurately estimate the *changes* in the variance of household expectational errors.

We estimate the log-linearised Euler equation (7), rather than the non-linear Euler equation (2), since measurement error makes non-linear GMM estimation (but not linear estimators) inconsistent. There is considerable debate in the literature over whether the elasticity of intertemporal substitution (EIS) can be consistently estimated from log-linearised Euler equation on micro data (Carroll [2001]). Attanasio and Low [2004] perform Monte Carlo studies, and find that consistent estimates can be obtained with long panels (at least 30 quarters), given sufficient variation in real interest rates. Alan et al. [2012] find that even with a short panel (14 years), estimates of the EIS are relatively accurate, even though standard instrument exogeneity and relevance conditions are not satisfied. Both studies conclude that non-linear Euler equation estimation is more likely to be biased. We have data spanning 24 years, over a period which saw large variations in interest rates (1980 to 2004). Importantly, ex post real interest rates in our sample are household specific, since they depend on a household's marginal tax rate and on the local inflation rate. Thus, we have substantially more variation in interest rates than in the Monte Carlo studies described above, which allows us to estimate the EIS more precisely.

Our ultimate goal is to estimate consumption volatility as the squared residuals in equation (7). In order to obtain these residuals, we need to consistently estimate all the parameters in this equation. This Euler equation, however, contains two unobserved terms. We now explain how we proxy for these two terms: $\ln(1+\lambda_{h,t-2})$, the normalised Lagrange multiplier on the borrowing constraint, and $\sigma^2_{h,t-2}$, the precautionary savings term.

1.1 Liquidity Constraints

The normalised Lagrange multiplier on the household's borrowing constraint, $\ln(1+\lambda_{h,t-2})$, is unobserved but enters the Euler equation. If we did not control for this

[13] If food consumption was subject to mean reverting error, as is true for income (see section 1.2.1 "Estimating Volatility of Family Income"), our parameters would all be biased downward, and we would need to adjust for this mean reversion to recover the true parameters. However, since to our knowledge there are no studies suggesting mean-reverting measurement error in consumption, we prefer to follow current literature and assume classical measurement error.

term, it would enter the residual, potentially biasing our estimates. This term would also enter our measure of consumption volatility, the squared Euler equation residual: if the cross-sectional variance of $\ln(1+\lambda_{h,t-2})$ has been, e.g., increasing over time, we would wrongly identify this as an increase in consumption volatility. We control for $\ln(1+\lambda_{h,t-2})$ by using information on households' access to credit from the Survey of Consumer Finances. The SCF directly measures whether households have been denied credit or discouraged from applying. We regress this variable on explanatory variables common to both PSID and SCF, and use our estimates to compute fitted values for the PSID sample representing their estimated probability of being denied credit. We then proxy for $\ln(1+\lambda_{h,t-2})$ with a polynomial in the estimated probability of being denied credit in our Euler equation regressions.

Researchers have used several methods to identify liquidity constrained households.[14] Jappelli et al. [1998] regress the probability of being constrained, constructed using 1983 SCF data on variables common to both SCF and PSID, and use the coefficients to estimate the probability of being constrained for PSID households. We combine SCF and PSID data in a similar way, with two important differences. First, we combine SCF data from all the eight surveys between 1983 and 2007 when regressing the liquidity constraints indicator on explanatory variables, thus allowing the relationship between household characteristics and access to credit to change over time. Second, while Jappelli et al. [1998] use the liquidity constraints variable to estimate switching regression models of the Euler equation, we use it to proxy for the Lagrange multiplier.

The SCF asks the following questions:

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 et al. [1998], we count a household as liquidity constrained if the head answers "yes" to question 1 and "no" to question 2, or if she answers "yes"

[14] Zeldes [1989b], Runkle [1991] and later Gorbachev [2011], used wealth information contained in PSID, Gross and Souleles [2002] credit card data, and Attanasio et al. [2008] data on auto loans; whereas Jappelli [1990] used direct data on liquidity constraints in SCF.

to question 3. That is, a household is constrained if it had an application for credit rejected, or if household members were discouraged from applying for credit because they thought they might be rejected.

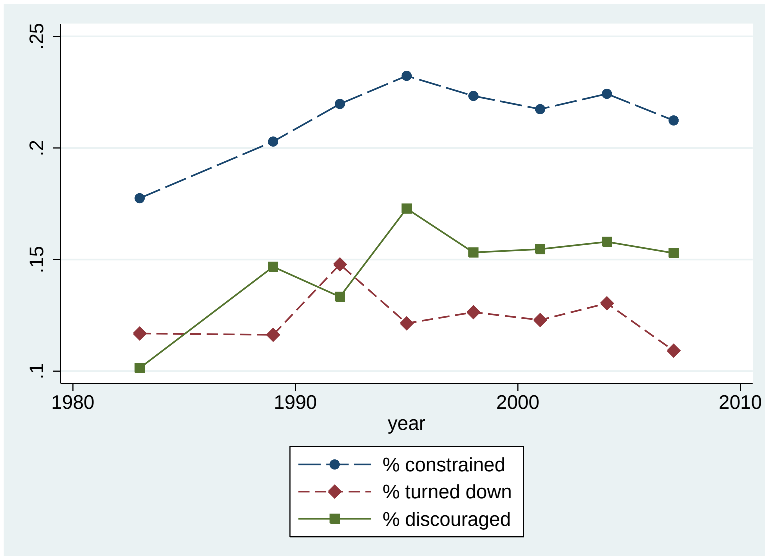


Figure 1: Proportion of liquidity constrained households

Note: 'rejected' households are those that had a request for credit turned down and were not later able to obtain the full amount; 'discouraged' households are those that thought of applying but did not because they thought they might be turned down; and 'constrained' households are those who were either 'discouraged' or 'rejected'.

Source: Survey of Consumer Finances.

Figure 1 plots the proportion of liquidity constrained, 'rejected' and 'discouraged' households between 1983 and 2007. This figure shows that the proportion of liquidity constrained households increased by 3 percentage points over this period, from 18 percent to 21 percent. This was driven by an increase in the proportion of discouraged households; the proportion of households with a loan application rejected stayed roughly constant. Poorer households and those headed by a single parent or a black individual, particularly those with low education, were the most likely to be constrained throughout this period, and this inequality in access to credit increased over time. Between 1989 and 1995, the probability of being denied credit increased for all households. But after 1995, this probability increased more for households with income below the 40th percentile, and for those with less than 12 years of education; for households with a college degree and those above the 40th income percentile, the percentage denied credit decreased.

Increased inequality in access to credit seems to be driven by changes in the supply of credit between different groups, not by changes in demand. From 1995, the SCF asked households whether they have applied for a loan in the last 5 years. We find that higher educated households are, in general, more likely to apply for a loan. However, the percentage of applicants denied a loan increased for households with less than 12 years of education, and decreased for college graduates. We test whether these changes in access to credit are due to differences in income between differently educated households, and reject this hypothesis, although it remains possible that some other characteristic of high-education households - future income, credit history - improved relative to that of low-education households. A complementary explanation is that lenders became increasingly able to identify borrowers' characteristics, and so could deny more loans to households with poor earnings prospects and credit histories, who are likely to have less education.[15]

Household debt increased over the same period. In 2007, 77 percent of households held some debt, compared to 70 percent in 1983; average real debt, in 1983 dollars, increased from \$17,000 to \$47,000.[16] It might seem surprising that household debt increased, while more households were unable to borrow as much as they want. One possible explanation is that demand for credit increased, and households applied for more loans. Consistent with this explanation, the percentage of SCF households applying for a loan increased from 64 to 66 percent between 1995 and 2007.

1.1.1 Estimating Constraints in the PSID

We estimate a probit regression model using the SCF sample, with the liquidity constraints dummy as our dependent variable, using explanatory variables common to PSID and SCF. Our explanatory variables include demographics, income, information on home value and mortgages, and a quadratic time trend.[17] A cubic in age is included to allow for variation in demand for debt over the life cycle. In addition to current income, the demand for debt should depend on a household's permanent income; since the SCF has no panel dimension, we proxy for permanent income using

[15]See Figures A.8 and Table A.1 in the Appendix for details.

[16]See Appendix Table A.2. These figures include mortgage debt, which may not always be useful for smoothing consumption in response to income shocks. Mortgage debt can be used to extract equity, but it does not help smooth consumption for a household with no equity. We thank an anonymous referee for this observation.

[17]See Appendix A.3 for a full description.

dummies for the head of household's years of education, interacted with the head's race. We also include financial variables common to both PSID and SCF - a cubic in households' house value, and quadratics in mortgage, annual mortgage payment, and asset income - since these variables are especially useful in predicting a household's access to credit (having a mortgage is prima facie evidence that a household has had access to credit in the past). Household demand for debt is further proxied using number of children, number of adults, marital status, a dummy for being a single parent. Finally, we allow for changes in access to credit over time. We use a quadratic trend, rather than a full set of time dummies, because we need to use the coefficient estimates to impute fitted values in our PSID sample, which contains different years of data than the SCF sample. We also interact income, mortgage, home value, and the dummy for positive asset income with a linear time trend.

Table 1 presents our estimation results. Since the model we estimate is only a reduced-form expression which does not distinguish factors affecting the demand and supply of credit, the estimated coefficients presented here do not have a straightforward interpretation: here we are more concerned with accurately predicting the probability of being constrained in the PSID. Nonetheless, our estimation results are broadly consistent with economic theory and previous studies (Jappelli [1990]). Single parents and black or Hispanic, 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 increases in transitory income, which should unambiguously decrease the probability of being constrained, from changes in permanent income, which has an ambiguous effect).

Since our goal is to predict the probability that a household is constrained, and not to estimate the causal effect of household characteristics on the probability of being constrained, the fact that several of our explanatory variables may be endogenous is irrelevant. What is important to us is that our prediction is as accurate as possible. We compute the accuracy of our predictions as follows. We label an SCF household as 'constrained' if their estimated probability of being constrained is greater than the average probability in that year, and label them 'unconstrained' otherwise. We find that we correctly classify 74 percent of constrained households and 66 percent of unconstrained households. That is, given that a household is truly constrained (respectively, unconstrained), we have a 74 percent (66 percent) chance of correctly identifying it as constrained (unconstrained).

Table 1: Predicting liquidity constraints in SCF

Age	-0.007	(0.054)	ln(family income)	1.419	(1.312)
Age^2	0.000	(0.001)	ln(family income)^2	-0.118	(0.140)
Age^3	-0.000	(0.000)	ln(family income)^3	0.002	(0.005)
White, no HS	0.060	(0.049)	Asset income > 0	0.693***	(0.150)
White, college	-0.123***	(0.035)	ln(asset income+1)	-0.306***	(0.045)
Black, no HS	17.677***	(5.577)	ln(asset income+1)^2	0.025***	(0.004)
Black, HS	17.722***	(5.572)	Black*ln(family income)	-6.269***	(2.053)
Black, college	17.665***	(5.580)	Black*ln(family income)^2	0.707***	(0.248)
Hispanic, no HS	25.515**	(11.316)	Black*ln(family income)^3	-0.025***	(0.010)
Hispanic, HS	25.532**	(11.310)	Hispanic*ln(family income)	-8.816**	(3.774)
Hispanic, college	25.336**	(11.323)	Hispanic*ln(family income)^2	0.959**	(0.418)
1 child	-0.004	(0.043)	Hispanic*ln(family income)^3	-0.033**	(0.015)
2 children	0.043	(0.044)	Black*ln(house value+1)	-0.257	(0.401)
3+ children	0.118**	(0.051)	Black*ln(house value+1)^2	0.070	(0.076)
1 adult	-0.244***	(0.071)	Black*ln(house value+1)^3	-0.004	(0.004)
2 adults	-0.162***	(0.062)	Hispanic*ln(house value+1)	0.208***	(0.075)
3 adults	-0.070	(0.069)	Hispanic*ln(house value+1)^2	-0.017***	(0.007)
Single parent	0.187***	(0.054)	ln(mortgage+1)*t	-0.004	(0.004)
Divorced/separated	0.120**	(0.050)	ln(mortgage+1)^2*t	0.000	(0.000)
Widow	0.068	(0.086)	ln(family income)*t	-0.098	(0.076)
Single	-0.008	(0.052)	ln(family income)^2*t	0.011	(0.008)
Receive welfare	0.193***	(0.050)	ln(family income)^3*t	-0.000	(0.000)
Have mortgage	-0.348	(1.592)	Homeowner*t	0.013	(0.017)
ln(annual mortgage payment + 1)	-0.117	(0.378)	ln(house value+1)*t	0.013	(0.018)
ln(annual mortgage payment + 1)^2	0.017	(0.023)	ln(house value+1)^2*t	-0.002	(0.003)
ln(mortgage+1)	0.060	(0.070)	ln(house value+1)^3*t	0.000	(0.000)
ln(mortgage+1)^2	-0.001	(0.006)	Asset income > 0 * t	-0.012***	(0.004)
Homeowner	-0.133	(0.287)	t	0.317	(0.234)
ln(house value+1)	0.205	(0.301)	t^2	-0.001***	(0.000)
ln(house value+1)^2	-0.045	(0.054)	Constant	-4.855	(4.217)
ln(house value+1)^3	0.002	(0.003)			
Observations	21,607				

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Authors' calculations based on SCF data as described in the text.

To assess the out-of-sample predictive accuracy of our model, we employ cross-validation (Stone [1974]). We randomly partition our sample 50 times into a "training sample", which we use for estimation, and a "hold-out" sample. For each training sample, we estimate the model and use it to predict the probability of being denied credit for each observation in the associated hold-out sample. We then "predict" that a household is denied credit if Pr(denied credit) is greater than the average probability of being denied credit in that year. Averaging across all 50 hold-out samples, we correctly predict 73 percent of constrained households, and 66 percent of unconstrained households.

We then use our coefficient estimates to compute fitted values for observations in the PSID sample, and interpret these fitted values as the probability that PSID households are liquidity constrained. Starting in 1992, relative to SCF households, PSID households are about 2 percentage points less likely to be constrained, most likely because our SCF households include more welfare recipients and households headed by Black and Hispanic individuals, and have lower average income. As long as the relationship between the probability of being constrained and the explanatory variables is the same in both samples, these differences should not matter.

We use the predicted probability of being constrained to proxy for the normalised Lagrange multiplier $\ln(1+\lambda_{h,t-2})$ in the household's Euler equation. We assume that

$$\ln(1+\lambda_{h,t-2}) = \phi(Pr(\widehat{\text{denied credit}})_{h,t-2}) + u_{h,t-2} \tag{9}$$

where ϕ is a polynomial function whose coefficients we estimate, $Pr(\widehat{\text{denied credit}})_{h,t-2}$ is the predicted probability that the household is liquidity constrained, and $u_{h,t-2}$ is orthogonal to our instrument set.

1.2 Precautionary Savings

The variance of the household's expectational errors, $\sigma^2_{h,t-2}$, appears in the Euler equation because of the precautionary savings motive (Carroll [1992]). Precautionary savings will be higher for households who are more uncertain about future income, and for households with lower wealth (Browning and Lusardi [1996]). We therefore assume that the variance of household expectational errors can be approximated as a linear function of the variance of income volatility and the probability that the household has positive wealth:

$$\sigma^2_{h,t-2} = \gamma_h + \gamma_1 \mathbb{E}_{t-2}[(\hat{\sigma}^Y_{h,t})^2] + \gamma_2 Pr(W_{h,t} > 0) + e^{\sigma}_{h,t-2} \tag{10}$$

We allow the constant term γ_h to vary across households, since some households face systematically higher uncertainty, regardless of their income volatility and wealth. In some specifications, we restrict γ_2 to be zero. We assume the approximation error $e^{\sigma}_{h,t-2}$ is orthogonal to our instruments set.

1.2.1 Estimating Volatility of Family Income

To construct our measure of family income volatility, we estimate a standard model of the household income process, and measure volatility as the square of changes in residuals. Our model is:

$$\ln(Y_{h,t}) = X'_{h,t}\vartheta_t + u_{h,t} \tag{11}$$

$Y_{h,t}$ is real family income, and $X_{h,t}$ is a set of household characteristics affecting income, which are observable, anticipated by consumers, and potentially time-varying.[18] Standard models of the income process (MaCurdy [1982]) assume that the residual $u_{h,t}$ can be decomposed into a permanent and a transitory component;[19] we do not make any particular assumption about $u_{h,t}$, and do not attempt to distinguish between permanent and transitory shocks in our main specification.We define income volatility, $\sigma^2_{\Delta u,t}$, to be the variance of $(u_{h,t} - u_{h,t-2})$.

Income is measured with error, and this measurement error appears to be non-classical. While the textbook errors-in-variables model assumes that measurement error is independent of true values, Kim and Solon [2005] find that measurement error in survey data on earnings is *mean-reverting* and is negatively correlated with true values. Following Kim and Solon [2005], we assume observed household income $\ln Y^*_{h,t}$ is a function of true income $\ln Y_{h,t}$:

$$\ln Y^*_{h,t} = \alpha_h + \lambda \ln Y_{h,t} + \varphi_{h,t} \tag{12}$$

where α_h is a household-specific fixed effect for reporting error, $\varphi_{h,t}$ is white noise with variance σ^2_m, and $0 < \lambda < 1$. Substituting this into our model of the income process, observed family income is:

$$\ln(Y^*_{h,t}) = \alpha_h + X'_{h,t}\vartheta_t\lambda + u_{h,t}\lambda + \varphi_{h,t} \tag{13}$$

Squared residuals from this equation will be consistent estimates of $\lambda^2\sigma^2_{\Delta u,t} + \sigma^2_m$, rather than $\sigma^2_{\Delta u,t}$. We compute income volatility as $\frac{(\Delta\hat{u}_{h,t})^2}{\hat{\lambda}^2}$, where $\hat{\lambda} = 0.67$ as estimated by Bound et al. [1994]. Notice that dividing observed income volatility by 0.67^2 more than doubles the level of volatility and its change over time. The presence of σ^2_m biases our estimate of the level of income volatility, but as long as this variance does not vary over time, it does not bias our estimate of the trend.[20]

Figure 2 illustrates average household income volatility over the period 1980-2004 in deviations from its 1980 mean and after the effect of change in the survey methodology (the effect of dummy for *year* > 1992) is corrected for, and its linear

[18] See Appendix A.3 for details.

[19] A recent literature, following Guvenen [2007], has examined models with more heterogeneous life-cycle income profiles and less persistent income shocks.

[20] Since in 1993, the PSID converted the questionnaire to electronic form. Kim and Stafford [2000] describe the changes PSID underwent. We therefore allow σ^2_m to be different before and after the change in the survey. We remove the change in the variance of measurement error, by regressing income volatility on a time trend and a dummy for year > 1992, and subtracting out the effect of the dummy.

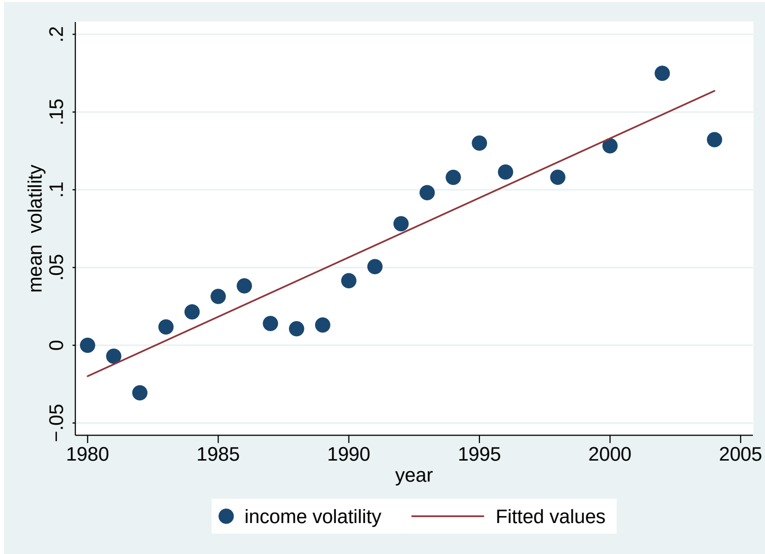


Figure 2: Mean Volatility of Household Income Shocks: deviations from 1980 mean.

Note: as $(\Delta\hat{u}_{h,t})^2/\hat{\lambda}^2$, where $\hat{u}^2_{h,t}$ is the squared residual from the family income regression (13) and $\hat{\lambda}^2 = 0.67^2$ is the mean reversion correction as described in the text. Volatility is presented in deviations from the 1980 mean to correct for the presence of the measurement error, σ^2_m, and after the effect of $year > 1992$ dummy is taken out, to correct for the change in the PSID survey methodology.
Source: Panel Study of Income Dynamics.

trend. Volatility of family income increased significantly between 1980 and 2004 for an average household. This finding is consistent with the most recent study by DeBacker et al. [2013], who use a confidential panel of tax returns from the IRS to show that family income volatility increased between 1987 and 2009, as well as earlier studies (Dynan et al. [2012], Keys [2008], Gottschalk and Moffitt [2009], and Gorbachev [2011]), based on PSID data, who find that household income volatility increased between 1970 and 2006.

1.2.2 Net Wealth

To measure cash on hand, we use information on households' non-housing wealth. Information on wealth holdings in PSID is available for 1984, 1989, 1994, 1999, and biennially thereafter. To fill in for the missing years and to reduce mis-measurement, we estimate the probability that the household had positive net non-housing wealth,

$Pr(W_{h,t} > 0)$, based on other variables available in all years.[21] We then predict the probability of having positive non-housing net wealth for this and 4 previous years, and use these predicted values as our proxy for cash on hand, $Pr(\widehat{W_{h,t} > 0})$.

2 Estimating Consumption Volatility

We are now ready to estimate our Euler equation 7. Due to presence of second and higher order terms in the residual, it is typical to estimate the Euler equation using instrumental variable techniques or GMM. By rational expectations, any variables known at time $t-2$ will be orthogonal to the expectational errors. However, since the second-differenced preference shocks may not be orthogonal to time $t-2$ variables, we use time $t-s$ variables as instruments, where $s \geq 4$.

If $X_{h,t-s}$ is our set of instruments, then our identifying assumptions are

$$\mathbb{E}\left[\varsigma_{h,t}\middle|X_{h,t-s}\right] = 0 \tag{14}$$

$$\mathbb{E}\left[\ln(1+\lambda_{h,t-2}) - \phi(Pr(\widehat{\text{denied credit}})_{h,t-2})|X_{h,t-s}\right] = 0 \tag{15}$$

$$\mathbb{E}\left[\sigma^2_{h,t-2} - \gamma_h - \gamma_1(\hat{\sigma}^Y_{h,t})^2 - \gamma_2 Pr(\widehat{W_{h,t} > 0})|X_{h,t-s}\right] = 0 \tag{16}$$

Restrictions (15) and (16) are necessary because we use proxy variables to estimate the effects of $\ln(1+\lambda_{h,t-2})$ and $\sigma^2_{h,t-2}$, which are unobserved, on the growth rate of consumption. Using proxy variables introduces approximation errors. The consistency of our estimates requires that the instruments we choose are orthogonal to these approximation errors. In practice, we may under predict or over predict the Lagrange multiplier or $\sigma^2_{h,t-2}$; what is crucial is that this error is not correlated with the characteristics of the household s years ago.

Combining household fixed effects into a single term, $\kappa_h = \dfrac{\beta}{\gamma}(\gamma_h - 2\delta_h - R_h)$, the

[21] See Appendix A.3 for details.

equation we estimate is:

$$\Delta \ln F_{h,t} = \kappa_h + \frac{\beta}{\gamma}\ln(1+r_{h,t}) + \alpha_1 \Delta \ln p_t^F + \alpha_2 \Delta \ln p_t^O \tag{17}$$

$$+ \frac{\beta}{\gamma}\left[\eta_W \Delta N_{h,t}^W + \eta_H \Delta N_{h,t}^H\right] + \mu \Delta Z_{h,t}$$

$$+ \frac{\beta}{\gamma}\left[\phi(Pr(\widehat{\text{denied credit}})_{h,t-2}) + \gamma_1(\hat{\sigma}_{h,t}^Y)^2 + \gamma_2 Pr(\widehat{W_{h,t} > 0})\right] + \varsigma_{h,t} \tag{18}$$

The standard fixed effects estimator is inconsistent in a dynamic panel data model (Nickell [1981]). We therefore estimate (17) using the Arellano and Bover [1995] two-step GMM estimator, which uses forward orthogonal transformations to remove the fixed effects. The forward orthogonal transformation subtracts the average of all future available observations of a variable, thus preserving the length of the sample.[22]

The observable variables affecting preferences, $\Delta Z_{h,t}$, include age, age squared, change in number of adults, change in number of children, change in marital status, and an indicator variable for change in home ownership.[23] After testing for autocorrelation in the residuals we find that it is present up to the third lag. We therefore use variables dated $t-4$ and $t-5$ as instruments. We limit the number of instruments to two lags and "collapse" our instruments to a single column to reduce the efficiency loss caused by too many instruments.[24] We allow for heteroskedasticity and intra-group correlation, and make the Windmeijer [2005] finite-sample correction to our standard errors.

Table 2 reports our estimation results. In column (1), we report results from our basic specification of the Euler equation in which we assume separable preferences between food, other non-durables, labour supply and housing. In Columns (2) to (4), we progressively relax these assumptions. Column (2) allows for non-separable preferences for food, other non-durables and labour supply, by including prices and the change in hours worked by both the spouse and head of the household.[25] In

[22]If $w_{h,t}$ is a variable, its forward orthogonal transform is $\sqrt{\frac{T_{h,t}}{T_{h,t+1}}}(w_{h,t} - \frac{1}{T_{h,t}}\sum_{s>t} w_{h,s})$.

[23]This variable equals 1 when the household goes from renting to owning, equals 2 when the household moves from public housing to owning, is negative if the direction is reversed, and equals zero when there is no change.

[24]Roodman [2009] describes the problems too many instruments could cause this type of GMM estimator.

[25]As discussed above, while hours worked are endogenous - in particular, because household members adjust labor supply to insure against shocks (Blundell et al. [2012]) - we deal with this endogeneity problem by using variables known at date $t-4$ or earlier as instruments. Our identifying

Table 2: Euler Equation Estimation, biennial sample, 1980 to 2004.

	(1)	(2)	(3)	(4)
$\ln(1+r_{h,t})$	0.570**	0.609**	0.704**	0.513*
	(0.266)	(0.257)	(0.289)	(0.293)
$(\sigma^Y_{h,t})^2$	0.054	0.039	0.093	0.069
	(0.076)	(0.051)	(0.062)	(0.063)
$\Pr(\widehat{\text{denied credit}})$	2.389	2.145*	2.741*	1.467
	(1.769)	(1.277)	(1.642)	(1.597)
$\Pr(\widehat{\text{denied credit}})^2$	-9.671*	-8.282*	-12.654*	-7.708
	(5.825)	(4.774)	(7.077)	(6.749)
$\Pr(\widehat{\text{denied credit}})^3$	10.818*	9.243*	14.837*	9.938
	(6.367)	(5.473)	(8.045)	(7.706)
$\Delta \ln p^O$		0.266	0.208	0.397*
		(0.197)	(0.211)	(0.236)
$\Delta \ln p^F$		-0.334	-0.244	-0.890
		(0.458)	(0.484)	(0.640)
Age	-0.008	-0.008	-0.007	-0.010
	(0.009)	(0.006)	(0.007)	(0.013)
Age^2	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Change in number of adults	0.127**	0.104**	0.065	0.114*
	(0.055)	(0.051)	(0.064)	(0.066)
Change in number of kids	0.052	0.066	0.108**	0.097
	(0.049)	(0.044)	(0.046)	(0.065)
Change in marital status	0.059	0.045	0.160	0.048
	(0.178)	(0.135)	(0.162)	(0.152)
Change in house ownership			-0.007	-0.001
			(0.101)	(0.109)
Change in number of hours worked, spouse		0.015*	0.018**	0.016
		(0.008)	(0.009)	(0.010)
Change in number of hours worked, head		-0.008	-0.025	0.023
		(0.045)	(0.047)	(0.050)
$Pr(\widehat{W_h > 0})$				0.221
				(0.284)
Number of observations	34,002	34,002	34,002	30,524
Number of households	5,514	5,514	5,514	5,102
Number of Instruments	24	36	30	32
F-stat	32.13	30.14	25.31	20.72
Prob>F	0	0	0	0
Sargan test of overid	16.12	21.20	18.13	15.56
df	14	22	15	16
Prob> χ^2	0.306	0.710	0.478	0.484
Hansen test of overid	13.06	17.93	14.63	13.49
df	14	22	15	16
Prob> χ^2	0.522	0.508	0.256	0.637

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

Note: we instrument: $\ln(1+r_{h,t})$, $\Pr(\widehat{\text{denied credit}})$ and its polynomial, $Pr(\widehat{W_h > 0})$, $(\hat{\sigma}^Y_h)^2$, $\Delta \ln p^O$, $\Delta \ln p^F$, change in the number of adults, change in the number of kids, change in marital status, change in the number of hours worked by head and spouse, with $t-4$ and $t-5$ lags of these variables, time dummies, and marginal tax rates. Authors' calculations based on PSID and SCF data as described in the text.

column (3), we also allow for non-separable preferences over housing by including the indicator variable for change in homeownership. In column (4) we add the probability that the household has positive wealth as a proxy for cash on hand in the precautionary savings term.

We report the results of the Hansen and Sargan tests for overidentifying restrictions. Unlike the Sargan test, the Hansen J test is robust to non-spherical errors but can be weakened by too many instruments. In all cases, we fail to reject the hypothesis that the overidentifying restrictions are valid. In addition, our set of explanatory variables is highly statistically significant in all specifications, according to the joint significance test.

In all specifications the coefficient on the interest rate is statistically significant at the 5 percent level. If we assume preferences over food are homothetic ($\beta = 1$), we estimate the intertemporal elasticity of substitution, $\frac{1}{\gamma}$, to be between 0.57 and 0.7. If we allow preferences to be non-homothetic ($\beta \neq 1$), because we believe that food is a necessity, then this coefficient cannot be interpreted as the intertemporal elasticity of substitution; rather, it equals the IES multiplied by the budget elasticity of food consumption with respect to total non-durable expenditure, β. Using Consumer Expenditure Survey data for 1980-1992 period, Blundell et al. [2008] estimated $\hat{\beta} = 0.85$, and found that the budget elasticity fell during that time period. We re-estimate Blundell et al. [2008]-type regressions on PSID data using the newly available information on non-durable expenditure for 2005-2009 data. We find $\hat{\beta} = 0.78$.[26] Using this estimate, our results imply an IES of between 0.73 and 0.9, which is in line with evidence from other studies using microeconomic data (Attanasio [1999]).

Consumption growth should be larger for liquidity constrained households and households experiencing higher income volatility, who have a higher precautionary saving motive. Our coefficients on the polynomial in $\widehat{\Pr(\text{denied credit})}$ imply a non-monotonic relationship between the probability of being constrained and consumption growth. The effect of $(\hat{\sigma}_h^Y)^2$ is always positive, though it is never statistically

assumption is that unexpected shocks to consumption growth are not correlated with predictable changes in hours worked. This is true under our maintained assumption that households have rational expectations.

[26] In addition to expenditure on food at home and away from home, starting in 1999, the PSID added information on the following non-durable (and services) categories: childcare (for working and non working spouses), utilities, gasoline, transportation, home and auto insurance, and vehicle repair. Moreover, in 2005, additional categories for non-durable consumption were added. These include expenditure on clothing, home repair, furniture, trips, and other recreation activities. We define non-durable consumption based on the information available starting 2005. We use data on detailed consumption categories kindly provided to us by Geng Li of Federal Reserve Board. Details of our estimation are described in the Appendix, section A.4.

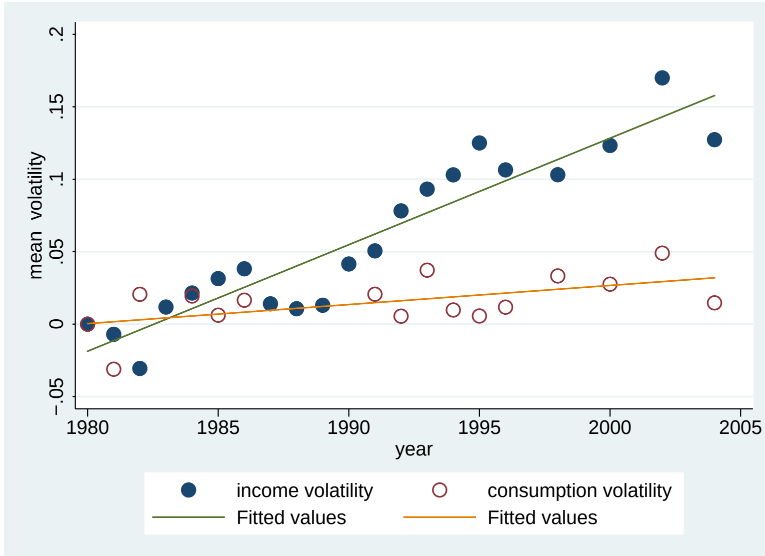


Figure 3: Mean income volatility and consumption volatility for 1980 to 2004

Note: Household income volatility is computed as $(\Delta \hat{u}_{h,t})^2/\hat{\lambda}^2$, where $\hat{u}^2_{h,t}$ is the squared residual from the family income regression (13) and $\hat{\lambda}^2 = 0.67^2$ is the mean reversion correction as described in the text. Consumption volatility is computed as $(\hat{\varsigma}_{h,t} - \hat{\kappa}_h)^2$, where $\hat{\varsigma}_{h,t}$ is the residual and $\hat{\kappa}_h$ is the household fixed effect from the Euler equation (18). Volatility of consumption and of income are presented in deviations from their respective 1980 means to correct for the presence of measurement error, and after the effect of year$>$ 1992 dummy was taken out, to correct for the change in the PSID survey methodology.
Source: Panel Study of Income Dynamics.

significant.

2.1 Evolution of Consumption Volatility

To compute volatility of household consumption, we first predict residuals, $\hat{\varsigma}_{h,t}$, from the above Euler equation, using our preferred specification, that in column 3 of the table 2. We then subtract out household fixed effects $\kappa_h = \dfrac{\beta}{\gamma}(\gamma_h - 2\delta_h - R_h)$, that are not directly computed by the AB-GMM estimator. Our measure of consumption volatility is $(\hat{\varsigma}_{h,t} - \hat{\kappa}_h)^2$. Recall that our measure of consumption volatility contains other terms, such as variances of measurement error, second and higher order terms and second-differenced preference shocks, which we are not directly interested in computing, but cannot estimate separately. Since our goal is to measure *the change* in consumption volatility over time, this is not a problem, assuming these other terms do not vary over time.[27]

Figure 3 shows deviations from the 1980 mean for income and consumption volatilities between 1980 and 2004, and their respective linear trends. As in Figure 2, the volatility series presented in deviations from their respective 1980 means to correct for the presence of measurement error. The graph in the figure is also corrected for the change in the survey methodology. Consumption volatility increased 3 volatility points, from an average of 14.6 in 1980-1984 to an average of 17.5 in 2000-2004, or by 19 percent. However, income volatility rose by 44 percent, or by 14 volatility points, over the same period. We should note that our estimate of the percentage point change in income volatility is highly sensitive to the mean-reversion correction, $\hat{\lambda}^2 = 0.67^2$, though the estimate of the *percentage change* in volatility of income is not affected by this correction. However, since measurement error causes us to overestimate the level of consumption and income volatilities, it biases downwards our estimates of their percentage change. Our estimate of a 19 percent increase in volatility of food consumption is therefore a lower bound.

Figure 4 shows consumption and income volatility for particular demographic groups. The levels of consumption and income volatility were around 7 and 10 volatility points higher, respectively, for black or Hispanic households relative to white households. Consistent with previous studies, income volatility was higher for less educated than for more educated households, though the trends in income volatility for these two groups have been converging over the sample period. Consumption volatility disaggregated by education, exhibited similar trends to those of income volatility, though the differences were not as pronounced.

To test whether the increase in volatility and the differences in the levels of volatility across households are statistically significant, we regress our squared Euler equation residuals on a time trend, change in survey methodology correction term

[27] To allow for the possibility that the variance of measurement error in consumption also changed following the move to electronic surveys in 1992, we regress consumption volatility on a time trend and a dummy for year > 1992, and subtract the effect of the dummy from our estimate, following the strategy we used for correcting volatility of income, described earlier.

Moreover, our Euler residuals also contain the error u_t, the difference between the Lagrange multiplier and the polynomial in the predicted probability of being denied credit, equation (9). In principle, the variance of u_t could trend over time, if for example, our probit estimates become more or less accurate over time, biasing our estimates of the trend in consumption volatility. In practice, the variance of our probit errors (within the SCF sample) has only a moderate trend over time, increasing from 0.13 in 1983 to 0.14 in 2007. If we attempt to purge our consumption volatility estimates of these errors, the trend in volatility remains positive, significant, and of the same magnitude (results are available upon request).

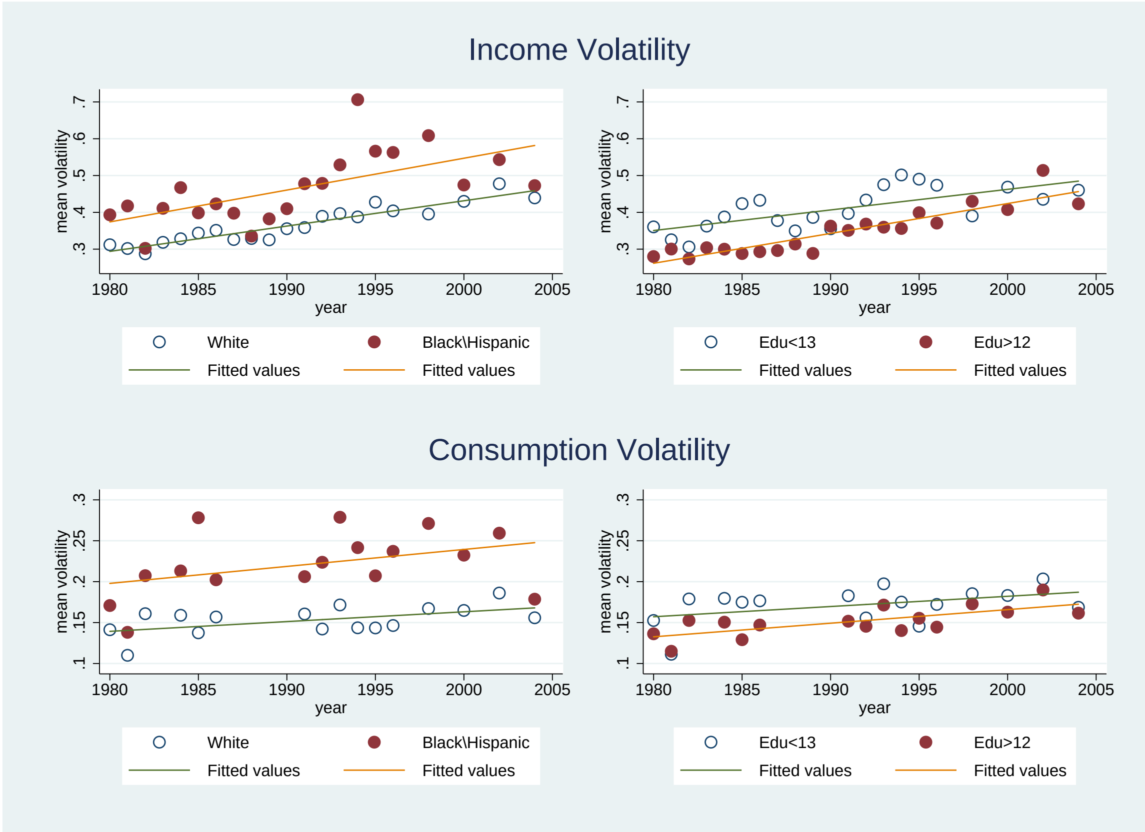


Figure 4: Mean income volatility and consumption volatility for 1980 to 2004

Note: Household income volatility is computed as $(\Delta \hat{u}_{h,t})^2/\hat{\lambda}^2$, where $\hat{u}_{h,t}^2$ is the squared residual from the family income regression (13) and $\hat{\lambda}^2 = 0.67^2$ is the mean reversion correction as described in the text. Consumption volatility is computed as $(\hat{\varsigma}_{h,t} - \hat{\kappa}_h)^2$, where $\hat{\varsigma}_{h,t}$ is the residual and $\hat{\kappa}_h$ is the household fixed effect from the Euler equation (18).
Source: Panel Study of Income Dynamics.

(year$>$ 1992 dummy), and demographic controls. For comparison, we run the same regressions using income volatility. Table 3 reports these results. Columns (1) and (2) provide results from a regression on a linear time trend. Volatility of consumption increased by 1.5 points every 10 years, or by 3.5 points between 1980 and 2004. In contrast, volatility of income rose by 7 points every 10 years, or 17 percentage points between 1980 and 2004. Both trends are statistically significant at the 1 percent level. In columns (3) and (4) we allow for differential levels in volatility by race

Table 3: Evolution of Food Consumption and Income Volatility, biennial sample, 1980 to 2004.

	(1) food	(2) income	(3) food	(4) income	(5) food	(6) income
Year/1000	1.464***	6.971***	1.585***	7.419***	1.652***	8.510***
	(0.509)	(1.490)	(0.507)	(1.494)	(0.566)	(1.742)
Year > 1992	-0.007	0.060***	-0.006	0.063***	-0.006	0.063***
	(0.007)	(0.022)	(0.007)	(0.022)	(0.007)	(0.022)
Black/Hispanic			0.067***	0.095***	-2.276	-4.030
			(0.010)	(0.027)	(2.206)	(6.038)
Education< 13			0.015***	0.046***	0.814	5.773*
			(0.005)	(0.016)	(1.215)	(3.488)
Black/Hispanic × year/1000					1.176	2.070
					(1.107)	(3.035)
Education< 13 × year/1000					-0.401	-2.875
					(0.610)	(1.753)
Age			-0.004**	-0.028***	-0.004*	-0.028***
			(0.002)	(0.006)	(0.002)	(0.006)
Age^2			0.000*	0.000***	0.000*	0.000***
			(0.000)	(0.000)	(0.000)	(0.000)
Constant	-2.755***	-13.507***	-2.921***	-13.840***	-3.054***	-16.015***
	(1.010)	(2.958)	(1.007)	(2.958)	(1.124)	(3.456)
Number of observations	33,652	33,652	33,652	33,652	33,652	33,652
Adj. R^2	0.001	0.006	0.005	0.008	0.005	0.008

Robust, clustered at household level, standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1
Note: in columns (3) to (6) other controls, not shown to conserve space, include change in marital status, change in the number of kids and the number of adults.
Source: Authors' calculations based on PSID and SCF data as described in the text.

and education, and in columns (4) and (5) also for different trends, and a quadratic polynomial in age. These results confirm that the differences between demographic groups shown in Figure 4 are statistically significant: consumption volatility is 7 points higher for Black and Hispanic households than for white households, and is 1.5 points higher for households whose head had less than 13 years of education. Unlike Gorbachev [2011], we do not find a statistically significant difference in the trends of income and consumption volatility for white and black or Hispanic households. We find support of previous findings that income volatility is u-shaped: it is high at a young age, falls during the mid-years, and rises again later in life. Consumption volatility follows a similar pattern. Nevertheless, controlling for age does not reduce the magnitude of the increase in income or consumption volatility, indicating that the increase in volatility is not explained by the ageing of our sample or by its life-cycle properties. In regressions not shown, but available in the Appendix, Table A.4, we also control for changes in marital status, and changes in the number of adults and children in the household. We find that marital status changes have a significant and positive impact on volatility of consumption and income (i.e. they

Table 4: Effect of Liquidity Constraints and Income Uncertainty on Volatility of Consumption, biennial sample, 1980 to 2004.

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV
Year/1000	1.145**	0.532	0.323	0.266	0.259	0.159
	(0.496)	(0.512)	(0.504)	(0.501)	(0.498)	(0.507)
Year > 1992	-0.010	-0.007	-0.010	-0.010	-0.011	-0.011
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$(\sigma^Y_{h,t})^2$	0.052***		0.050***	0.062***	0.071***	0.088***
	(0.004)		(0.004)	(0.008)	(0.009)	(0.019)
$\Pr(\widehat{\text{denied credit}}_{h,t-2})$		0.221***	0.186***	0.216***	0.167***	0.220***
		(0.024)	(0.024)	(0.025)	(0.050)	(0.066)
$\Pr(\widehat{\text{denied credit}}_{h,t-2}) \times (\sigma^Y_{h,t})^2$				-0.051**		-0.081
				(0.024)		(0.077)
Black/Hispanic	0.061***	0.024**	0.026**	0.025**	0.028**	0.025**
	(0.010)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Education< 13	0.012**	-0.000	-0.000	-0.000	0.000	-0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age	-0.002	0.000	0.001***	0.001***	0.001**	0.001***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Change in Marital Status	0.092***	0.096***	0.085***	0.085***	0.081***	0.080***
	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
Constant	-2.119**	-0.987	-0.595	-0.488	-0.279	-1.310
	(0.985)	(1.015)	(0.999)	(0.994)	(0.999)	(2.613)
Number of Observations	33,652	33,652	33,652	33,652	33,652	33,652
Adj. R^2	0.036	0.015	0.040	0.040	0.035	0.036
Number of excluded instruments					3	3
Kleibergen-Paap rk LM statistic					135.4	69.97
Prob > χ^2					0	0
weak id Kleibergen-Paap rk Wald F statistic					167.7	29.38
Hansen J statistic					1.147	-
p-value					0.284	-

Robust, clustered at household level, standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1

Note: Columns (5) and (6) instrument $\Pr(\widehat{\text{denied credit}})$ and $(\sigma^Y_{h,t})^2$ with cohort-year-industry averages of $(\sigma^Y_{h,t})^2$, and $\Pr(\widehat{\text{denied credit}})$ with cohort-year-state averages of $\Pr(\widehat{\text{denied credit}})$, and their interaction, with the interacted instruments.

Source: Authors' calculations based on PSID and SCF data as described in the text.

increase volatility). However, changes in the size of the household appear to be unimportant. In addition, inclusion of cohort and state fixed effects, to account for compositional changes and for differential levels of volatility that are cohort and/or geography specific, do not change our main results.

Next we investigate the relation between liquidity constraints, income volatility and consumption volatility. Table 4 presents these results. Columns (1) and (2) illustrate the individual effects of income volatility or liquidity constraints, respectively, on volatility of consumption; column (3) includes both variables, and column (4) adds an interaction between them. Each of these variables, volatility of income and our proxy for liquidity constraints, has a positive and significant effect on consumption volatility. The interaction term has a negative sign; this is surprising, since in theory income shocks should have a larger effect on consumption volatility for liquidity constrained households. This appears to be driven by a nonlinear relation between income volatility and consumption volatility when income volatility is extremely high.[28] We find that the trend in consumption volatility is completely explained by the trend in liquidity constraints, either alone or together with the trend in income volatility. A household which is 10 percentage points more likely to be liquidity constrained has, on average, between 1.9 and 2.2 points higher consumption volatility. Reducing volatility of income by 10 points would reduce volatility of consumption by between 0.5 and 0.6 points. These results remain unchanged with the inclusion of state and cohort fixed effects.

To deal with potential mis-measurement of true liquidity constraints and income uncertainty, we instrument for income volatility and the probability of being denied credit. Columns (5) and (6) report these results. To instrument for income volatility we construct industry-time-cohort specific averages of income volatility. Although the choice of industry in itself is endogenous, the level of volatility for a specific year-cohort pair within an industry will be a good indicator of the level of volatility experienced by individuals working in that sector, and will be subject to less variation than an individual specific measure, alleviating the problem of mis-measurement. To instrument for liquidity constraints, we construct state-time-cohort averages of the probability of being denied credit. This instrument will pick up state level lending differences as well as differences within state and over time for a specific cohort of individuals. We interact these averaged effects to instrument for the interaction of liquidity constraint and income volatility term. In column (5) we drop the interaction term and use all three instruments, and in column (6) we also instrument the interaction term. In both cases, the effect of income volatility and the probability of

[28]Income volatility occasionally takes extremely large values, whereas this is not true for consumption volatility. Thus when income volatility is high, consumption volatility is likely to be a concave function of income volatility, even if there is generally a linear relation between the two variables. Since income volatility and liquidity constraints are correlated, the negative interaction term may, in part, be proxying for a nonlinear relation between income and consumption volatility. Consistent with this observation, we find that if we omit observations with income volatility in the top 1 percent of the income volatility distribution, the interaction term falls to zero, while the other coefficients remain similar. These results are available upon request.

being denied credit remains positive, and of a similar size as in our OLS specification (columns (3) and (4)), although the effect of income volatility is slightly larger. When instrumenting, we loose the significance of the interaction term. In both specifications, the tests of the validity of our instruments are passed with high statistical significance. Moreover, our instruments do not suffer from the problems caused by weak identification, as the F-statistics are large for both regressions, especially for the overidentified case in column (5).

Households with higher transitory income volatility will find it harder to smooth consumption, and will be more likely to be denied credit. Thus although households who are more likely to be denied credit have higher consumption volatility, this might not be because they have less access to credit; instead, it might be because these households might have higher transitory income volatility. It is hard to address this concern directly: since the SCF has essentially no panel dimension, we cannot separately estimate temporary and permanent income shocks. One approach is to split our sample by education. It is well known that individuals with less education face more volatile transitory income shocks, and less volatile permanent shocks (Gundersen and Ziliak [2008]). If we find that splitting the sample by education reduces the effect of liquidity constraints on consumption volatility, that would suggest that what we call an "access to credit" affect merely reflects differences in transitory volatility. We do not find this to be true.[29] The effect of liquidity constraints is larger for the less educated than for the better educated group, 0.24 vs. 0.18, but this difference is statistically insignificant; more importantly, the average effect of liquidity constraints is similar to the effect in our whole sample. This suggests that the endogeneity problem described here is not of great concern in practice.

Our results indicate that if we took an average household in the 25th percentile of the $\widehat{\Pr(\text{denied credit})}$ distribution, with a 9 percent probability of being liquidity constrained, and moved this household to the 75th percentile with a 31 percent probability of being constrained, while holding the size of their income shock constant, we would raise their consumption volatility by 5 points, or around 40 percent. Note that when we control for both volatility of income and probability of being denied credit, the time trend becomes insignificant. This suggests that if these key variables remained unchanged during this period, volatility of consumption would have also remained constant. In all specifications, our main conclusion remained unchanged: liquidity constraints play a crucial role in propagating income shocks.

These results are important given the substantial inequality in households' access to credit. In our SCF sample, around 40 percent of households with a black or Hispanic head of household were liquidity constrained, compared to 20 percent of

[29]These results are available in Appendix Table A.5.

households headed by a white individual; around 30 percent of households whose head had less than 13 years of education were constrained, compared to 20 percent of households with at least 13 years of education. There is no evidence that these groups are more likely to apply for loans. In fact, according to SCF data, black individuals and less educated individuals were less likely to apply for loans than white or highly educated individuals between 1995 and 2007 (although they were significantly more likely to be discouraged from applying because they thought they would be denied). It remains unclear whether lenders are less willing to extend credit to these households because they have more volatile incomes and a higher risk of default, or because of other reasons, such as discrimination.

Wealth inequality can also explain differences in consumption volatility between households. According to SCF data, asset poverty (defined as households with net assets less than two months' income) among blacks and Hispanics fell by a quarter between 1983 and 2007, nevertheless, blacks and Hispanics remain twice as likely to be asset poor as whites. College educated households are significantly less likely to be asset poor. Although we do not attempt to identify the causal affect of asset poverty on consumption volatility, it seems likely that wealth inequality, in addition to inequalities in access to credit markets, contributed to disparities in households' ability to smooth consumption.[30]

3 Conclusion

The volatility of US household income increased by 44 percent between 1980 and 2004. Households were not able to completely smooth consumption in response to their increasingly volatile income shocks: over the same period, the volatility of unpredictable changes in household consumption increased by around 19 percent. One factor limiting households' ability to smooth was limited access to credit. Between 1983 and 2007, around 1 in 5 households were denied a loan or were discouraged from applying for a loan in the past 5 years, and the proportion of liquidity constrained households increased slightly over time. While financial sector innovations such as credit scoring and risk-based pricing may have increased lenders' willingness to lend, it seems that households' demand for credit has increased by the same amount, so that the fraction of households unable to borrow as much as they would like re-

[30]Another partial insurance mechanism, which we do not explore in this paper, is risk-sharing within family networks. Our measure of income volatility is post-transfers (both private and public) but pre-tax. Thus, the income volatility process is smoother than it would have been if transfers were excluded. A proper investigation into the effect of household risk sharing on consumption volatility is left for future research.

mained unchanged. Differences in households' net wealth and access to credit led to significant differences in their ability to smooth consumption.

The increase in the volatility of household consumption has a significant welfare cost. Accurately estimating this welfare cost is beyond the scope of this paper. To show that the welfare cost is likely to be substantial, we use Lucas [1987]'s formula for the cost of consumption fluctuations to obtain a rough estimate. Lucas [1987] considered a representative consumer with isoelastic, time separable utility, and assumed that log consumption is normally distributed with variance σ_c^2 around a linear trend. Under these assumptions, eliminating all consumption volatility would provide the same welfare benefit as increasing annual consumption by $\mu = \frac{1}{2}\gamma\sigma_c^2$ percent. Unlike Lucas, we are considering the variance of unpredictable changes in household consumption, not the variance of deviations of aggregate consumption from a trend.[31] Since the elasticity of food consumption with respect to total non-durable consumption is β, shocks to food consumption growth will be β times as large as shocks to total consumption growth, and the variance of shocks to food consumption growth (our measure of consumption volatility) will be β^2 times as large as the variance of shocks to total consumption growth. We therefore divide our measure of food consumption volatility by β^2, using our estimate of $\hat{\beta} = 0.78$. In our Euler equations, we estimate $\beta/\gamma = 0.6$; we therefore take $\gamma = 0.78/0.6 = 1.3$. Under these assumptions, reducing consumption volatility by 2.8 points from its 2000-2004 level to its 1980-1984 level would produce the same welfare gain as increasing annual non-durable consumption by 3 percent.[32] While this number is only a back of the envelope estimate, and is sensitive to assumptions, it is clear that the rise in consumption volatility is of first order importance for household welfare.

Similarly, since disadvantaged groups face higher levels of consumption volatility, driven in part by differences in access to credit, decreasing their consumption volatility would have a clear welfare benefit. Households headed by a black or Hispanic individual have on average 7 points higher consumption volatility than whites. Reducing consumption volatility for the average black or Hispanic household to the level experienced by the average white household would provide the same welfare

[31] In our model consumption is close to a random walk with drift, rather than trend-stationary. Reis [2009] shows that this change in assumptions can increase the welfare cost of fluctuations by an order of 50. Our welfare cost estimate should therefore be considered a lower bound. Our results are of the same order of magnitude as Hai et al. [2013], who calculate the welfare cost of fluctuations in a structural model with memorable goods, fitted to CEX data.

[32] We compute welfare cost as $\frac{1}{2}\gamma(\sigma^2_{c,2000-2004} - \sigma^2_{c,1980-1984}) = \frac{1}{2}\gamma\frac{(\sigma^2_{f,2000-2004} - \sigma^2_{f,1980-1984})}{\beta^2} = \frac{1}{2} * 1.3 * \frac{0.028}{0.78^2} = 0.03$.

gain as increasing annual consumption by around 7.3 percent. The difference between consumption volatility for the quarter of households most likely to be liquidity constrained and the quarter of households least likely to be constrained is of the same magnitude. This suggests that improving access to credit for disadvantaged groups, or providing them with other ways to smooth consumption, could significantly improve household welfare.

A Web Appendix

A.1 Data Sample: Panel Study of Income Dynamics

The Panel Study of Income Dynamics (PSID), which began in 1968, is a longitudinal study of a representative sample of U.S. individuals (men, women, and children) and the family units in which they reside, and is conducted by the University of Michigan. The PSID's sample size has grown from 4,800 families in 1968 to more than 7,000 families (and over 60,000 individuals) in 2001. Some families are followed for as much as 36 consecutive years.

Consumption data in 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. The core 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 total food consumption levels are also eliminated. In order to minimise 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 95 percent (see for example Zeldes [1989b] or Blundell et al. [2008]).

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 the previous year, the biennial sample has data for *even* years from 1976 to 2004. In addition, food consumption data was not collected in 1973, 1988 and 1989. We do not impute for the missing years in order to keep measurement error and misidentification to a minimum.

At the time of the interview, the respondent is asked questions about income, transfers, wealth and expenditures on food and shelter. The families are asked to report income and transfers received during the previous year. We use total family income to compute income uncertainty. We adjust income data by one period to correspond to the appropriate demographic characteristics for each household. The timing of consumption data is more ambiguous. We follow Blundell et al. [2008], among many others, and assume that the respondent provided information on food expenditures for the previous year. We use interest rates on two-year constant maturity Treasury bills.

All the income, expenditure, wealth, and interest rate data are expressed in real terms. Nominal data are converted into real using item specific regional not seasonally adjusted all urban Consumers Consumer Price Index (CPI-U) with base period of 1982-1984=100. Thus, food expenditures are deflated using the Food and Beverages CPI; housing expenditures, using the Housing CPI; and all income, wealth and interest rate series, using All-Items CPI.

A.2 Data Sample: 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 multi-stage 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, therefore the total sample is not representative of US households. The SCF provides probability weights which account for the sample design, and also for differential patterns of non-response among families with different characteristics; unless otherwise noted, all SCF data presented here is weighted.

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. We average across all five implicates to reduce the likelihood of biasing our results. 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.

A.3 Variables Used in Regressions

In our probit regression model for the probability of being denied credit in SCF data, our explanatory variables are: a cubic in age, categorical variables for a female head of household, a single parent, marital status, receiving welfare payments, having positive asset income; cubics in log income and house value, quadratic functions of log annual mortgage payments, mortgage, and asset income; and interactions between race, education (no high school, high school, or college), and the cubic in log house value. We test for coefficient stability by interacting these variables with linear and quadratic time trends, and checking whether the coefficients on these interactions are significant. In our final specification, we include a quadratic time trend, and interact several variables, which we found to have time-varying coefficients, with a linear trend.

Next, we describe the explanatory variables used in our income regressions, which we use to estimate income volatility. In individual labour income models, these variables usually include age, age squared, dummy variables for education, occupation and industry, sex, race, cohort dummies, time dummies (to control for aggregate shocks), and various interaction. Since we model the family income process, we redefine these variables as those pertaining to the head of household, and include additional variables, such as head's marital status, number of hours worked by head and his partner, and the number of children and adults in the household.

Finally, we describe our probit regression model for the probability of having positive cash on hand. For each year wealth data is available, we estimate the probability of having positive net non-housing wealth as a function of observable characteristics such as age, age squared, cohort, race, gender, education, real house value, real rental and mortgage cost, home ownership, marital status, number of children and adults, real family income, real asset income, information on welfare, public transfers, and state of residence.

A.4 Estimating the Demand for Food in PSID.

To estimate our β coefficient for the food demand equation 6, we follow methodology outlined in the Blundell et al. [2008]. In particular, we estimate:

$$\ln F_{h,t} = \alpha_0 + \alpha_1 \ln p_t^F + \alpha_2 \ln p_t^O + \beta \ln C_{h,t} + \theta'_F Z_{h,t} + \iota_{h,t}$$

where we measure $\ln C_{h,t}$ using additional information available in the PSID starting 2005. In particular, in addition to food, starting 1999, the PSID added information on the following non-durable and service categories: expenditure on childcare (for working and non working spouses), utilities, gasoline, transportation, home and auto insurance, and vehicle repair. Moreover, starting 2005, additional expenditure on non-durable (and semi-durables) categories include clothing, home repair, furniture, trips, and other recreation activities. To construct our measure of total nondurable consumption, we use the sum of the above listed items. We then estimate food demand equations using 2005-2009 data following the methodology outlined in Blundell et al. [2008].[33]

[33]For these regressions we use data kindly provided to us by Geng Li of Federal Reserve Board.

Table A.6 provides the results of our estimation. This table reports IV estimates of the demand equation for (the logarithm of) food spending in PSID. We instrument the log of total nondurable expenditure, defined above, (and its interactions with time, education, and kids dummies) with the cohort-education-year specific average of the log of the husband's hourly wage and the cohort-education-year specific average of the log of the wife's hourly wage (and their interactions with time, education, and kids dummies). Other controls in this regression include a polynomial in age, education and cohort dummies, dummies for the number of kids, race, gender, marital status, region, and (the logarithm of) prices for food, tobacco and alcohol, prices for transportation, and prices for utilities. The estimates of the coefficients on these controls are not shown in the table to preserve space, but are available upon request.

The first 5 columns of the table present results of the estimation for a narrower definition of nondurables, that based on the available categories as of 1999 interview. In column 5, we restrict the time span to 2005-2009, to be comparable to the regression results in columns (6)-(8) that are estimated using 2005 definitions. In the first column of the table, we allow the elasticity to vary over time, by education, and with the number of kids. This specification does not pass the validity of instruments tests. Moreover, we find that the elasticity does not vary with the number of kids. The next columns restrict the elasticity to be invariant in time, by education, and/or the number of kids. Finally in column (4), we find that the best specification using 1999 definition, gives us an estimate of $\hat{\beta} = 0.73$. Looking at the wider set of categories available from 2005 onward, results shown in column (6), we again allow the elasticity to vary with time, education and the number of kids. We again reject that the elasticity varies across all of these dimensions. Finally, in our preferred specification, results in column (8), we allow the elasticity to vary with the number of kids, but not over time or with education. This regression passes all the over- and under-identification tests. We estimate $\hat{\beta} = 0.78$. Not surprisingly, if we compare beta estimate from column (5) and that of colum (8), we see that the beta on a narrower definition of non-durables (1999) is larger ($\hat{\beta} = 0.85$) than beta using 2005 definition ($\hat{\beta} = 0.78$).

A.4.1 Supplementary Tables and Figures

Table A.1: Regression of the liquidity constraint dummy on demographic variables and current income, interacted with a time trend.

	Coefficient		Standard errors
age	0.024	**	(0.012)
age^2	-0.000	**	(0.000)
female	0.099		(0.091)
white, no HS	0.403	***	(0.100)
white, college	-0.389	***	(0.081)
black, no HS	0.037		(0.212)
black, HS	0.138		(0.175)
black, college	-0.417		(0.297)
lowest income quartile	-0.220	*	(0.121)
second income quartile	-0.002		(0.104)
highest income quartile	-0.118		(0.088)
single parent	0.070		(0.161)
on welfare	0.063		(0.163)
time trend	-0.207		(0.320)
Observations	30,152		
R-squared	0.161		

Coefficients on interactions with the trend, coefficients are multiplied by 100
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table A.2: Summary statistics: PSID vs. SCF samples

Year	Age		percent Black		percent Hispanic		Family size	
	PSID	SCF	PSID	SCF	PSID	SCF	PSID	SCF
1983	39.17	41.60	0.08	0.13	0.02	0.04	3.02	3.05
1989	39.71	41.40	0.08	0.12	0.02	0.10	2.97	3.05
1992	40.34	41.53	0.08	0.13	0.02	0.09	2.98	2.98
1995	40.83	41.66	0.08	0.14	0.02	0.06	2.93	2.89
1998	41.41	42.18	0.08	0.12	0.03	0.09	2.87	2.91
2000	41.53		0.08		0.03		2.86	
2001		42.85		0.14		0.09		2.91
2002	41.92		0.08		0.03		2.80	
2004	41.96	43.23	0.09	0.14	0.03	0.11	2.80	2.88

Year	Education		percent on welfare		percent unemployed		Family income	
	PSID	SCF	PSID	SCF	PSID	SCF	PSID	SCF
1983	13.49	12.86	0.07	0.08	0.04	0.07	34,218	31,551
1989	13.64	13.20	0.04	0.08	0.03	0.04	39,442	37,869
1992	13.69	13.52	0.05	0.07	0.05	0.06	39,714	33,623
1995	13.73	13.47	0.05	0.08	0.02	0.03	40,416	32,550
1998	13.73	13.49	0.03	0.05	0.03	0.04	43,035	37,180
2000	13.69		0.04		0.04		45,805	
2001		13.58		0.04		0.03		43,809
2002	13.69		0.04		0.05		42,391	
2004	13.75	13.63	0.06	0.06	0.03	0.04	46,071	41,929

Source: SCF and PSID

Table A.3: Summary statistics: SCF

Year	Age		percent female		percent black		Family size		Single parent	
	C	UC	C	UC	C	UC	C	UC	C	UC
1983	36.34	42.91	0.33	0.19	0.26	0.11	3.04	3.02	0.22	0.09
1989	37.9	42.72	0.28	0.2	0.21	0.1	3.15	2.93	0.14	0.07
1992	37.75	42.89	0.29	0.19	0.26	0.11	2.89	2.89	0.21	0.06
1995	38.42	43.04	0.3	0.22	0.27	0.11	2.91	2.8	0.25	0.11
1998	39.08	43.59	0.3	0.19	0.24	0.1	3.02	2.78	0.25	0.1
2001	39.28	44.27	0.33	0.19	0.28	0.11	2.95	2.81	0.27	0.11
2004	39.83	45.08	0.34	0.2	0.3	0.11	2.81	2.78	0.25	0.1
2007	40.47	45.73	0.34	0.2	0.28	0.12	2.97	2.79	0.3	0.1

Year	Education		percent homeowners		percent have credit card		percent on welfare		percent unemployed	
	C	UC	C	UC	C	UC	C	UC	C	UC
1983	12.69	13	0.4	0.73	0.5	0.79	0.19	0.05	0.12	0.05
1989	13.08	13.53	0.51	0.74	0.58	0.82	0.14	0.05	0.08	0.02
1992	13.48	13.94	0.48	0.75	0.59	0.86	0.13	0.04	0.07	0.05
1995	13.3	13.72	0.51	0.75	0.6	0.86	0.16	0.05	0.06	0.03
1998	13.23	13.92	0.48	0.78	0.63	0.85	0.1	0.03	0.06	0.03
2001	13.18	14	0.49	0.8	0.68	0.88	0.08	0.02	0.04	0.03
2004	13.18	14.27	0.51	0.83	0.6	0.88	0.12	0.03	0.06	0.03
2007	13.02	14.19	0.54	0.8	0.53	0.85	0.16	0.04	0.07	0.03

Year	Family income		Assets		Net worth		Debt		percent with some debt	
	C	UC	C	UC	C	UC	C	UC	C	UC
1983	20,919	34,508	74,902	213,678	42,503	143,480	19,650	25,502	0.8	0.84
1989	26,719	43,144	95,525	215,014	71,876	183,503	23,649	31,511	0.89	0.86
1992	22,670	39,024	79,271	202,323	58,387	167,366	20,884	34,957	0.87	0.86
1995	20,873	37,485	69,617	212,156	47,039	175,727	22,577	36,429	0.88	0.88
1998	24,631	43,681	91,898	262,861	64,021	219,662	27,877	43,199	0.89	0.88
2001	23,827	52,648	74,747	331,351	47,245	284,408	27,502	46,944	0.88	0.88
2004	22,881	51,944	83,913	387,465	49,587	322,327	34,326	65,138	0.85	0.89
2007	23,753	56,236	99,431	422,507	61,275	353,158	38,157	69,349	0.86	0.89

Source: Survey of Consumer Finances

Table A.4: Evolution of Food Consumption and Income Volatility, allowing for state fixed effects and cohort dummies, biennial sample, 1980 to 2004.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	food	income	food	food	income	food	income
Year/1000	1.525***	7.295***	1.520***	1.448***	6.867***	2.876*	13.948***
	(0.504)	(1.486)	(0.505)	(0.505)	(1.482)	(1.696)	(5.157)
Year > 1992	-0.006	0.064***	-0.006	-0.006	0.065***	-0.010	0.062***
	(0.007)	(0.022)	(0.007)	(0.007)	(0.022)	(0.007)	(0.022)
Black/Hispanic	0.066***	0.092***	0.066***	0.064***	0.086***	0.065***	0.085***
	(0.010)	(0.027)	(0.010)	(0.010)	(0.027)	(0.010)	(0.027)
Education< 13	0.014***	0.044***	0.014***	0.014***	0.045***	0.017***	0.050***
	(0.005)	(0.016)	(0.005)	(0.005)	(0.016)	(0.005)	(0.016)
Age	-0.003	-0.027***	-0.003	-0.003	-0.026***	-0.009***	-0.040***
	(0.002)	(0.006)	(0.002)	(0.002)	(0.006)	(0.003)	(0.009)
Age^2	0.000	0.000***	0.000	0.000	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Change in marital status	0.104***	0.240***	0.104***	0.104***	0.234***	0.104***	0.234***
	(0.012)	(0.030)	(0.012)	(0.012)	(0.030)	(0.012)	(0.030)
Change in number of adults	-0.005	-0.012					
	(0.005)	(0.011)					
Change in number of kids	-0.001	-0.007					
	(0.004)	(0.011)					
Constant	-2.830***	-13.646***	-2.820***	-2.679***	-12.821***	-5.598*	-26.797***
	(1.003)	(2.943)	(1.003)	(1.003)	(2.933)	(3.353)	(10.191)
Observations	33,652	33,652	33,652	33,594	33,594	33,594	33,594
State FE	No	No	No	Yes	Yes	Yes	Yes
Cohort dummies	No	No	No	No	No	Yes	Yes
Adjusted R^2	0.0104	0.0108	0.0104	0.0126	0.0142	0.0152	0.0148

Robust, clustered at household level, standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1
Source: Authors' calculations based on PSID and SCF data as described in the text.

Table A.5: Effect of Liquidity Constraints and Income Uncertainty on Volatility of Consumption, by education, biennial sample, 1980 to 2004.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	all	$ed < 13$	$ed \geq 13$	all	$ed < 13$	$ed \geq 13$	all	$ed < 13$	$ed \geq 13$
Year/1000	1.128**	1.174	1.039*	0.514	-0.101	0.934	0.268	-0.135	0.522
	(0.496)	(0.798)	(0.628)	(0.512)	(0.830)	(0.650)	(0.501)	(0.820)	(0.630)
Year > 1992	-0.010	-0.012	-0.008	-0.007	-0.008	-0.006	-0.010	-0.011	-0.008
	(0.007)	(0.011)	(0.009)	(0.007)	(0.011)	(0.009)	(0.007)	(0.011)	(0.009)
$(\sigma^Y_{h,t})^2$	0.052***	0.046***	0.056***				0.062***	0.051***	0.068***
	(0.004)	(0.005)	(0.007)				(0.008)	(0.009)	(0.011)
$\Pr(\widehat{\text{denied credit}})$				0.222***	0.265***	0.181***	0.215***	0.242***	0.187***
				(0.024)	(0.036)	(0.032)	(0.025)	(0.036)	(0.034)
$\Pr(\widehat{\text{denied credit}}) \times (\sigma^Y_{h,t})^2$							-0.051**	-0.023	-0.075**
							(0.024)	(0.029)	(0.035)
Black/Hispanic	0.061***	0.066***	0.055***	0.024**	0.025	0.019	0.025**	0.025	0.023
	(0.010)	(0.014)	(0.012)	(0.011)	(0.016)	(0.015)	(0.011)	(0.015)	(0.014)
Education<13	0.012**			0.000			-0.000		
	(0.005)			(0.005)			(0.005)		
Constant	-2.116**	-2.178	-1.952	-0.977	0.238	-1.804	-0.493	0.303	-0.991
	(0.985)	(1.585)	(1.246)	(1.016)	(1.644)	(1.290)	(0.994)	(1.625)	(1.249)
Observations	33,652	14,683	18,969	33,652	14,683	18,969	33,652	14,683	18,969
Adjusted R^2	0.036	0.029	0.043	0.015	0.016	0.013	0.040	0.034	0.046
The effect of $(\sigma^Y_{h,t})^2$ is the same across groups (p-value)							0.229		
The effect of $\Pr(\widehat{\text{denied credit}})$ is the same across groups (p-value)							0.269		
The effect of $\Pr(\widehat{\text{denied credit}} \times (\sigma^Y_{h,t})^2$ is the same across groups (p-value)							0.249		

Robust, clustered at household level, standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1
Source: Authors' calculations based on PSID and SCF data as described in the text.

Table A.6: Estimating the Demand for Food in the PSID: The budget elasticity of Food with respect to total Nondurable Consumption.

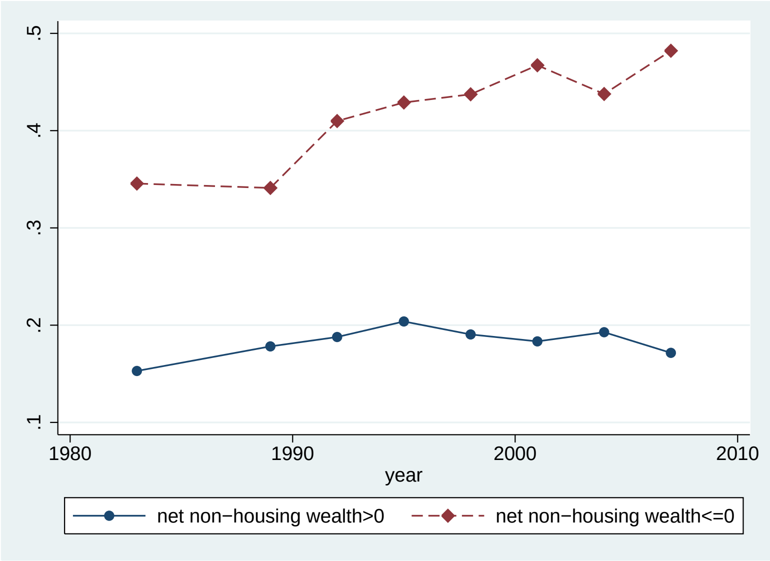
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
years of data used:	1999-2009	1999-2009	1999-2009	1999-2009	2005-2009	2005-2009	2005-2009	2005-2009
$ln(ND_{1999})$	0.741***	0.681**	0.810***	0.734***	0.850***			
	(0.260)	(0.280)	(0.254)	(0.236)	(0.201)			
$ln(ND_{2005})$						0.516***	0.863***	0.783***
						(0.155)	(0.268)	(0.255)
Observations	20,853	20,853	20,853	20,853	10,718	10,718	10,718	10,718
R-squared	0.606	0.595	0.614	0.613	0.609	0.477	0.415	0.436
Underid test	8.351	7.654	9.697	9.075	16.72	15.69	9.481	9.843
p-value	0.820	0.663	0.406	0.028	0.001	0.109	0.009	0.020
Hansen J overid test	10.80	6.262	7.221	2.207	0.227	9.830	0.00484	1.688
p-value	0.546	0.713	0.287	0.332	0.893	0.364	0.945	0.430
weak id Cragg-Donald Wald F statistic	0.471	0.612	1.115	4.461	4.689	0.754	5.384	2.768
elastcity is time invariant (p-value)	0.0796	0.0639	0.0917	-	-	0.592	-	-
elastcity is edu invariant (p-value)	0.0423	0.0456	-	-	-	0.117	-	-
elastcity is kid invariant (p-value)	0.215	-	-	-	-	0.408	-	-
time varying elasticity	Yes	Yes	Yes	No	No	Yes	No	No
elasticity varies with education	Yes	Yes	No	Yes	Yes	Yes	No	No
elasticity varies with number of children	Yes	No	No	No	No	Yes	No	Yes

Note 1: This table reports IV estimates of the demand equation for (the logarithm of) food spending in PSID. We instrument the log of total nondurable expenditure, defined below, (and its interactions with time, education, and kids dummies) with the cohort-education-year specific average of the log of the husband's hourly wage and the cohort-education-year specific average of the log of the wife's hourly wage (and their interactions with time, education, and kids dummies). Robust, clustered at household level, standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Note 2: $ln(ND_{1999})$ is defined as ND expenditure, given available expenditure data as of 1999 forward, on the following categories: expenditure on food at home and away from home, food stamps, childcare, utilities, gasoline, transportation, home and auto insurance, and vehicle repair.

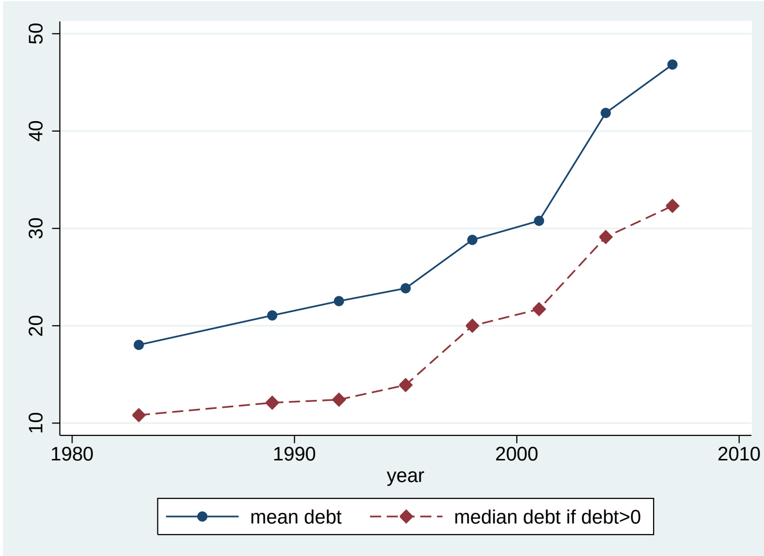
$ln(ND_{2005})$ includes ND expenditure given available expenditure data as of 2005 forward. It includes categories in 1999 definition, plus expenditure on clothing, home repair, furniture, trips, and other recreation activities.

Figure A.1: Proportion of liquidity constrained households, by wealth



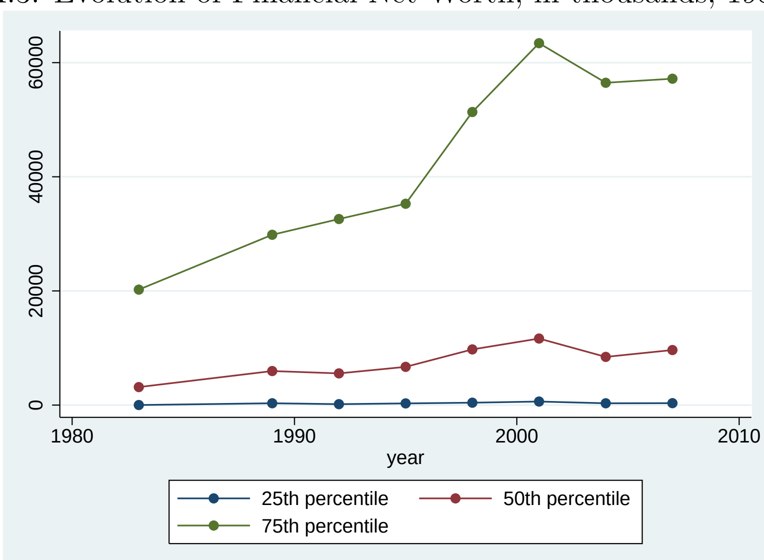
Source: Survey of Consumer Finances.

Figure A.2: Increase in average and median debt, in thousands, 1983 dollars



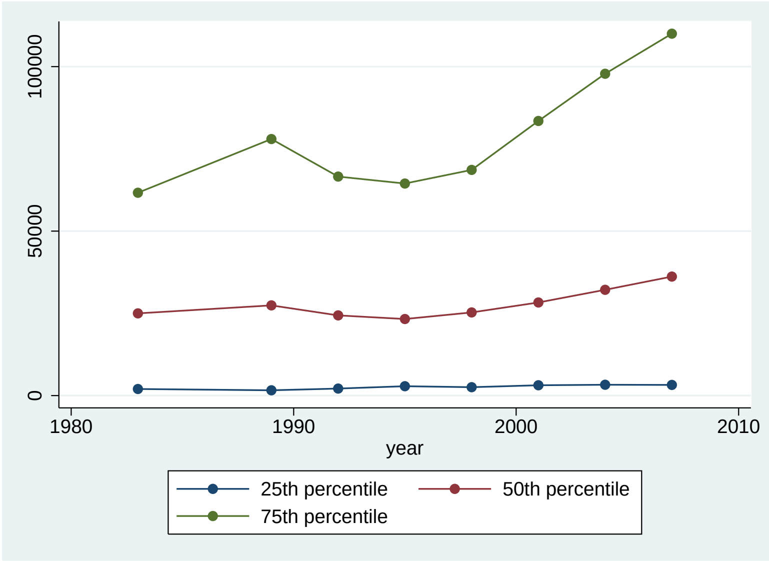
Source: Survey of Consumer Finances.

Figure A.3: Evolution of Financial Net Worth, in thousands, 1983 dollars



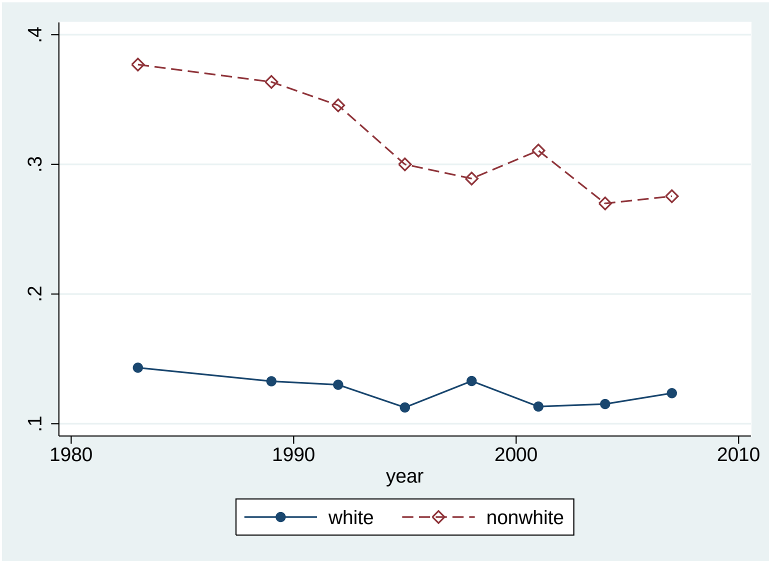
Source: Survey of Consumer Finances.

Figure A.4: Evolution of Nonfinancial Net Worth, in thousands, 1983 dollars



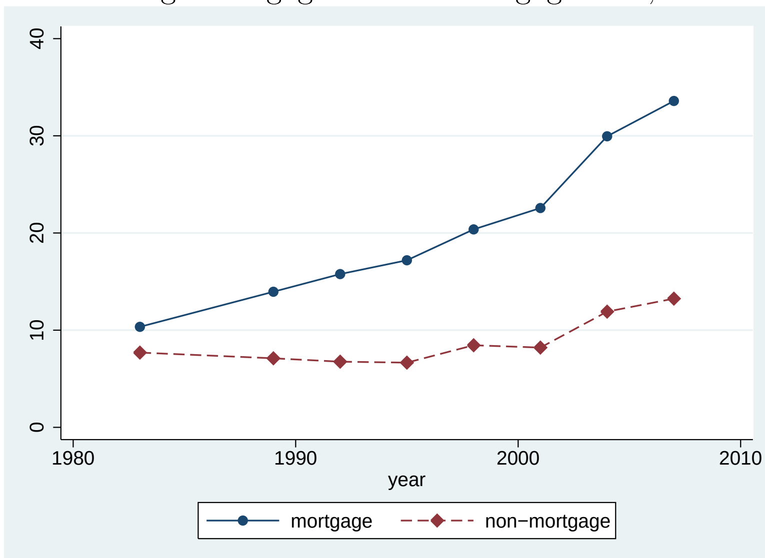
Source: Survey of Consumer Finances.

Figure A.5: Percent of Households with net assets less than two months of income.



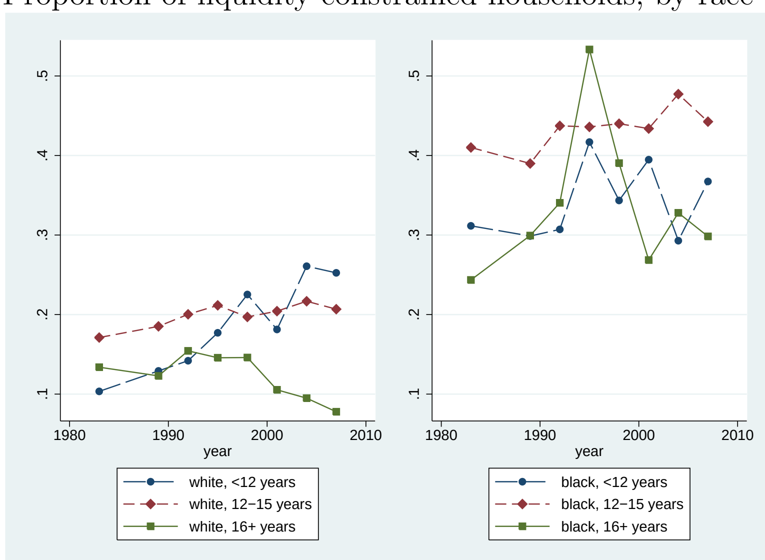
Source: Survey of Consumer Finances.

Figure A.6: Average mortgage vs. non-mortgage debt, in 1983 dollars



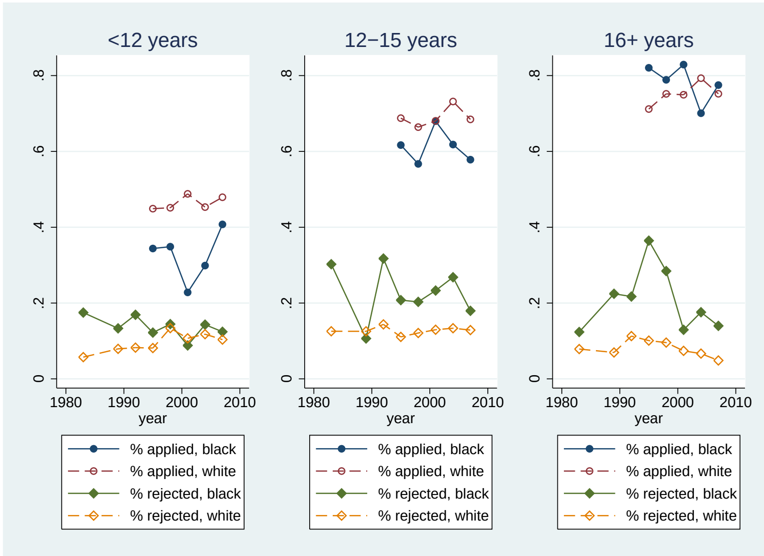
Source: Survey of Consumer Finances.

Figure A.7: Proportion of liquidity constrained households, by race and education



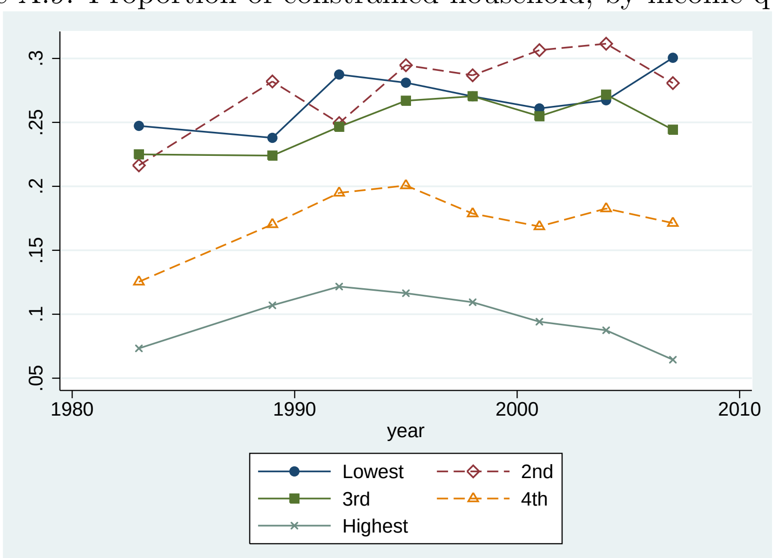
Source: Survey of Consumer Finances.

Figure A.8: Proportion of households applying for credit and rejected, by race and education



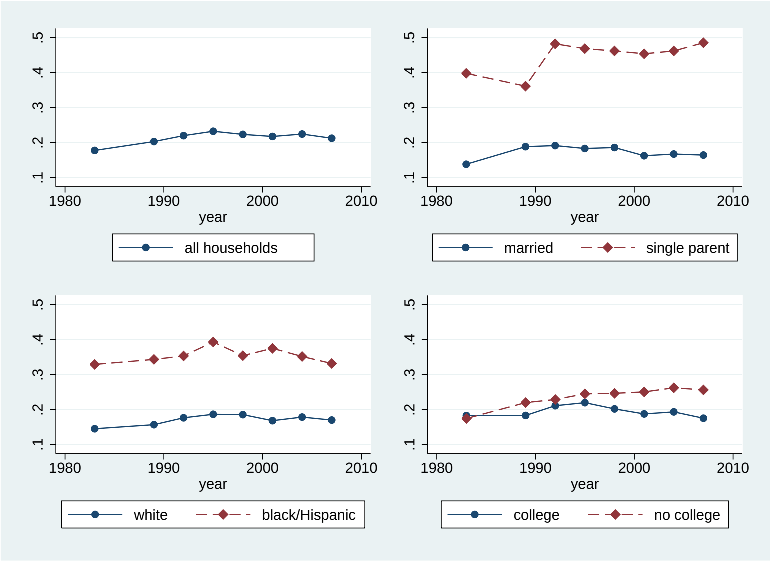
Source: Survey of Consumer Finances.

Figure A.9: Proportion of constrained household, by income quintile



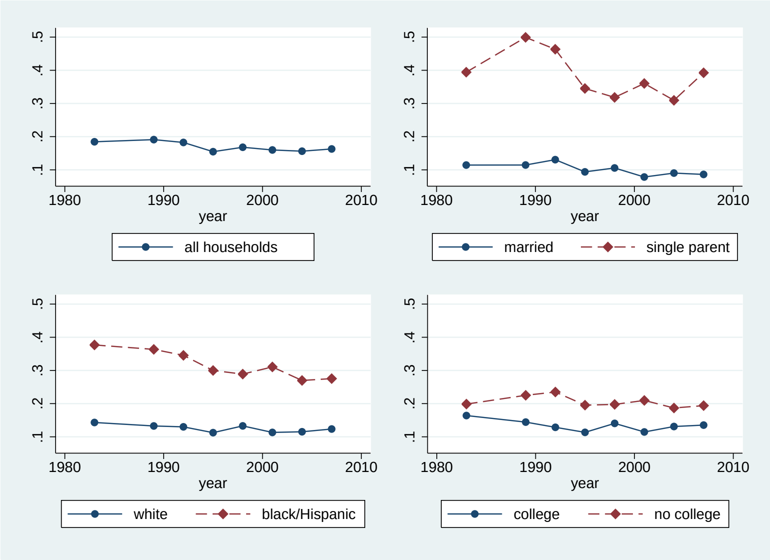
Source: Survey of Consumer Finances.

Figure A.10: Proportion of constrained households, by demographic group



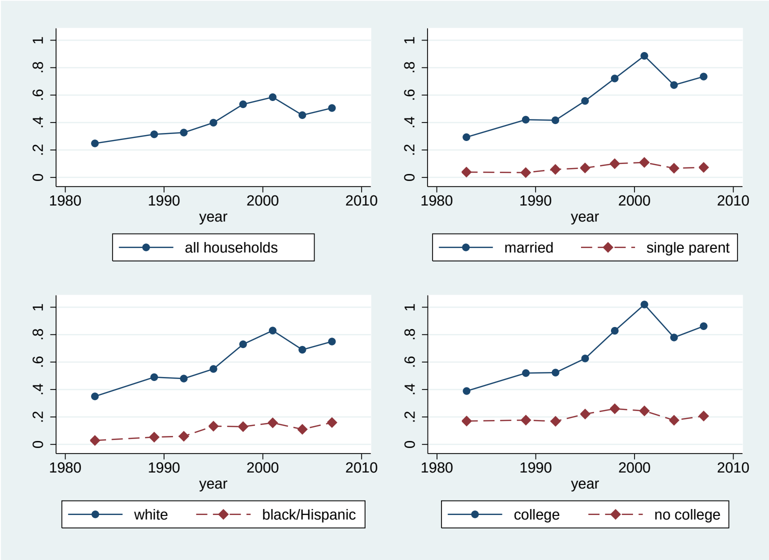
Source: Survey of Consumer Finances.

Figure A.11: Percentage with net assets less than two months' income, by demographic group



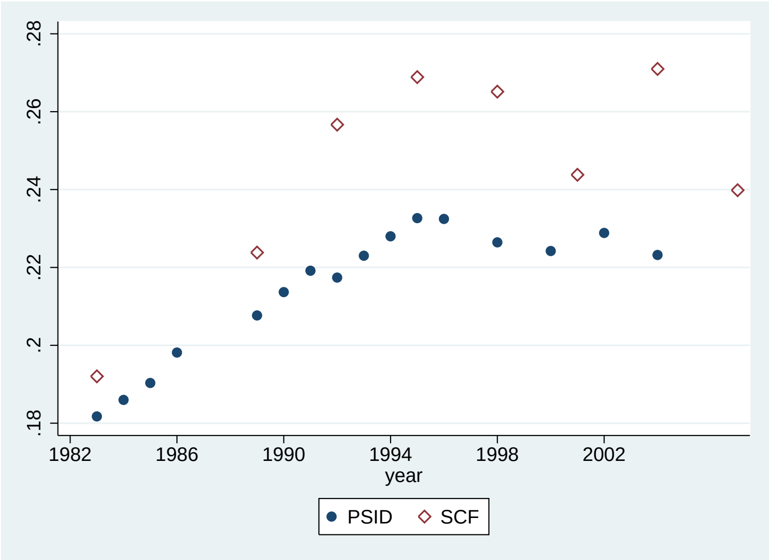
Source: Survey of Consumer Finances.

Figure A.12: Median net assets to income ratio, by demographic group



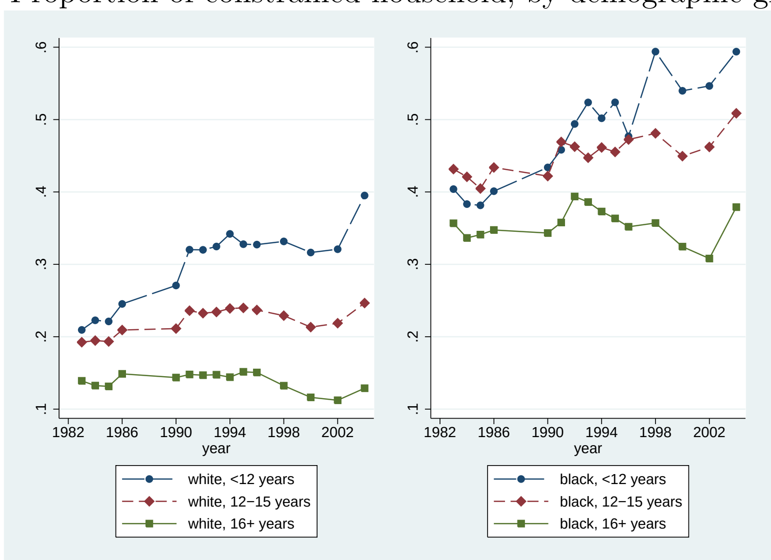
Source: Survey of Consumer Finances.

Figure A.13: Mean Estimated Probabilities in the SCF and the PSID



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

Figure A.14: Proportion of constrained household, by demographic group in PSID



Source: Panel Study of Income Dynamics.

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