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The marginal propensity to consume out of liquidity*

[PRELIMINARY AND INCOMPLETE]

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Abstract

This paper presents novel tests of competing models of inter temporal consumption behavior using unique European administrative panel data on income, spending and assets. I estimate the marginal propensity to consume (MPC) out of 'liquidity' -the debt response to a change in borrowing capacity- using changes in credit card limits in a randomized controlled trial implemented in September 2014 involving thirty thousand individuals. I obtain four empirical results: (i) borrowing constraints change consumption dynamics even when they are not binding, and a large fraction of consumers, even those that are away from a binding borrowing constraint, respond aggressively to a change in borrowing limits, accumulating an average of 20 cents of debt per dollar limit increase, *relative to the control group*; (ii) there is substantial heterogeneity in MPC, exclusively in line with models featuring precautionary motives. Immediately constrained consumers increase consumption one-for-one, and, in line with a concave consumption rule, the MPC is a decreasing function of cash-on-hand; (iii) the cumulative response of debt and credit utilization is mean reverting: for those with less than one month of income as cash-on-hand, the additional debt accumulated drops back to zero after 18 months.[1] (iv) additional liquidity is spent mostly on durables using installments, with a smaller fraction on spent on non-durables and taken out as cash advances. I then study the joint dynamics of consumption, debt and the balance sheet to a change in borrowing constraints, in a Bewley model with realistic income risk. Simulated moments estimators use the MPC out of liquidity to calibrate and test apart intertemporal models. Hump-shaped debt response, as well as the mean-reverting credit card utilization are not consistent with impatience or myopia as the underlying preferences.

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[1]Long term responses are estimated using observational data.

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1 Introduction

What is the effect of a change in borrowing limits on household spending and debt? Do households that are not immediately constrained respond to a change in borrowing capacity? What accounts for the heterogeneity of the response, and is the heterogeneity quantitatively important, i.e. do policies that affect those with low cash-on-hand have greater consequences for consumption? What kind of inter temporal preference generates the high amount of unsecured debt we observe? Does the credit card market function to insure against income shocks of various nature?

The primary contribution of this paper is to measure the magnitude, duration, composition and distribution of the marginal propensity to consume out of changes in liquidity, i.e. the debt response to a change in borrowing capacity. An increase in borrowing capacity do not entail any wealth effects. Therefore, under the benchmark permanent income hypothesis (PIH) often used for policy evaluation, it should have no effects on consumption behavior, i.e. the marginal propensity to consume out of liquidity is zero. Models featuring concave consumption rules, such as those with liquidity constraints/precautionary savings predict positive MPCs out of liquidity.

I utilize unique European panel data on income, spending and liquid asset information, and pursue an event study of how consumption and debt respond to a change in credit card limits. I implement a randomized controlled trial including more than thirty thousand individuals, where I randomly withhold credit card limit increases to half of the eligible population. The experiment is then used in conjunction with observational data on 100,000 individuals with direct deposit to interpret the long run effects. I yield four novel insights into dynamics of consumer leveraging.

Firstly, the MPC out of liquidity is significantly different from zero for a large fraction of the population who are not immediately constrained. For example, an individual with three months of cash-on-hand, defined as net liquid assets plus available credit, responds to a change in borrowing limit by accumulating 10 cents of debt, per dollar of limit increase, *relative to the control group*. This implies that liquidity constraints change the consumption dynamics even if they do not bind. Consumption response to a change in borrowing capacity happens via both a direct channel, where constrained borrowers are forced to lever/delever, and a precautionary channel, where unconstrained consumers also readjust.

Secondly, the MPC out of liquidity exhibits a clear heterogeneity in cash-on-hand, exclusively in line with the precautionary savings model. Debt increases more than one-for-one for those with cash-on-hand of less than one month of income at the time of limit increase. The findings are in line with a concave consumption rule's interaction with borrowing constraints. If a consumer expects low income or binding constraints, a buffer stock of cash-on-hand will be necessary to avoid very low consumption in a bad state, leading to depressed current consumption and high marginal utility of consumption today. In Section 2.1, I use data on individual balance sheets, and, accounting for credit demand and supply in turn, I characterize individuals that are at a corner solution to their inter temporal problem. I then show that the MPC is a decreasing function of cash-on-hand, which implies a consumption rule that is concave.

Thirdly, the cumulative response of debt to a change in borrowing limits is hump shaped: an increase in credit capacity does not push consumers to a new high leverage optimum, but individuals accumulate debt only to deaccumulate it after 6-18 months. Individuals in the lowest cash-on-hand quartile deaccumulate debt further to push their cumulative response to negative. Moreover, credit card utilization is mean-reverting: individuals that are high utilizers at any point in time, are not persistent high utilizers in the long-run, but asymptote to an average utilization of 30%, in 24 months. See Figure 13. The mean reversion of debt level and credit utilization, constitutes a puzzle for the standard inter temporal models. [2]

Finally, I decompose the consumption and debt response by debt type (revolving and installments) and by consumption sector. Durables purchased using installments constitute half of the debt stock.

Section 3 outlines the conceptual framework used to interpret the empirical estimates. I use simulation techniques to estimate a structural model of intertemporal consumption choice with realistically calibrated, uninsurable income risk a la Bewley (1977). Consumer borrowing is bounded below by an exogenous limit L. The existence of a borrowing constraint and uninsurable risk leads to a consumption rule that is concave in cash-on-hand. In addition, a concave consumption rule implies a decreasing MPC out of liquidity. These findings contrast with the perfect-certainty and the certainty-equivalent versions of the inter temporal consumption models, which imply linear consumption rules with linear MPCs.

I then estimate the model parameters using a simulated moments estimator (SME) akin to Duffie and Singleton (1993) and Gourinchas and Parker (2002), matching the simulated impulse responses to liquidity shocks to their empirical counterparts. I find reasonable estimates of the preference parameters.The estimated model matches the concavity of the consumption as a function of cash-on-hand, and is then used to interpret the consumption and debt accumulation behavior.

Debt response to liquidity shocks documented in this paper provide novel tests of theories of intertemporal consumption behavior. The standard model predict that consumption and debt levels are a function of lifetime wealth, with growth rates governed by the interest rate, discount factor, and the inter temporal elasticity of substitution. Therefore, a relaxation of borrowing constraints imply a permanent shift in debt rather than a temporary accumulation followed by a deaccumulation. The hump shaped cumulative debt response and mean reverting credit utilization constitute a puzzle for the standard framework. Motivated by the spending patterns, I then extend the model to feature durables. The individual now faces a portfolio problem, and the relaxation of the constraints induces the individual to adjust durable stock to accumulate durables and debt, the latter being paid gradually.

The findings of this paper have implications for business cycle dynamics and policymaking at the macro level, in addition to improving our understanding of household leveraging at the micro level. Representative agent models that fail to incorporate the heterogeneity in the MPC out of liquidity may miss out on important consequences of policies. I perform a brief policy experiment to discipline the magnitude of the effect of credit crunches. If credit growth were zero for 6 months, the partial equilibrium consumption demand would decrease by 1.7 % of GDP.

[2] Stress the importance of duration here. How does the accumulation rate and duration of debt holdings relate to cash-on-hand, impatience and risk aversion?

In a companion paper, I ask two very related questions: 1) Is the excess sensitivity and smoothness of consumption is due to borrowing constraints? 2) Does the credit market provide consumption insurance? In particular, I adopt a parsimonious permanent-transitory stochastic model of income to estimate simultaneously MPC out of shocks of differing persistence. I then estimate the sensitivity and smoothness parameters on the covariance restrictions imposed on the joint behavior of consumption, income and debt.

1.1 Literature

The consumption response to liquidity shocks has received much less attention on the empirical domain than other parameters of PIH, such as sensitivity to transitory shocks and smoothness with respect to permanent shocks, mainly due to lack of data.

Empirical studies of liquidity constraints document high propensities to consume out of transitory income. (Jappelli and Pistaferri (2010) for a recent survey.) Early works have measured the response of consumption to total income changes, or used proxies for permanent and transitory shocks. (Altonji and Siow (1987); Cochrane (1991)). Based on quasi-natural experiments on the 2001 and 2008 fiscal stimulus payments, Agarwal et al. (2007), Johnson et al. (2006) and Parker et al. (2013) find that in both episodes households immediately consume 20-40 percent of the rebate.[3] Shapiro and Slemrod (2003a) Shapiro and Slemrod (2003b) offer qualitative surveys on the pattern of consumption.

Two early papers by Deaton (1991) and Zeldes (1989b) investigated the properties of the consumption rule if the consumer is facing borrowing constraints. The existence of constraints concavifies the consumption rule at low cash-on-hand; However at high cash-on-hand consumption is linear and abides the PIH. In this paper, I do a complementary comparative statics exercise: holding constant the asset level, I analyze the effects of a relaxation of the borrowing constraint.

The great recession has further increased interest in studying the effects of credit availability on consumer spending and aggregate fluctuations via heterogenous agent incomplete markets models. These models study the consequences of a change in borrowing constraints on consumption and debt servicing decisions, with the key moment being the marginal propensity to consume out of liquidity.[4] Guerrieri and Lorenzoni (2011) considers a Bewley model with no capital and a coefficient of relative risk aversion equaling 4. Their calibrations suggest that a tightening of the credit limit that reduces household debt-to-GDP by 10 percentage points generates a 1% drop in output on impact.

The study most similar to mine is Gross and Souleles (2002), who uses proprietary data from multiple US credit card companies, and document that a $100 increase in credit card limit raises credit card debt by $10-14. This study improves on theirs on multiple dimensions. Firstly, I

[3] Also see Souleles (1999) on federal tax refunds and Parker (1999) on changes in social security taxes.

[4] See Eggertsson and Krugman (2012) and Hall (2011). Hall (2011) suggests the consumption response to credit tightening is essential to understanding the Great Recession. As liquidity constrained individuals rely on credit to finance their consumption growth, if lenders cut lending, but instead ask for the repayment of pre-existing debt, consumption drops. Such a tightening forces constrained individuals to increase saving, causing a drop in consumption.

achieve clean identification with exogenous assignment of the credit card limits. Secondly, the comprehensive measure of income, consumption, debt and cash-on-hand allows me to understand the comovement of debt with idiosyncratic shocks given a balance sheet position. Finally, (using observational data) following individuals for a longer horizon allows novel insights into the dynamics of leveraging, mainly that both the cumulative debt response and cash-on-hand is mean reverting.

2 Data and Environment

The study utilizes unique proprietary administrative data from a European financial institution. The institution is a top ten credit card platform in Europe, with more than 5 million customers. It holds a 20% market share in the local retail banking market, and offer a multitude of financial products, including credit cards, personal deposit and brokerage accounts, as well as other consumer loans. Its customer base is representative of the population of the country as a whole. There are four types of data available.

Firstly, credit card data includes card limits, end-of-month balances, and revolving balances as well as very detailed measures of expenditures. Every transaction is categorized according to its type: conventional purchases and cash advances, as well as installments, which is unique to the market in study. The spending data is very comprehensive: more than a third of all household consumption flows through credit cards, and purchases are categorized into 18 different sectors, which are later recategorized into durables, nondurables and services.

Secondly, balance sheet data contains information on the end of month balances on all the liquid assets and liabilities at the particular financial institution. Liquid asset accounts include checkings, savings, money market accounts, stocks, bonds, and mutual funds. Liquid debt includes any personal loans, vehicle loans and mortgages. Credit bureau data contains information on liabilities from other banks, such as the number of credit cards, their limit and balances, balances of other debt (mortgage, auto loans) as well as the credit scores.

Income data exists for a smaller fraction of consumers. In particular, only if there's a direct deposit agreement between the bank and the employers, then the monthly income is observed. It contains only after tax labor income and does not include financial income or transfers. The data also allows to identify each stream of income according to it's type, i.e. wage, overtime, bonus, advance etc. The credit bureau data also contain an implicit self-reported earnings value. Recent banking regulation requires that credit card limits be less than four months of stated income, therefore the most recent sectoral credit card limit reflects information on most recent subjective income report.

Finally, there exists a rich but only partially complete set of demographic data, including age, gender, education, and profession. Information on occupation, marital status and household size is incomplete. Table 1 contains summary statistics on the participant population.

The unit of analysis is an individual. If an individual has multiple accounts of the same product, than the account information such as balances are aggregated on a monthly basis. Individuals may be followed monthly for different periods of time, depending on when the account is

opened and if it is closed. The sample used in the observational part of the study extends from January 2011 to December 2013. Majority of the information regarding balance sheet variables are end-of-month calculations; however, credit card variables are end-of-billing-cycle calculations.

The high-frequency longitudinal nature of the data on income and comprehensive measure of consumption improves on the survey datasets that are commonly used in US consumption studies. Compared to surveys like PSID or SCF, the sample is large and data does not suffer from problems of attrition and non-response. In addition, the panel structure of the dataset allows me to look at dynamics and individual fixed effects in estimating the MPC out of liquidity.

The credit card market under study has a few distinctions from the US market. Firstly, credit card interest rates are capped above by the central bank, and almost all issuers charge this upper limit for almost all of their customers. Therefore, I do not separately include interest rates as an explanatory variable. Monthly dummies control for the variation on the cap rate, in addition to seasonality and aggregate effects. The impossibility of competing over the interest rates, induced response from the borrowers As competition in the credit card market has not been over interest rates, it has been over other marketing perks, most importantly allowing of purchases with installments. A considerable fraction of buyers finance their durables purchases with credit card installments that extend over a period of several months. For example, if an individual only bought a refrigerator costing $2000 with 4 installments, then his end-of-month balances would be $500 plus the interest charges, and the remaining $1500 plus the interest charges would show up under the the installments balance. If he is unable to pay any part of this $500 installment payment, it would show up under revolving balances.

2.1 Who is liquidity constrained?

The macroeconomic implications of borrowing constraints are proportional to the fraction of individuals effected by them: the only agents whose consumption would react significantly to a relaxation of borrowing constraints are those with low cash-on-hand.However, since the time of Hall and Mishkin (1982), the literature has not reached any consensus about the fraction of liquidity constrained individuals. This is partly due to data limitations, as liquidity constrained individuals are not directly observable and had to the identified via indirect evidence. For example, early studies by Hayashi (1985) and Zeldes (1989a) split the sample on the basis of ratios of financial assets to income, and Jappelli (1990) uses data from the 1983 Survey of Consumer Finances (SCF), finding that 12.5% of households report being rejected for credit, and a further 6.5% being discouraged to apply, putting the fraction of liquidity constrained individuals to about 20%. On the structural front, Hubbard and Judd (1986) calibrate a life-cycle economy to match the distribution of net worth of the US economy, and put the number of constrained consumers to around 10%.

I begin by documenting the likelihood of being short-term liquidity constrained along various demographic dimensions. An individual is liquidity constrained if he is unable to finance current consumption with resources to accrue to him in the future. These individuals are at a corner solution to their inter temporal problem, as they have no liquid assets and they utilize most available credit credit. However, individuals need not have binding constraints (utilize all avail-

able credit) to be liquidity constrained: in models where precautionary motives interact with liquidity constraints, possibly binding in the future, an optimal amount of credit line is kept free as a precautionary buffer.[5]

I consider two definitions of being liquidity constrained. According to the first, an individual is liquidity constrained if the cash-on-hand is less than two months of income, where cash-on-hand reflects net liquid assets, and available credit capacity. (Hall, 2011) Liquid assets include checkings, savings, money market accounts. Available credit is credit card limit minus unpaid balances. The second definition makes use of the information in credit card balances, classifying an individual as constrained if his unpaid credit card balances exceed half the credit limit. The fraction of constrained individuals according to each criteria, by age and income bins, as well as the distribution of cash-on-hand, are given in Figure 2.

2.2 Sampling and randomization

I am interested in identifying the causal effect of a change in credit capacity on consumption and debt. However, credit supply is endogenous: credit card limits are a function of the consumers propensity to utilize debt, and issuers profit from and extend credit to individuals that revolve credit card balances but do not default. In addition, macroeconomic events that affect liquidity supply often change permanent and transitory income or investment returns and also effect credit demand. Therefore, in time-series, predictable growth in consumer credit is significantly correlated with consumption growth, even beyond the variation in predictable income, i.e. credit supply increases when credit demand is expected to rise. Ludvigson (1999) In the cross-section of consumers, issuers can well identify individuals that are likely to incur and roll over balances, i.e. issuers extend credit to those that are likely to utilize it.

I now describe the sampling and the randomization of the RCT. The assignment of credit line was done in three steps. First, the credit sales group pre-selected customers according to a set of profitability criteria. These criteria include the expected value added from limit increase, as well as macro prudential criteria imposed by the banking regulation authority, such as having pre-existing unpaid balances exceed half the card limit. The pre-selected individuals were then filtered by the bank's risk group, according to a set of risk criteria. These criteria include predicted likelihood of default on a product (credit card) and customer basis, as well as if the individuals have any late payments. Finally, the remaining customers were entered into the central bank's credit limit clearing system to check if they are eligible for a credit limit extension, i.e. if their current limit is below four times their income. The randomization was done after the final step; therefore, the control group consists of individuals that pass all criteria for being assigned an increased credit limit, but are not.

I then group individuals on the basis of credit card utilization, defined as the ratio of end-of-month credit card balances to credit limit. I first estimated a distributed lag-model on the observational data for each utilization percentile. The standard errors of the MPC estimates are higher for high utilization individuals; therefore, I under-sample individuals that have a low credit card utilization, proportional to the standard errors. The sampling strategy is summarized in Figure 5.

[5] Deaton (1991) Adams et al. (2009)

I do stratified sampling, therefore in order to evaluate average effects, I need to re-weigh data. I should do this by select a random sample from each utilization bin, in accordance with the sampling binning, where the sample reflects the number of individuals initially at that bind, and reflects initial distribution of utilization.

3 Conceptual Framework

I address the key features of the data using a standard incomplete markets model a la Bewley (1977). The individual is facing uninsurable permanent and transitory idiosyncratic income shocks, and smooths consumption via borrowing and lending, subject to a borrowing constraint. Since the model does not permit analytical solutions, firstly, I analyze steady state given the borrowing limit. Then I look at the transitional dynamics following a shock to borrowing limit.

The model is expected to deliver the following empirical observations:

1. Consumption is a concave function of cash-on-hand. (Figure 14)
2. Consumption is a function of debt-service commitments. (Debt overhang, Figure **??**)
3. MPC out of liquidity is a decreasing function of cash-on-hand. (Figure 10)
4. MPC out of liquidity is mean reverting. (Figure 12)
5. Cash-on-hand and credit card utilization is mean reverting. (Figure 13)
6. Empirical distribution of cash-on-hand in steady state is lognormally distributed.[6] (Figure 3)

I consider two models in turn. First, I consider a model with a single consumption good and a single interest rate for borrowing and lending. The model abstracts from durable purchases, health purchases, educational purchases and from any life-cycle motives. This model is unable to deliver my third empirical finding, the mean reverting dynamics of the debt stock. I then consider a model with durables.

3.1 Baseline model

I begin with a discrete time, infinite horizon model of consumption behavior. Preferences over non-durable consumption C_{it} take additively separable isoelastic expected utility form, with discount factor β and risk aversion γ,

$$V() = \max \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \frac{C_{it}^{1-\gamma}}{1-\gamma} \right] \tag{1}$$

subject to the intertemporal budget constraint,

[6] Do I need an initial asset level for households? Assume cash-on-hand to income is log normally distributed with mean and variance.

$$C_{it} \leq Y_{it} + B_{it+1} - B_{it}R \tag{2}$$

where B_{it} is the amount of borrowing (minus bond holdings) and R_t the gross real interest rate. The model imposes a single asset for inter temporal substitution, with borrowing and lending rates being equal. In the extended model with durables, I allow for separate rates for borrowing and lending. Most importantly, household borrowing at time t is bounded above by the exogenous limit L_{it}, tighter than the natural borrowing limit.

$$B_{it+1} \leq L_{it} \tag{3}$$

In what follows, it will be helpful to introduce X_t, *cash-on-hand*, defined as the distance to the borrowing constraint, or equivalently, net assets plus available credit,

$$X_{it} \equiv Y_{it} + L_{it} - B_{it}R \tag{4}$$

and combining Equations 2 3 and 4 implies an upper cap on consumption,

$$C_{it} \leq X_{it} \tag{5}$$

Uninsurable idiosyncratic income uncertainty, and prudence, induces households to keep a buffer stock of cash-on-hand, in order to insure themselves against low-income, low-consumption future realizations. Gourinchas and Parker (2002) analyze the consumption profiles in age, which are hump-shaped, as individuals have larger precautionary motives earlier on.

I analyze the model by numerical simulations and briefly describe the consumption policy in steady state. The solution is a consumption rule $C_t(X_t)$, a positive, increasing and concave function of cash-on-hand and permanent shock. Figure 6 shows consumption as a function of cash-on-hand for the realizations of the income process. For high levels of cash-on-hand, consumer reacts in line with the PIH; whereas for lower levels of cash-on-hand, the consumption rule is concave. For the concave part of the consumption rule, the MPC out of liquidity is decreasing. At low levels of cash-on-hand, they exhibit buffer stock behavior, and borrow most, but not all, of their borrowing capacity.

I adopt a parsimonious permanent-transitory stochastic model of income. ...

3.2 Recursive problem and the shadow price of debt

$$V(B_{it}, Y_{it}; L) = \max_{C_{it}, B_{it+1}} \frac{C_{it}^{1-\gamma}}{1-\gamma} + \beta\, \mathbb{E}_t \Big[V(B_{it+1}, Y_{it+1}; L) | Y_{it} \Big] \tag{6}$$

$$\text{s.t. } C_{it} \leq Y_{it} + B_{it+1} - B_{it}R \tag{7}$$

$$B_{it+1} \leq L \tag{8}$$

$$\mathcal{L} = \frac{C_{it}^{1-\gamma}}{1-\gamma} \tag{9}$$

$$\frac{\partial V(B_{it}, Y_{it}; L)}{\partial L} = \tag{10}$$

3.3 Simulated moments estimation

As the sample moment restrictions do not admit a closed form, I estimate the model parameters $\theta \in \Theta$ using a simulated method of moments estimator (SME). I partition the θ into two subvectors, $\theta^1 \in \Theta^1 \subset \mathbb{R}^k$ and $\theta^S \in \Theta^S \subset \mathbb{R}^l$. In the first stage estimation, I calibrate the parameters of the environment

$$(r, L, \Delta L, \sigma_P, \sigma_T, \pi_s, \pi_f, \upsilon) = \theta^1 \in \Theta^1 \tag{11}$$

Then given θ^1, for each

$$(\beta, \gamma) = \theta^S \in \Theta^S \tag{12}$$

I solve numerically for the optimal consumption rules, given the old and the extended borrowing limits and calculate the MPCs. Then, the estimation procedure minimizes the distance between the simulated MPCs and the empirical counterparts.

MPCs are a function of parameters θ as well as the state variables

$$(B_{it}, Y_{it}, L_{it}) = \pi_s \in S \tag{13}$$

$$\log C_{it} = \log C(s_{it}; \theta) + \eta_{it} \tag{14}$$

where η_{it} is an idiosyncratic shock in debt levels. Define transition function $\mathcal{T}$,[7]

$s_{t+1} = \mathcal{T}(\pi_s, PTshock; \theta^1, \theta^S)$

$$\begin{aligned}
\log C_t(\theta) &= \mathbb{E}\left[\log C_t(\pi_s; \theta^1, \theta^S) | \theta^1, \theta^S\right] \\
&= \int_S \log C_t(s; \theta^1, \theta^S)\, dF(s; \theta^1, \theta^S) \\
&= \int_S \int_E \log C_t(\mathcal{T}; \theta^1, \theta^S)\, dF_{t-1}(s; \theta)\, dF_t^{\epsilon}(\epsilon)
\end{aligned}$$

[7] future state variables (cash-on-hand and income shock), are a function of current state variables, realizations of permanent and transitory shocks, as well as the parameters

Approximate equation above using Monte-Carlo integration.

The second-stage estimation procedure is then

$$\hat{\theta}^S := \arg\min g(\theta;\theta^1)' \, W \, g(\theta;\theta^1) \tag{15}$$

The estimator is consistent and asymptotically normally distributed, under conditions stated in Pakes and Pollard (1989) and Duffie and Singleton (1993).

3.3.1 First stage

First stage parameters θ^1 include the gross real interest rate R, borrowing limit L, change in borrowing limit ΔL, the variances of the permanent and transitory innovations σ_P and σ_T, finding and separating rates π_f and π_s, unemployment benefit υ. The baseline parameters are reported in Table 3.

I estimate the gross real interest for borrowing, from the, as well as the implicit price deflator for personal consumption expenditures.

Income. I estimate the variance of the permanent and transitory components of shocks to income, using the covariance restrictions imposed, and using GMM methodology following Hall and Mishkin (1982) and Blundell et al. (2008). I decompose real (log) income $y_{it} = \log Y_{it}$ to a predictable life-cycle component Ω^Y_{it}, a permanent component y^P_{it} and a stationary transitory component y^T_{it}. Permanent shocks to income may include long-term unemployment, promotions and demotions, health shocks; whereas transitory shocks may include overtime labor supply and bonuses.

$$\log(Y_{it}) = y_{it} = \Omega^Y_{it} + y^P_{it} + y^T_{it} \tag{16}$$

Ω^C_{it} conditions on a set of variables known by the consumers and observable to the econometrician at time t, and includes dummies for year-of-birth, gender, marital status, region of residence, education, employment status. [8] The data on family size and occupation (profession, sector, title, years worked) is very sparse, therefore are not included in the regression. However, I do include individual fixed effects to control for persistent characteristics.

I assume that the permanent component is a random walk,

$$y^P_{it} = y^P_{it-1} + \varepsilon^P_{it} \tag{17}$$

with $\varepsilon^P_{it} \sim (0, \sigma^2_P)$.[9] I allow the transitory component to follow a general MA(q) process, order of which is to be established empirically,

[8] Blundell et al. (2008) allows effects to shift with calendar time; adds cohort effects. I do not allow for the effect of most of these characteristics to vary with calendar time.

[9] In the appendix I also consider income processes of various persistence

$$y_{it}^T = \sum_{j=0}^{q} \rho_j \varepsilon_{it-j}^T \tag{18}$$

with $\varepsilon_{it}^T \sim (0, \sigma_\varepsilon^2)$. The idiosyncratic shocks ε_{it}^P and ε_{it}^T are orthogonal to given information, and their variances are constant over the cross-section. Then the unpredictable income growth is given by,

$$\Delta y_{it} = \varepsilon_{it}^P + \Delta y_{it}^T \tag{19}$$

I approximate both innovations by a 3-state Markov chain, following Tauchen (1986).

Unemployment. I calculate the job finding and separation rates, using gross worker flow data on the local labor market. In particular, I follow Shimer (2005), to infer finding and separating rate from the dynamic behavior of unemployment and short term unemployment.[10] For u_{t+1}^s denoting the number of short term unemployed workers, workers unemployed for less than a month at period t, and assuming all unemployed workers find a job with probability π_f in the given month, the unemployment rate next month is given by the number of unemployed workers that failed to find a job plus the number of the unemployed, given by,

$$u_{t+1} = u_t(1 - \pi_f) + u_{t+1}^s \tag{20}$$

Solving this for π_f,

$$\pi_f = 1 - \frac{u_{t+1} - u_{t+1}^s}{u_t} \tag{21}$$

In order to calculate the separation rate, I assume that whenever an employed worker loses his job, he becomes unemployed.

$$u_{t+1}^s = \pi_s(1 - u_t)(1 - \frac{1}{2}\pi_f) \tag{22}$$

Then, the separation rate is given by the ratio of short term unemployed workers, to the employed workers this month,

$$\pi_s = \frac{u_{t+1}^s}{(1 - u_t)\left(1 - \frac{1}{2}\pi_f\right)} \tag{23}$$

where the correction term $\frac{1}{2}$ is due to the short term unemployed has on average half a month to find a job before she is recorded as unemployed.

[10] A drawback of this approach is, measurement error and classification error leads to an overestimate of gross worker flows.

3.3.2 Second stage

Identification of β and γ use can be visualized in **??**. Consumption, as a function of cash-on-hand, reach differentially to shifts in impatiance and risk aversion.

3.4 Transitional dynamics

I now explore the magnitude and heterogeneity of the consumption and debt response to a change in the borrowing limit. I consider a consumer with ...

$$L' = L + \Delta L \tag{24}$$

[Incomplete]

3.5 Durables

Consumer preferences are represented by the following utility function,

$$\mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t U(c_{it}, k_{it})\right] \tag{25}$$

I choose a simple Cobb-Douglas specification to aggregate durable and non-durable consumption, with α governing the ratio of non-durables in total consumption. This value is calibrated from the empirical share of non-durables and services.

$$U(c,k) = \frac{\left(c^{\alpha} k^{1-\alpha}\right)^{1-\gamma}}{1-\gamma} \tag{26}$$

Durables depreciate at rate δ. Households can adjust durables stock with the adjustment function $g(k_{it+1}, k_{it})$ summarised in Equation 27.

$$g(k_{it+1}, k_{it}) = \begin{array}{ll} k_{it+1} - k_{it} + \delta k_{it} & \text{if } k_{it+1} \geq k_{it} \\ (1-\zeta)(k_{it+1} - k_{it}) + \delta k_{it} & \text{if } k_{it+1} < k_{it} \end{array} \tag{27}$$

[Incomplete]

4 Consumption and debt response to change in borrowing limit

This section analyzes the response of a change in borrowing constraints on debt and spending. First, I estimate the overall response of unpaid credit card balances to a change in credit card

limits. Secondly, I decompose the change in credit card debt to revolving balances and balances in installments. Third, I analyze the heterogeneity of response by cash-on-hand. Finally, I look at the pattern of spending across 18 categories of credit card transactions, and cash advances.

I estimate a standard distributed lag model of the form:

$$\Delta \mathrm{Y}_{it} = \sum_{\tau=0}^{T} \phi_\tau \Delta L_{it-\tau} + m_t + f_i + \varepsilon_{it} \tag{28}$$

The specification is an event study of how consumption/debt responds to changes in credit supply, but can account for multiple shocks to credit supply. The dependent variable $\Delta \mathrm{Y}_{it} = \mathrm{Y}_{it} - \mathrm{Y}_{it-1}$ represents either the change in unpaid credit card balances $\Delta \mathrm{D}_{it}$, which includes revolving end-of-month balances that incurs interest and installment balances, or consumption spending C_{it} . The main explanatory variables are the change in credit limits $\Delta L_{it-\tau} = \mathrm{L}_{it-\tau} - \mathrm{L}_{it-\tau-1}$. About 5% of customer credit limits are changed every month, and if an individual has not received a line increase, then the corresponding ΔL_{it} equals zero, and these individuals serve as the *control* group.

The coefficient ϕ_0 measures the contemporaneous change in the dependent variable in response to per unit credit limit increase, and the partial autocorrelation coefficients $\phi_1, \ldots, \phi_\tau$ measure the additional responses after τ months. The structural parameters of interest are the marginal propensity to consume out of additional liquidity, defined as the cumulative increase after τ months $\Phi_\tau = \sum_{t=0}^{\tau} \phi_t$. The problem for inference, without the RCT, is that the assignment of credit card limits is nonrandom. In particular, the change in limits is a function of consumption and debt growth, both in the cross-section and time-series, therefore $\mathbb{E}\left[\varepsilon_{it} | \Delta L_{it}\right] \neq 0$. The sampling and assignment of ΔL_{it}, as explained in Section 2.2, assures that $\mathbb{E}\left[\varepsilon_{it} | \Delta L_{it}\right] = 0$. The full data-generating process is given, and identification discussed in 6.1.

I allow for a time-specific fixed-effect m_t[11] and an individual specific fixed-effect f_i. The vector month dummy m_t absorb the seasonal variation in consumption and debt, that are common to both the control and the treatment groups, as well as all macroeconomic aggregate activity. Fixed effects, in conjunction with first differencing, control for the persistent characteristics of the individual.[12]

Unless stated otherwise, Equation 28 is estimated via ordinary least squares. Standard errors are clustered by individual, allowing for arbitrary heteroskedasticity and within-individual serial correlation.

Estimates are reported in Figures 7 - 12.

Figure 11 reports the response of credit card consumption to a change in credit card limits.

[11] Why do I need to control for time? I perhaps should not need this?

[12] With fixed effects, regression coefficients explain how variation over time within each individual? Should I still add in a term for the interest rate?

4.1 Heterogeneity of MPC by cash-on-hand

I analyze the heterogeneity of the response, by estimating Equation 28 seperately for each cash-on-hand bin.

4.2 Mean reversion of MPC and cash-on-hand

4.3 Spending patterns

4.4 MPC by debt type

Figure 8 reports the response of unpaid credit card balances to a per dollar limit increase, by debt type.

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Figure 1: Intertemporal models by by MPC out of 'liquidity', as a function of cash-on-hand. Models are ordered by their predicted values of moment $\Delta D/\Delta L$, the debt response to a change in borrowing limits. Simulated values for the models are calculated in Section **??**. See Table for values MPCs under different assumptions. Abbreviations: PIH, permanent income hypothesis; P, precautionary savings; M, myopia; A, autoarky

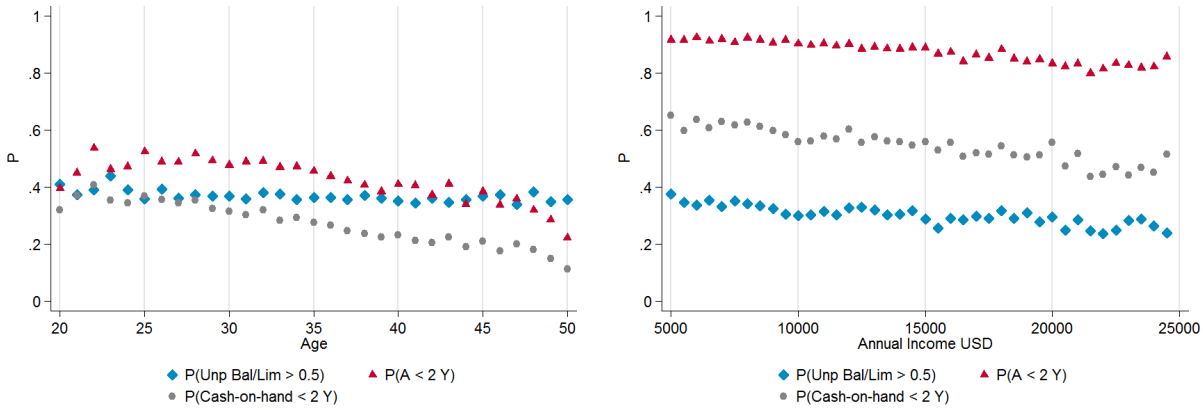


Figure 2: Who is liquidity constrained? The two plots above graph the population averages of being liquidity constrained by age and income bins. Three definitions are considered. First, if an agent is utilizing most available credit supply, i.e. the ratio of unpaid balances to credit card limit is more than a half. This is not the definition of a strict corner solution, but precautionary models would suggest a buffer stock be left free. Secondly and thirdly, if an individual has liquid assets or cash-on-hand less than two months of income. Cash-on-hand includes liquid assets and available credit. I use the variable cash-on-hand throughout the remainder of the paper.

5 Tables and figures

Table 1: Summary statistics on the participant population, before the intervention. pre-intervention participant population. All values from September 2014 local currency. The conversion rate is 2.1 per dollar.

Variable	Mean	Standard deviation	Tenth percentile	Median	Ninetieth percentile[13]
Age	39	11	26	38	56
Gender	0.79				
Married	0.67				
Customer for months	112	73	20	105	216
Credit score	1059	387	506	1091	1443
Credit card variables					
Number of cards	1.78	0.98	1	2	3
Limit	8153	21520	700	4000	20000
Volume	1392	6790	0	387	2977
End-of-month balance	1657	5224	0	656	3622
Unpaid balance	1959	10129	0	650	4236
Revolving balance	591	2514	0	0	1607
Installment balance	1367	9707	0	280	2883
Credit card variables (outside of bank)					
Number cards	1.5	1.7	0	1	4
Limit	11857	25836	0	2973	32450
Volume	1881	479079	0	154	4062
Unpaid balance	4145	12434	0	500	9838
dL					
Volume/Total volume					
Unpaid balance/Total unpaid balance					
Assets	8317	142411	0	0	3503
Cash, checking, savings, money-market	6899	133808	0	0	1803
Stocks, bonds, mutual funds	1417	36999	0	0	24
Debt (excluding credit card)	6316	19096	0	1213	15142
Monthly Wage	2807	3205	891	1924	5791
Cash-on-hand/Wage					
Limit/Wage					
dL/Wage	0.6				
Non-performing loans					

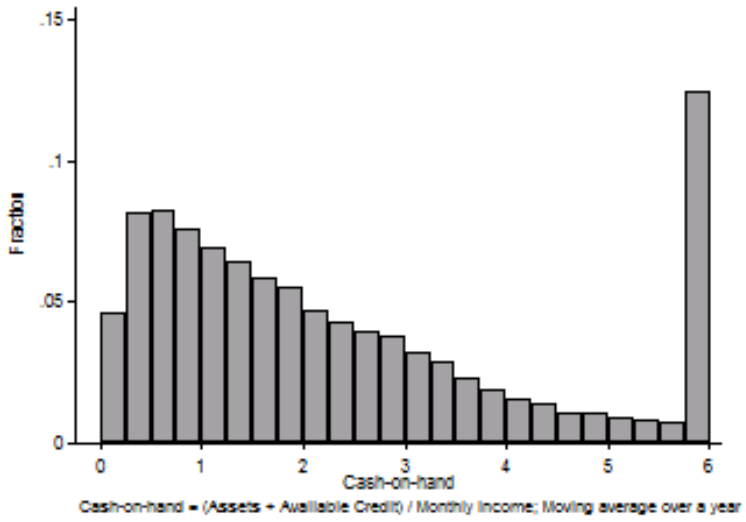


Figure 3: The empirical density function of cash-on-hand (moving average over a year) is plotted in the graph below.

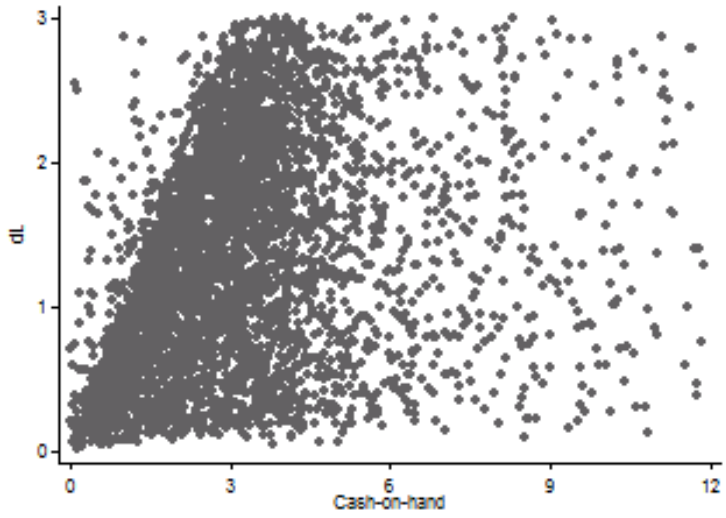


Figure 4: Scatterplot of non-zero limit changes by cash-on-hand. Cash-on-hand is net assets plus available credit. Variables normalized by monthly income.

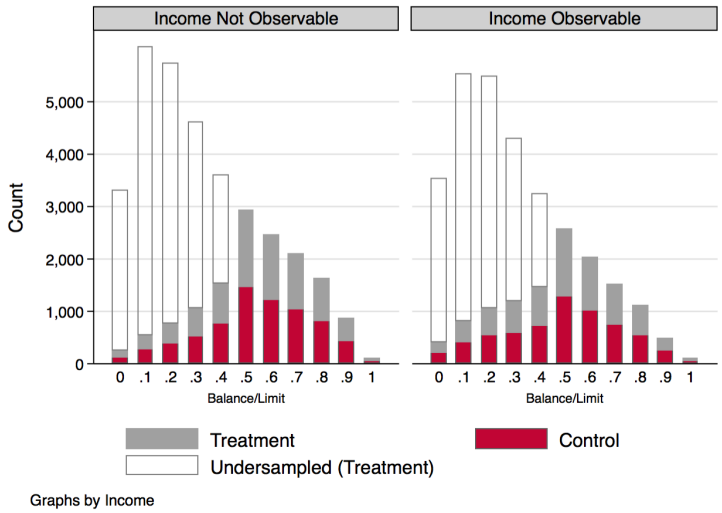


Figure 5: Sampling for the RCT. The histograms above show the experiment participants with respect to average credit card utilization (balances over limits) bins (x-axis) and if have direct deposit (therefore can observe wages) (left/right). In order to maximize statistical power, I over sample high credit card utilization individuals. As the standard errors of their MPC coefficient estimates are higher, one can estimate with high confidence that the low utilizers will not respond to liquidity. However, the population distribution is skewed towards the right. Therefore I include all high-utilizers (defined as average balance over limits larger than 0.5) in the experiment; however, if an individual is a low-utilizer, then I under sample them if they have credit cards at other banks, or never revolve credit card balances.

Table 2: Correlation between alternative measures of cash-on-hand.

	Utilization	Net assets	Income	Income growth	Credit score	Education
Cash-on-hand						
Utilization						
Net assets						
Income						
Income growth						
Credit score						

Table 3: Parameter values for the Bewley model

Parameter	Definition	Value	Source
r	Interest rate	0.04	
L	Borrowing limit	3	
ΔL	Change in borrowing limit	0.65	Average change in credit card limits
σ_P	Variance of permanent income shock	0.05	Author's calculations[14]
σ_T	Variance of transitory income shock	0.05	
π_f	Transition to employment	0.089	
π_s	Transition to unemployment	0.011	Author's calculations[15]
υ	Unemployment benefit	0.4	40% of average labor income [16]
α	Coefficient on non-durables	0.65	Ratio of non-durable to total consumption
δ	Durable depreciation rate	0.05	
ζ	Durables adjustment cost	0.15	

Notes: See Section 3.3.1 for details on the first stage estimation.

Table 4: Parameter estimates

Parameter	Definition	Estimate	Standard error
β	Discount factor		
γ	Coefficient of relative risk aversion		

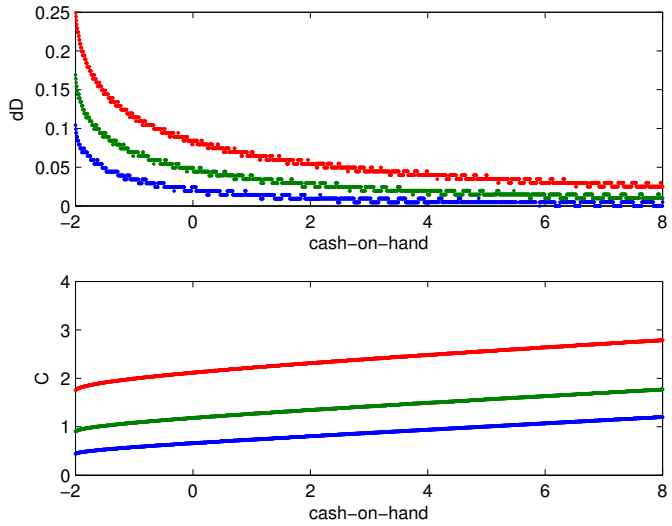


Figure 6: Here, I should display the Consumption rule for both borrowing levels. The consumption rule and MPC out of liquidity (change in bond holdings given a change in borrowing limits) from the simulated Bewley model. X axis denotes cash-on-hand. Y axis denotes change in bond holdings for the graph above and consumption for the graph below. Note that concavity of the consumption rule and the decreasing MPC.

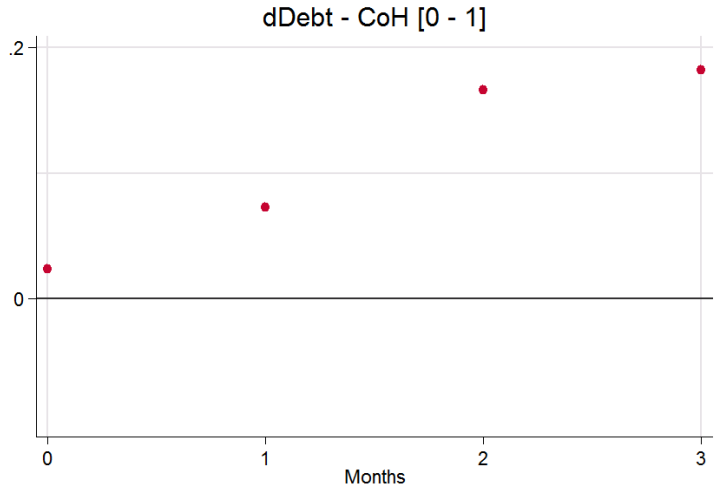


Figure 7: Data from experiment. The MPC out of liquidity, i.e. cumulative response of debt to a increase in credit card limit, per dollar of extra limit. Estimated for the whole population. Grouped by the type of debt (total debt, debt in installments, revolving debt). An increase in credit card limits causes an immediate rise in debt.

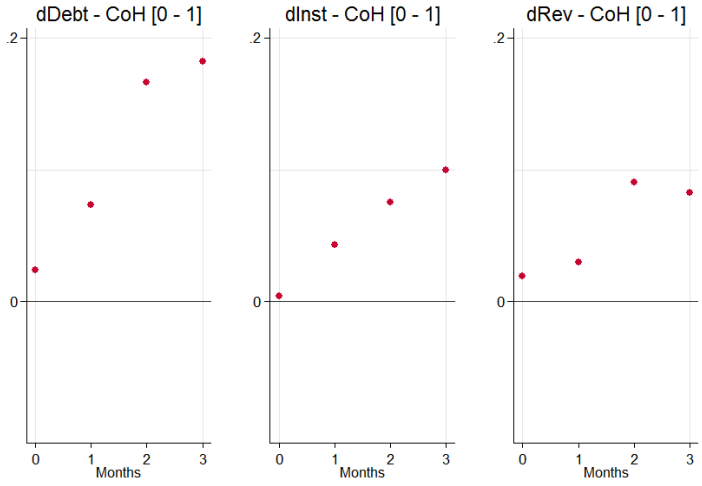


Figure 8: Data from experiment. The MPC out of liquidity, i.e. cumulative response of debt to a increase in credit card limit, per dollar of extra limit. Estimated for the whole population. Grouped by the type of debt (total debt, debt in installments, revolving debt). An increase in credit card limits causes an immediate rise in debt.

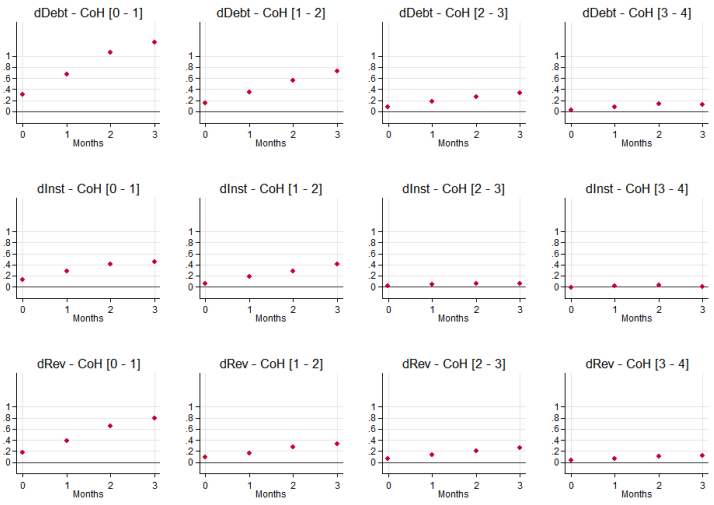


Figure 9: Data from experiment. The MPC out of liquidity, estimated separately for cash-on-hand (assets+available credit)/monthly income bins, for those with cash-on-hand less than 4 months of income. Rows represent the type of debt (total debt, debt in installments, revolving debt) and columns represent cash-on-hand bins. The effect is larger for those that are near their constraints; however, still positive even for those that are away from the constraint.

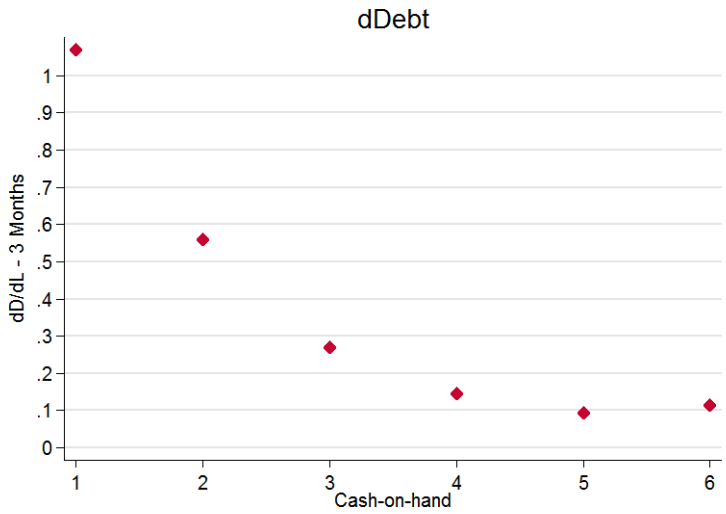


Figure 10: Data from experiment. MPC is a decreasing function of cash-on-hand. X axis denotes bins of cash-on-hand (by monthly income) and Y axis the cumulative response of debt after 3 months. Rows stand for additional debt incurred in installments, revolving balances and their total. Decreasing MPC follows from the concavity of the consumptionsumption rule.

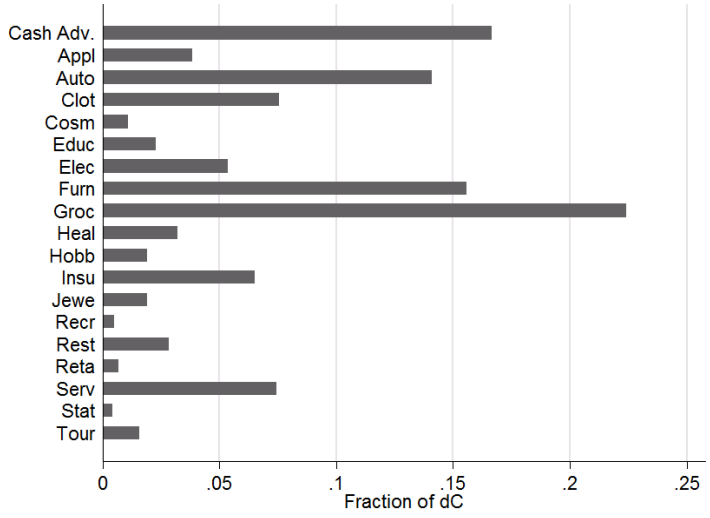


Figure 11: Data from experiment. The composition of spending by those with additional liquidity, compared to those in the control group.

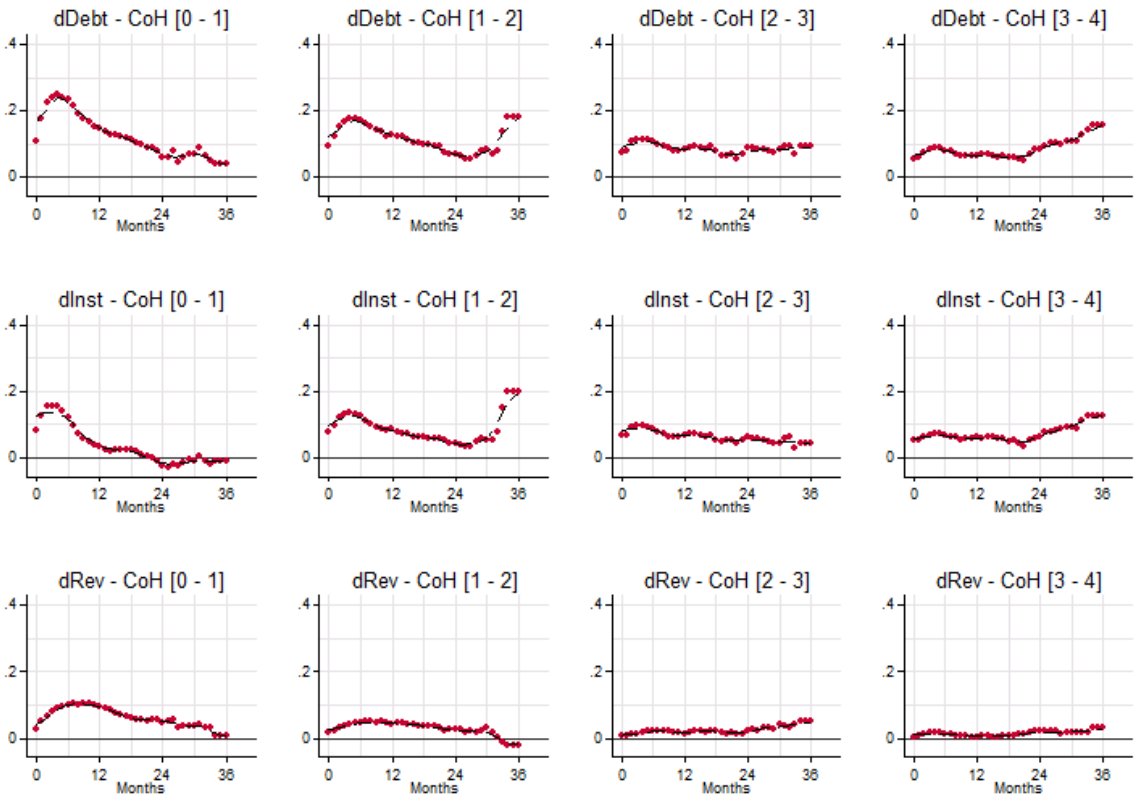


Figure 12: Observational data. Figure shows the debt response to a change in borrowing capacity, estimated using observational data following one hundred thousand individuals between January 2011 - December 2013. Estimation is done via OLS, therefore estimates are biased. Columns one to four represent individuals with cash-on-hand between 0-1 months of income and so on. The first row is the total response of credit card debt, and the bottom two rows are the response in installments and revolving balances. Firstly, the total debt response is significantly different than zero for all four cash-on-hand groups, not only for those that have an immediately binding constraint. Secondly, individuals with lower cash-on-hand respond more aggressively, with the MPC being 0.25 for the lowest cash-on-hand group and 0.1 for the cash-on-hand group 3-4. Thirdly, the cumulative response of debt is hump-shaped: individuals accumulate debt up to the first 6 months of the liquidity shock, and deaccumulate it after 6-18 months. Finally, individuals with available credit (higher cash-on-hand) respond only with installments purchases, not by revolving more credit card debt.

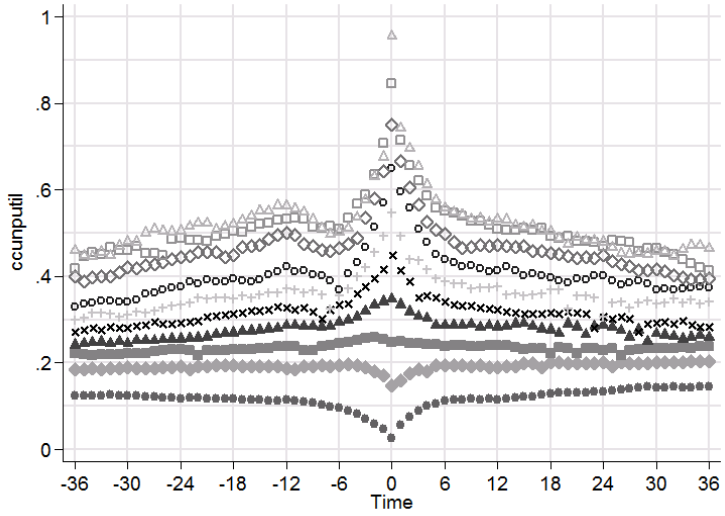


Figure 13: Credit card utilization is mean reverting. Y axis indicate credit card debt utilization i.e. the ratio of unpaid credit card balances to the credit card limit. X-axis indicates time t. At any time t, individuals are grouped into deciles by utilization (Y-axis). Then their average utilization in any $t' \in \{t-36, \ldots, -1, 0, 1, \ldots t+36\}$ are plotted. t' does not represent the time of limit increase, but any given time. Individuals that are high or low utilizers at any given point tend to converge to average utilization in the long run. Therefore high credit card utilization is not a persistent state, on average. Information here can be used to test apart theories. For example, a myopic individual would repeatedly utilize credit and persistently hit the limit.

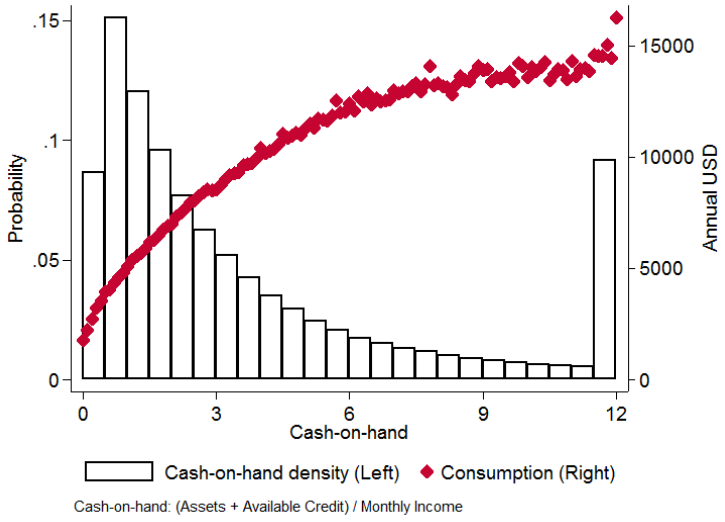


Figure 14: Observational data. The consumption rule. X axis is cash-on-hand. Y axis (right) is annual consumption in USD. Y axis (left) is the empirical frequency. Red line indicates the average credit card volume for each cash-on-hand bin. White bars indicate the empirical density of cash-on-hand.

6 Appendix

6.1 Identification

The true model is given by,

$$\begin{aligned}\Delta \mathrm{D}_{it} &= \sum_{\tau=0}^{T} \phi_\tau \Delta L_{it-\tau} + f(Z_{it}) + m_t + f_i + \varepsilon_{it} \\ &= \sum_{\tau=0}^{T} \phi_\tau \Delta L_{it-\tau} + f_i + e_{it}\end{aligned}$$

Now the error $e_{it} = \varepsilon_{it} - \mathbb{E}[\varepsilon_{it}|Z_{it}, m_t]$ is mean independent of ΔL_{it}.[17] The control function $f(Z_{it})$ is given by,

[17] Should I only control for RHS variables that are not orthogonal to the exogenous variation in the variable of interest, ΔL_{it}? Experimental variation is not orthogonal to fixed effects. Should I control for anything except fixed effects?