

The Marginal Propensity to Consume Out of Liquidity: Evidence from Random Assignment of 54,522 Credit Lines*

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Abstract

This paper studies how consumer spending, debt, and labor supply decisions respond to an exogenous shock to credit availability. I design and implement a randomized trial at a European retail bank where I deliberately vary credit card limits to 54,522 pre-existing card holders. I obtain four empirical results: (1) credit availability has a large and significant effect on spending and the use of credit; (2) this propensity remains substantial even for those who are far from the limit; (3) increases in spending are concentrated in durables and services (e.g., health, education); (4) credit line utilization displays mean-reverting dynamics. The findings are qualitatively inconsistent with the predictions of a simple permanent income model, as well as myopic (e.g., rule-of-thumb, impatient) behavior. I then build a partial equilibrium precautionary savings model with illiquid durables, and I use the endogenous ex-post heterogeneity to study the cross-sectional features of the responses with respect to balance sheet position and income shocks.

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1 Introduction

This paper studies how consumer spending, debt, and labor supply decisions respond to an exogenous shock to credit availability. I design and implement a randomized trial at a large European retail bank where I deliberately vary credit card limits to 54,522 pre-existing card holders. First, I use the exogenous variation in credit capacity to provide novel evidence on the consumer response to liquidity shocks. Second, I use this evidence to test key implications of commonly used intertemporal models. Third, I build a structural model to evaluate the impact of changes in the credit regime on household behavior and welfare.

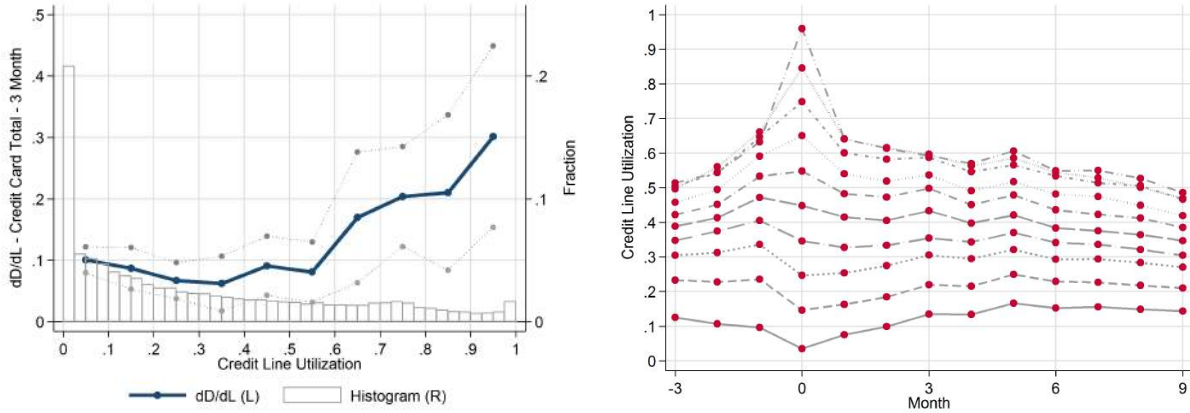
The effect of credit availability on consumer behavior is a central object in many areas in economics. From an applied perspective, household consumption expenditures account for two-thirds of GDP, and understanding the determinants of consumption is important for quantifying the linkages from the financial sector and the real economy, evaluating the impact of tax and labor market reforms, and designing macroeconomic stabilization policies.¹ From a theoretical perspective, an empirical measure of the sensitivity of spending to credit can be used to test and discipline competing models of the household sector, ranging from the permanent income hypothesis (where liquidity has no effect on behavior) to rule-of-thumb behavior (where spending increases one-for-one with liquidity). Despite its centrality, recovering a consistent estimate of the magnitude, heterogeneity and composition of the sensitivity of consumer behavior to liquidity, as well as uncovering the underlying preferences generating the sensitivity, has been a major empirical challenge. This is due in part to the limitations of the existing microeconomic data on consumer spending and balance sheets, and the difficulty of isolating unexpected and exogenous shocks to credit supply.²

In this paper, I use comprehensive longitudinal data on consumer income, expenditure, balance sheets, and available credit from a large European financial institution. The experiment is unique because of its sample size, and the randomized nature of the intervention. My subject pool consists of 54,522 cardholders preapproved by the bank for credit line increases. I select at random 13,438 of this group as my control group using a random number generator, and these consumers are withheld from credit line increases for 9 months, starting September 2014. The treatment group have their credit card limits extended by a median 120% of monthly income. The increases in limits are initiated by the issuer and they are unannounced. Other features of the contract, such as the interest rate, also remain unchanged. Therefore, the intervention can be classified as an unexpected and, by construction, exogenous shock to credit availability. I then use the variation in credit to trace out the impulse responses of spending, debt, and labor

¹See Hall (2011) and Jappelli and Pistaferri (2014). For example, (i) fiscal stimulus is effective at boosting durable or nondurable consumption only if household spending is sensitive to disposable resources (Kaplan and Violante, 2014); (ii) liquidity versus moral hazard effects of unemployment benefits depend on the elasticity of labor supply behavior to disposable resources (Chetty, 2008); (iii) redistributive effects of monetary policy depend on the covariance between the consumers' marginal propensity to consume and unhedged interest rate exposure (Auclert, 2015); (iv) optimal macroprudential policies aimed at curbing leverage ex-ante relate the marginal propensities of borrowers and lenders (Farhi and Werning, 2013) (Korinek and Simsek, 2015). See Auclert (2015) for an explicit relationship between the consumption and labor supply response to a income shock versus a shock to credit availability.

²Credit availability is tied to macroeconomic variables such as aggregate income, interest rates, uncertainty, and sentiments. See Ludvigson (1999) and Guiso et al. (2013).

Figure 1: Preview of Results



Note. The figure on the left displays the cross-sectional distribution of the *marginal propensity to consume out of liquidity* after 3 months, by credit line utilization bins. Credit line utilization is calculated as the ratio of interest bearing credit card debt to credit card limit. Estimates are obtained using the distributed lag equation (6) in Section 4 on a sample of 54,522 experiment participants. The figure on the right displays the mean-reverting dynamics of credit line utilization. 54,522 experiment participants are grouped at $t = 0$ according to their credit line utilization. The figure then plots the average credit line utilization for each bin in time.

supply decisions.

My empirical analysis leads to four main findings. First, credit availability has a large and significant effect on spending and the use of credit. The marginal propensity to consume out of liquidity (MPCL), averaged across the treatment group, asymptotes to 14 cents on the dollar after 4 months. Second, this effect is not confined to a small fraction of credit constrained or hand-to-mouth consumers who are up against their credit limits. While proximity to the credit limit is positively correlated with MPCL, this propensity remains substantial even for those who are far from the limit.³ Third, the increases in spending that result from credit extensions are concentrated in durables and services with investment features (e.g., health, education). Often these purchases are made in the wake of positive income shocks, and the consumer then pays down the incremental debt over time. Fourth, credit line utilization displays mean-reverting dynamics. For example, among those who use more than 90% of their available credit at a given point in time, average utilization drops to 60% after three months. Those who remain at their credit limit month after month represent a sliver of the population (see Figure 8).

These findings are difficult to reconcile with a range of commonly used models of consumption behavior. First, the experiment does not result in a change in the borrowing rate, and an increase in credit availability does not entail any wealth effects. Therefore, in a model where consumption is proportional to lifetime wealth, or where consumers are only constrained by the *natural limit* of their lifetime resources, the MPCL is zero. The findings indicate that deviations from the stylized permanent income (PI) benchmark are substantial, even for consumers with sizable

³I also find substantial heterogeneity in MPCL with respect to balance sheet position, age, income and other demographics.

resources. Second, the findings are not consistent with a simple rule-of-thumb model, as only a small fraction of consumers are strictly constrained, but most keep a buffer of credit availability, in line with forward looking models. Third, the dynamics of the impulse response is not consistent with consumers viewing the increase in credit as a transitory income shock, or informative about future income prospects. This story would predict that households would annuitize this one time income shock. Finally, there is no evidence of an increase in non-performing status or defaults throughout the course of the experiment, implying the loans are repaid.

In Section 2, I outline a recursive framework in order to demonstrate the effect of credit availability in incomplete markets settings. If borrowing is bounded above by an exogenous credit limit, consumption will be depressed relative to the permanent income benchmark in order build a precautionary buffer to insure against income shocks. A relaxation of the limit will lead to increases in consumption, until precautionary savings are drawn down. A central insight of this *buffer-stock* behavior is that consumption will be depressed even for consumers who have sizeable resources and borrowing constraints need not bind to change consumption dynamics. My empirical findings quantify the magnitude of the precautionary motive, and suggest that deviations from the permanent income benchmark are substantial, even for consumers who have sizeable resources.

Theories of precautionary savings, despite being able to account for the basic qualitative patterns, are unable to account for the magnitudes. In particular, the magnitude of the MPCL indicates that consumers are either impatient or very willing to substitute intertemporally. However, mean-reverting credit line utilization require that consumers be sufficiently patient and risk averse to prefer saving out of debt. Formal modeling points to the limitations of the baseline buffer-stock model, as well as a range of myopic models, in simultaneously accounting for the magnitude of the MPCL and the mean reversion of credit line utilization.

In order to *quantitatively* account for the magnitude and heterogeneity of the responses, I build a partial equilibrium heterogeneous agent incomplete markets model featuring illiquid durables. Durables in the model correspond to semi-durable components of non-residential consumption, such as appliances, furniture, as well as investments in health and education. In this environment, increases in credit availability lead to a rebalancing of consumer portfolio by investment in durables and services, and by accumulating debt. Endogenous ex-post heterogeneity in the structural model generates a rich set of cross-sectional and dynamic features of the responses with respect to balance sheet position, and income shocks. First, the portfolio dynamics imply that the distribution of households tends to be concentrated around the boundaries of the adjustment region. Therefore, a relaxation of the credit constraint leads many consumers to adjust. Second, consistent with my empirical findings on the dynamics of credit line utilization, this model naturally leads to mean-reverting debt dynamics.⁴ Third, this model can deliver the ergodic distribution of state variables, in addition to the responses. This makes it suitable for counterfactual policy prediction and normative program evaluation. I demonstrate how the structural model aids interpretations of the heterogenous effects of monetary tools.

Layout. The rest of this paper is structured as follows. To pave the way for the empirical findings

⁴Consumers invest in durables when hit by positive income shocks. As income shocks are persistent, they eventually pay off their debt. Hence, a sizable proportion of consumers at the credit constraint are productive consumers that invest in durables.

coming from the field experiment, Section 2 presents a partial equilibrium incomplete markets model, which studies the effect of credit availability on consumption decisions. I use this model to derive testable predictions of competing models, with respect to the magnitude and heterogeneity of MPCL, as well as dynamics of credit line utilization. Section 3 describes the data, institutional background and the randomized trial. Section 4 presents the empirical results on the consumer spending and debt response to credit availability. Section 5 builds a structural model with durables and borrowing lending wedge to assess the magnitude and heterogeneity of the marginal propensities. Section 6 discusses potential for future work.

1.1 Related literature

My findings contribute to the empirical literature on credit constrained consumer behavior in two important ways. First, my credit market approach complements a large literature that estimates the reduced form sensitivity of consumption to shocks to disposable resources. These studies measure the sensitivity of consumption to total income changes, or use proxies for permanent and transitory shocks. See [Cochrane \(1991\)](#), [Blundell et al. \(2008\)](#), and [Jappelli and Pistaferri \(2010\)](#) for a comprehensive survey. Previous studies have often attributed excess sensitivity of consumption spending to disposable income due to the existence of credit constraints. Tests of this hypothesis involve splitting the observations into groups on the basis of levels of liquid wealth or total wealth, however splitting on an endogenous variable conflates credit supply and demand ([Zeldes, 1989a](#)) ([Eberly, 1994](#)). Based on quasi-natural experiments during the 2001 and 2008 fiscal stimulus payments, [Johnson et al. \(2006\)](#) and [Parker et al. \(2013\)](#) find that households immediately spend 20 to 40 percent of the rebate on nondurable goods in the quarter it was received, and responses are larger for households with low liquid wealth or low income. Also see [Broda and Parker \(2014\)](#) and [Misra and Surico \(2014\)](#) for the 2008 stimulus payments, [Souleles \(1999\)](#) on federal tax refunds and [Parker \(1999\)](#) on changes in social security taxes. [Shapiro and Slemrod \(2003\)](#) and [Shapiro and Slemrod \(2009\)](#) offers qualitative surveys on the pattern of consumption.

My sharp research design and larger samples allow me to identify more precisely the magnitude and heterogeneity of the consumption response. For example, [Johnson et al. \(2006\)](#) studies the spending response to the receipt of fiscal stimulus payments, and the 95% confidence intervals for the estimates reported range from 5 to 65 cents on the dollar. Moreover, as the increases in credit limits for the treatment group are large -median change is equivalent to 120% of after-tax monthly labor income, the welfare cost of failing to smooth would not be small ([Cochrane, 1989](#)).

Second, information on income and balance sheets, as well as spending patterns, allows me to take the data to the model, and study the findings structurally. I therefore bridge a gap between (a) a sizeable literature in macroeconomics and labor economics that measures the response of consumption to income shocks; and (b) a smaller literature in finance that investigates the effect of credit on borrowing behavior. The former literature lacks high frequency longitudinal data therefore mostly ignore the effect of credit on consumption. The latter literature, observes only credit supply and demand, with no information on spending patterns, balance sheets or income. For example, a seminal paper by [Gross and Souleles \(2002\)](#) and a recent paper by [Agarwal et al.](#)

(2015) document some sensitivity of household borrowing to credit availability using naturally occurring variation in credit limits, however, leave important questions about spending patterns, as well as income and balance sheet correlates unidentified.

On the theoretical front, papers by Zeldes (1989a), Deaton (1991) and Carroll (1997) investigate consumption behavior if the consumer is facing borrowing constraints. They build on the work of Friedman (1957) and Bewley (1977), and highlight deviations from the permanent income model with respect to consumption income comovement. Campbell and Mankiw (1989) argue that deviations from the permanent income behavior can be rationalized by a spender-saver model, where a small fraction of consumers set consumption equal to disposable resources. Kaplan and Violante (2014) is a second generation spender-saver model, that underline the importance of a *wealthy hand-to-mouth* household sector. This paper complements this theoretical literature, as it derives testable implications of these models with respect to changes in credit availability and dynamics of borrowing behavior, and tests their competing predictions. Similarly, Card et al. (2007) use a discontinuity in Austrian severance pay eligibility to test intertemporal job-search models. Karaivanov and Townsend (2014) take a quantitative approach, providing tests of consumption and investment behavior implications of alternative dynamic financial and information environments in a developing country context.

The financial crisis of 2008 has brought renewed attention to studying the macroeconomic effects of credit crunches using heterogeneous agent incomplete markets models. Such models study the distributional consequences of financial shocks in a leveraged system through the spending and borrowing decisions of the household sector, with the key moment being the marginal propensity to consume out of liquidity. Hall (2011) suggests that understanding the consumption response to the credit tightening is essential to understanding the Great Recession. Such a tightening forces both constrained and unconstrained individuals to cut back on durables spending and increase saving for precautionary reasons, causing a large drop in consumption. Mian et al. (2013) and Mian and Sufi (2014) argue that 40% spending decline during the Great Recession is due to a housing net worth shock, leading to lower home equity lines, lower credit card limits, lower credit scores, and inability to refinance into lower interest rates and Berger and Vavra (2015) finds that consumer durables accounted for 24% of the decline in GDP between 2007 and 2009. This view recently has been formalized in a number of theoretical models, such as those proposed by Eggertsson and Krugman (2012) and Guerrieri and Lorenzoni (2015). Also see Guerrieri and Lorenzoni (2009) and Challe and Ragot (2015) on the effects of precautionary behavior on business cycles, and Philippon and Midrigan (2011) on the dynamics of household leveraging/deleveraging. My findings quantify the strength of the precautionary motives in such models, and highlight the importance of consumer durables and the need for separately accounting for liquid and illiquid assets, when studying the effects of the linkages between financial sector and the macroeconomy.⁵

⁵Carroll (1997) is an early paper that studies uses a model with durables to study consumer spending and debt responses to uncertainty shocks. Also see on consumer durables adjustment Mankiw (1982), Bernanke (1984), Grossman and Laroque (1990), Eberly (1994) and Berger and Vavra (2015).

2 Liquidity in a Recursive Intertemporal Model

In this section, I present a partial equilibrium intertemporal framework to demonstrate the effect of credit availability on consumer behavior.⁶ The consumer is facing uninsurable income uncertainty, and smooths consumption by borrowing and lending. The framework nests the spectrum of commonly used models -ranging from the benchmark permanent income model to rule-of-thumb behavior. I use this framework is used to derive testable economic predictions to distinguish the models. First, I demonstrate how a relaxation of the borrowing constraint affects consumption decisions in each model. Second, I analyze the magnitude and heterogeneity of the responses coming from each model. Finally, I highlight how longitudinal data on the balance sheets, in particular the dynamics of credit line utilization, can be used to discipline parameters of the utilit

Model setup. Consider a discrete time, infinite horizon model of intertemporal consumption behavior. Consumer has flow utility $u(C_t)$ defined over nondurable consumption. Unless otherwise noted, u is strictly increasing, strictly concave, thrice continuously differentiable and satisfies the Inada condition $\lim_{C \rightarrow 0} u'(C) = \infty$. The discount factor between periods 0 and τ is generalized $\beta(\tau)$, to nest exponential discounting, hyperbolic discounting, and hand-to-mouth behavior. For the often used case of exponential discounting, $\beta(\tau) = \beta^\tau$.

Markets are exogenously incomplete. Important forms of incompleteness include lack of enough securities to insure against idiosyncratic income shocks and forms of credit constraints where consumers cannot borrow as they would like. Assume that income labor income Y_t follows an exogenous Markov process $\Pi(Y'|Y)$. Income fluctuations are smoothed using a single liquid asset with interest rate R . Borrowing on this asset is given by D_t , with exogenous credit limit L tighter than the natural borrowing limit. Let $\Delta D_t = D_{t+1} - D_t R$ denote the change in debt stock between two consequent periods. The budget constraint is then given by $C_t \leq Y_t + \Delta D_t$, implying consumption beyond income is financed by debt growth.

The recursive problem is given by,

$$V(D, Y; L) = \max_{C, D'} \left\{ U(C) + \beta \mathbb{E}_t \left[V(D', Y'; L) | Y \right] \right\} \quad (1)$$

$$C \leq Y + \Delta D \quad (2)$$

$$D' \leq L \quad (3)$$

$$Y' \in \Pi(Y) \quad (4)$$

Optimality condition for the intertemporal consumption problem equates marginal benefits and expected marginal costs, and gives the usual *credit constrained* Euler equation,

⁶This model is a simplified version of the full model in Section 5. In order to clarify exposition, I abstract away from other motives for borrowing (e.g., life-cycle motives, durables, arbitrary consumption shocks), as well as labor supply and the wedge between borrowing lending rates. I use an infinite horizon model as there is no detectable difference in the life-cycle profile of MPCL, controlling for cash-on-hand. I study the full model quantitatively and discuss how each assumption affects my results.

Table 1: Intertemporal models: MPCL and Testable implications

	MPC out of liquidity $\xrightarrow{1}$				
	0				
	PI	Buffer-stock	Buffer-stock w/Durables	Impatience	Rule-of-thumb
Borrowing limit	$+\infty$	L	L	L	L
Discount factor	$\beta = \frac{1}{R}$	$\beta < \frac{1}{R}$	$\beta < \frac{1}{R}$	$\beta \ll 1$	$\beta = 0$
(1) <i>Liquidity affects behavior?</i>	N	Y	Y	Y	Y
(2) <i>Unconstrained respond?</i>	N	Y	Y	Y	N
(3) <i>Utilization mean-reverting?</i>	N	Y	Y	N	N
(4) <i>Spending patterns and the distribution of liquid assets.</i>	N	N	Y	N	N

Note. This figure orders a set of intertemporal models by their predicted values of the *marginal propensity to consume out of liquidity*, a normalized measure of sensitivity to credit availability. The empirical value of MPCL from the data is based on the distributed lag model estimates in column (1) of Table 3. See Section 2 for calibrated values of MPCL for the buffer-stock and myopic models under alternative assumptions. See Section 5 for a discussion of prediction (4). Figure adapted from Card et al. (2007) whom orders intertemporal job search models by the sensitivity of search behavior to unemployment benefits.

$$U_c(C) = \beta R \mathbb{E}_t [U_c(C')] + \mu \tag{5}$$

where μ is the Lagrange multiplier on the credit constraint. As the model does not permit analytical solutions under general conditions, I obtain numerical results. I assume isoelastic utility with a coefficient of risk aversion $\gamma = 2$. I calibrate the model parameters for which there is reliable external evidence (e.g., income process, interest rate) in Section 7.7. The solution is the consumption rule, a positive, non-decreasing function of net assets, income shock and credit limit. Table 1 summarizes how each model is nested. Figure 2 highlights the relevant features of the consumption rule under various models.

Competing intertemporal models. First, consider the benchmark *permanent income* (PI) model.⁷ Consumption then admits an explicit formula, and is a linear function of disposable resources. It's slope -the marginal propensity to consume out of income- is equal to the annuity factor $\frac{r}{1+r}$ and constant at all levels. Consumption depends only on the first moment of the value of endowment, therefore precautionary motives are absent. Importantly, consumption is a martingale, and debt is a unit root process. As credit availability does not entail any wealth effects, intertemporal behavior is not affected by changes in liquidity.

Introducing a limit on borrowing changes the shape of the consumption rule significantly. If the

⁷ For brevity, I summarize the certainty equivalent version, as popularized by Hall (1978).

sponse depends on the fraction of rule-of-thumb consumers. This is an extreme case of discount factor heterogeneity, where some consumers have $\beta = 0$. The behavior of these infinitely impatient consumers is indistinguishable from rule-of-thumb behavior. Finally, *myopic* behavior then lies at the lower envelope of rule-of-thumb and buffer-stock behavior. The discount factor determines the level of consumption between the two extremes.

Prediction 1: Liquidity affects consumer behavior. Consider the effect of an unexpected relaxation of the credit limit to $L + \Delta L$. A looser credit constraint makes consumption less responsive to income shocks, therefore decreases the volatility of future consumption and expected marginal utility. Consumer then relaxes the precautionary buffer, and the consumption rule expands *upwards* towards the PI benchmark. The marginal propensity to consume out of liquidity is then given by the change in consumption per unit change in credit limit.

Note that liquidity affects consumer behavior only if markets are incomplete and the borrowing limit is tighter than the *natural limit* -the present value of the sum of endowment sequence. If consumers are only bounded by the natural limit of their resources, borrowing constraints will never be binding, as borrowing would up to this limit would imply zero consumption in every subsequent period, which is ruled out by the Inada condition. Similarly, if consumers can securitize the idiosyncratic innovations to income stream at no risk premium, leading to value of endowment of $W = -D_t + \mathbb{E}[\sum_{t=0}^{\infty} R^{-t} Y_t]$, then consumption would again be a linear function of W .

If the consumption rule is close to the permanent income model, then the effect of liquidity is small. In contrast, if the consumer faces a binding credit constraint, or depress consumption to maintain a buffer-stock of resources, the response is larger. Therefore there is a direct connection between the sensitivity of behavior to credit availability and the amount of consumption smoothing implied by an intertemporal model.

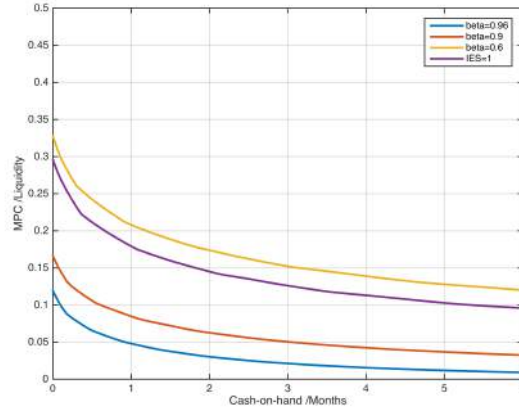
The dynamics of the response is informative about the underlying preferences generating the sensitivity to credit. For example, if consumers viewed additional credit as a transitory income shock, or as informative about their future income prospects, then MPCL would be a line with slope equal to the annuity factor. However if credit has no long-run effects, but only shifts the timing of purchases, then the cumulative consumption response would revert back to zero, and the MPCL would be a mean-reverting spike. If the consumers were to permanently increase their debt level, in line with the buffer-stock model, then the impulse response would monotonically asymptote to its new level.

On the top panel of Figure 2, I show the predicted values for the average marginal propensity to consume out of liquidity for a range of commonly used models. At the left extreme is the permanent income model, where an increase in credit availability has no effect on behavior (i.e. MPCL=0). At the right extreme is the rule-of-thumb model where consumers do not smooth consumption, and credit availability increases consumption one-for-one (i.e. MPCL=1). The interior of the continuum includes models that exhibit have intermediate amount of sensitivity to credit, including the buffer stock models, a credit-constraint model where agents are forward-looking but face a binding asset constraint, and a model where the consumer is highly impatient.

Prediction 2: Heterogeneity. An important element in the previous line of argument is that ex-

Krugman (2012) to study household leveraging dynamics.

Figure 3: Intertemporal models: MPCL and Dynamics



istence of constraints depresses consumption at all levels. Therefore consumers that respond to a change in credit availability are not only those with binding constraints, but unconstrained consumers too will respond. Consider the alternative interpretation where credit constraints are binding for a small fraction of the population. These consumers may be at the limit either because they are impatient or rule-of-thumb. Or they may be forward looking with a currently binding credit constraint, binding due to a series of persistent income shocks. These models predict a mass of consumers at the credit constraint, and the average response will be driven by these small fraction of consumers.

In order to provide a benchmark, the left panel of Figure 3 displays the simulated MPCL as a function disposable resources. In relating the empirical estimates to the consumption/savings model, I define each period as an interval of three months. I then compare the empirical estimate of the MPCL to values predicted by the benchmark models. I cast the model in terms of a single state variable, disposable resources to be allocated at t , given by $Z_t = -D_t + Y_t + L_t$, i.e. the value of endowment plus the maximal credit capacity.

Under the plausible calibration of $\beta = 0.96$, immediately constrained exhibit MPCLs of 10%. The response of consumers with more than two month of disposable resources are much smaller, approximately 3%. The magnitude and heterogeneity of MPCL is directly tied to underlying model parameters. For example, MPCL and risk aversion are tightly linked as both are determined by the curvature of utility over consumption. If the marginal utility of consumption diminishes quickly, a highly risk averse individual will become satiated with consumption as the credit constraint relaxes. Similarly, as the discount factor decreases, consumer behavior approaches hand-to-mouth behavior, and the level of the MPCL increases. The additional plots on the left panel of Figure 2 display the effect of a change in the discount factor on the MPC out of liquidity.

Prediction 3: Dynamics of credit utilization. I derive a final set of predictions that utilizes data on the dynamics of credit line utilization. The key observation is that debt growth creates the wedge between income and consumption. For example, under the permanent income model, consumption is a martingale, therefore debt would also be a martingale -ex-ante debt is the best predictor of next periods debt-. On the contrary, buffer-stock behavior predicts that consumers

have a target level of disposable resources that they should asymptote to. Under this model, credit line utilization will display predictability towards the target. This target will be a function of model parameters, including the discount factor, risk aversion, permanent income and the credit limit.

The right panel in Figure 3 displays the dynamics of credit line utilization under various models. I first calculate the ergodic distribution of assets under various models. I then analyze how the credit line utilization evolves for consumers at the limit. As an extreme, consider the spender/saver model. If a fraction of consumers is hand-to-mouth, i.e. sets consumption equal to disposable resources, then their savings in any period is equal to zero. Therefore, consumers at their limits are expected to remain at their limit. Similar conclusions apply if consumers are impatient, i.e. sufficiently impatient to exhibit 14% MPCLs. Therefore, credit line utilization disciplines the discount factor and risk aversion. The rest of the figure displays credit line utilization under various parameters. This argument is parallel to calibrating an incomplete markets models, identifying the discount factor from the ergodic distribution of assets. If consumers are relatively impatient, they draw down assets and cluster around the credit limit. Conversely, if the consumers are patient, they would accumulate wealth without bounds. Here, I pose a similar question: what are the restrictions on preference parameters that imply mean-reverting credit line utilization?¹¹

3 Data and Environment

I utilize administrative data from a European retail bank. The financial institution has more than 5 million customers, holds a 20% market share in the local retail banking market, and its customer base is representative of the local banked population. It offers a multitude of financial products, including credit cards, personal deposit and investment accounts, as well as consumer loans.

There are four types of data available. First, credit card data includes card limits, end-of-month balances, payments, interest rate, interest bearing debt, and transaction details. The expenditure data is comprehensive, and each transaction is later categorized into 18 subcategories (e.g., groceries, appliances, education). Second, consumer 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 checking, savings, money market accounts, stocks, bonds, mutual funds and other investments. Debt includes personal loans, vehicle loans and mortgages. I supplement this with consumer credit bureau records, which record total balances on liabilities at other banks, as well as credit scores.

Third, income information is available for a subset of consumers with direct deposit. It contains only after tax labor income and does not include financial income (e.g., interest, dividend, other capital income) or government transfers (e.g., benefits and social security income). Total income can be decomposed to its components (e.g. overtime, bonus, severance pay). Finally, there exists

¹¹The Euler Equation 5 indicates that consumption growth will be a function of βR . If this ratio is larger than one, consumption growth will be positive and the consumer will deaccumulate debt. Therefore the leptokurtic distribution of liquid assets bounds the discount factor between $\beta \in (\frac{1}{R^+}, \frac{1}{R^-})$

a rich set of demographic data, including age, gender, marital status, education, city of residence and profession. Table 2 reports summary statistics on the experiment participants and a 50,000 random subsample of the universe of all customers of the financial institution.

The data is of monthly frequency and the unit of analysis is an individual. If an individual has multiple accounts of the same product, then balances are aggregated. Information regarding balance sheet variables are end-of-month calculations; however, credit card variables are end-of-billing-cycle calculations. The data has a large sample, deep longitudinal structure, and have far fewer problems with attrition, non-response, and measurement error than US survey data sources. However, information on illiquid assets (e.g., housing) is sparse and information liquid assets outside the financial institution, including cash holdings and transactions are not available.

Credit card market. Credit cards are the marginal source of credit for most consumers in the sample, and are used pervasively to finance consumption expenditure within pay-periods, as well as to transfer resources across pay-periods. Focusing on experiment participants with information on labor income, I find that the median participant spends in excess of 30% of their post tax monthly labor income using credit cards at the bank, and has interest bearing credit card debt equaling 34% of monthly income. For the remainder of the paper, credit card debt indicates only interest-bearing balances, not transactions balances that are paid off.

The credit card market under study has three important distinctions from the US market. First, the maximum interest rate that can be charged is capped by the central bank at 24% APR, and this upper limit is binding for almost all customers. Second, credit card limits are capped by the regulatory authority to a maximum of four months of income. Third, the credit card contract allows for purchases with installments. Installment credit is used to finance large and less frequent expenditures. Payments are made periodically over a predetermined horizon, typically 2 to 12 months.

The installment contract works as follows. Suppose the consumer buys a refrigerator costing \$2000 if bought in cash, with 4 installments. Her end-of-month balance then increases by \$500 plus the interest charges. The remaining \$1500 plus the interest charges shows up under the installments balance. If the consumer chooses to not pay any part of this \$500 installment payment due at the end of the month, it starts bearing additional interest charges, and would show up under revolving balances. The data therefore allows me to separate two distinct types of debt contracts with distinctive mechanisms. Total credit card debt is the sum of this installment debt and revolving debt.

Randomized trial. Experiment participants are 54,522 pre-existing cardholders approved for a limit extension between June 2014 and August 2014. These extensions are ‘automatic’ i.e. initiated by the issuer, and reflect the credit supply function. First, customers are selected from the universe of all cardholders on the basis of their profitability. Second, risky borrowers are filtered using a number of proprietary risk scores developed by the bank. Finally, the remaining customers are entered into the central bank’s credit limit clearing system to check if their pre-existing limit is below four times their most recent stated income. The full credit supply function is given in the Appendix Table 5.

Table 6 in the Appendix compares the 54,522 experiment participants to a 50,000 random sub-

Table 2: Summary Statistics

Variable	RCT participants		All cardholders	
	(1) Mean	(2) s.d.	(3) Median	(4) Mean
Age	37.3	9.5	36	41.3
Gender	0.81			0.77
Married	0.67			0.67
Schooling	12.3	3	12	12.1
Customer for months	101	69	96	115
Credit card variables (at bank)				
Number of cards	1.82	1.01	2	1.73
Limit	5,450	5,875	3,400	8,581
Spending	1,034	1,882	496	1,458
Debt	1,236	2,061	627	2,229
Revolving debt	307	1,097	0	688
Installment debt	928	1,653	390	1,540
Debt/Limit (at bank)	0.28	0.36	0.19	0.31
Credit card variables (outside of bank)				
Number cards	1.08	1.48	1	1.7
Limit	6,179	16,198	1,000	16,675
Spending	992	61,896	0	1,991
Debt	2,370	8,494	671	5,937
Spending at bank/Total spending	0.7	0.45	0.99	0.49
Debt at bank/Total debt	0.66	1.18	1	0.35
Assets				
Assets	5,755	41,135	0	15,794
Checking	1,604	10,525	0	3,229
Time deposits	3,044	34,363	0	11,102
Investments	1,106	12,248	0	1,463
Other Debt (excluding credit card)				
Other Debt (excluding credit card)	5,684	17,316	0	3,109
Mortgages	2,702	15,937	0	1,211
Vehicle loans	167	2,140	0	367
Personal loans	2,814	6,440	0	1,530
Monthly Wage				
Monthly Wage	2,977	5,032	1,801	2,576
Credit score				
Credit score	1,480	262	1,506	1,460
Non-performing loans				
Non-performing loans	0		0	0.0024

Note. Columns (1), (2) and (3) are based on a 50,000 random sample of all credit card holders in August 2014. Column (4) is based on 54,522 experiment participants in August 2014. Unit of analysis an individual. Variables expressed in local currency. Labor income information for the subset of customers with direct deposit. See text for definitions of variables.

sample of the universe of all cardholders. Experiment participants are, on average, relative to the universe of cardholders, 4 years younger, have 20% more labor income, and carry only half of the debt. Participants also score lower on three proprietary risk scores, indicating lower credit risk. All of these differences are significant ($p < 0.001$). However, the average pre-intervention credit line of a typical experiment participant is lower than the typical cardholder, and the average limit increase as a part of the randomized intervention, increases a typical experiment participants credit line to the typical cardholders credit line. Therefore, despite some differences, experiment participants appear to be cardholders that are *catching up* with the typical consumer in terms of credit line magnitude.

I determine from the 54,522 consumers a control group of 13,438. First, I group the participants into non-overlapping and exhaustive bins with respect to their end-of-month balances over limits. Second, I draw a random sample from each bin, using a random number generator. Sampling rates are unequal across bins to increase efficiency. Further details on the sampling and randomization are given in Appendix 7.2.

Subjects in the control group are given no credit extensions for a period of 9 months, between September 2014 and June 2015. Therefore the experimental intervention consists of including an additional cutoff in the credit supply rule that blocks any credit card limit extensions to the control group. Subjects in treatment group have their limits extended. Experiment participants in the treatment group learn about the limit extension through their credit card statement. Although the assignment of consumers to treatment and control is random, the magnitude of limit changes for treatment group is endogenous, and is determined by the credit supply function.

4 Spending and Debt Response to Liquidity

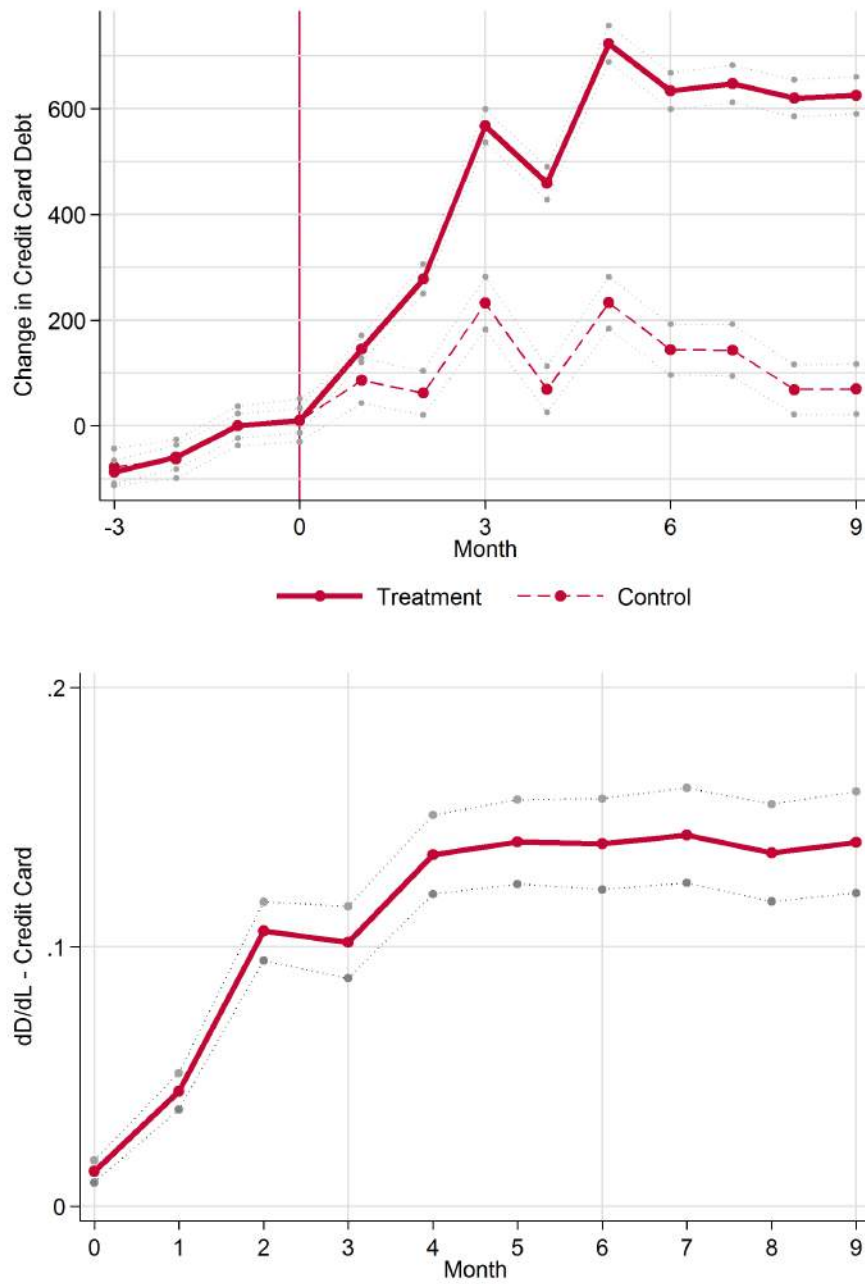
I begin my empirical analysis by plotting the average credit card debt for the treatment and the control groups, between June 2014 and June 2015, in the top panel of Figure 4. I normalize the level of debt by pre-intervention values, therefore the y-axis displays the cumulative change in debt relative to the onset of the experiment. The figure shows that the relative debt level of the treatment and control group remain stable prior to the intervention, but a large and significant increase in borrowing is done by the treatment group after the intervention. The difference in debt levels between the treatment and control group is the causal effect of credit availability.

I normalize the change in debt by change in limits using a distributed lag form,

$$\Delta D_{it} = \sum_{j=0}^{T=t} \phi_j \Delta L_{it-j} + \varepsilon_{it} \quad (6)$$

The explanatory variable is the change in credit card limits $\Delta L_{it} = L_{it} - L_{it-1}$. For the customers that did not experience a limit increase in a particular month, the corresponding ΔL_{it} equals zero. The error ε_{it} accounts for debt growth due to factors other than credit line extension, such as shifts in preferences or income shocks. The sampling and randomization ensures the dispersion in the explanatory variable ΔL_{it} is orthogonal to all variables, most importantly to ε_{it} . I

Figure 4: Impulse Response to Liquidity



Note. The top figure plots the average interest bearing credit card debt for the control and treatment group. The x-axis is time in months and $t = 0$ corresponds to September 2014. The y-axis is the average interest bearing credit card debt. The level of debt is normalized by pre-intervention values. The bottom figure displays the *marginal propensity to consume out of liquidity*. Estimates are obtained using the distributed lag equation (6) in Section 4 on a sample of 54,522 experiment participants.

therefore do not control for any cross-sectional or time variables.

The left hand side of Equation (6) corresponds to consumption, to proxy for which I use four variables.¹² The main dependent variable is the change in credit card debt. Second, I decompose this variable to its subcomponents: change in revolving debt and change in installment debt. Third, in order to check for balance shifting, I analyze the response of credit card debt outside the bank. Finally, to analyze spending patterns, I use the volume of total and sectoral spending done with the credit card in a given month. Because debt is a stock variable, I use the change in debt as the dependent variable. Spending is a flow variable linked to the change in debt via an accounting identity, therefore is analyzed in levels.

The coefficient ϕ_0 measures the contemporaneous effect of a unit increase in credit card limits to a change in the dependent variable. The partial autocorrelation coefficients ϕ_1, \dots, ϕ_τ measure the additional responses after τ months. The marginal propensity to consume out of liquidity is then defined as the cumulative increase in debt after τ months $\Phi = \sum_{j=0}^{\tau} \phi_j$. Equation (6) is estimated via ordinary least squares on the whole sample of 54,522 experiment participants, using data from $T = 9$ months between September 2014 to June 2015. Use of survey weights and calculation of standard errors are explained in Appendix 7.2. Estimates are reported in Table 3 and Figures 4 - 15.

Baseline estimates. I begin by documenting the impact of a unit change in credit card limits on total interest bearing credit card debt after τ months, using results from estimation of equation (6). For brevity, I only report the cumulative response, which gives the impulse response to credit availability, and summarizes the long-run effects. Table 3 reports the cumulative coefficients after 3 and 9 months, and the bottom panel of Figure 4 plots the entire paths of cumulative coefficients on total credit card debt for Equation (6).

A dollar increase in credit limits increases credit card debt by 10 cents after 3 months and by 14 cents after 9 months. This response is highly statistically significant. Debt rises sharply and significantly in the first quarter following a credit limit increase, with convergence happening only after four months. Subsequent marginal coefficients decline in magnitude and significance, and there is no evidence that debt changes beyond the first four months following the limit change, with marginal coefficients ϕ_5, \dots, ϕ_9 jointly insignificant. ($p = 0.52$).

These results are robust to a number of alternative specifications. In Table 7 in the Appendix, I add to the main regression, first, a complete set of month dummies, and second, controls for the persistent characteristics of the account holder. The average cumulative increase in debt is approximately equal to a specification with controls, taking the estimate of MPCL after 9 months from 0.14 to 0.125.

The cumulative response of the treatment group does not exhibit a reversal, implying that liquidity does not only shift the timing of the spending by pulling it forward from the future, but on the contrary has long-run effects. When the credit limit is relaxed, consumers increase their debt,

¹²For the rest of the paper, I assume that the increase in credit card debt represents an increase in consumption, for three reasons. First, foreshadowing my results, I find that two-third of the additional debt is accumulated to finance direct expenditure on durables and services. Second, I verify from transaction data that consumers in the treatment group increase their expenditures, not just revolve debt keeping spending constant. Third, payday loans, and other forms of relatively expensive unsecured borrowing, is not a feature of the credit market under consideration.

Table 3: Response of credit card debt to a change in credit card limits

Variable	Φ_3	Φ_9
(1) Credit card debt	0.101 (0.007)	0.140 (0.009)
(2) Revolving debt	0.031 (0.004)	0.044 (0.006)
(3) Installments	0.070 (0.005)	0.096 (0.007)
(4) Credit card debt at other banks	-0.017 (0.003)	-0.012 (0.004)

Note. Table reports the cumulative response of credit card debt to a dollar change in credit card limits. Estimates are obtained using the distributed lag Equation (6) on a sample of 54,522 experiment participants. The first and second columns report the cumulative coefficients $\Phi_\tau = \sum_{j=0}^{\tau} \phi_j$ after 3 and 9 months respectively.

and appear to asymptote to a new target debt level. As there is little evidence of non-linear dynamics, a static specification that allows for only an immediate debt response, with consumers permanently leveraging up to a new debt level, is well suited to rationalize the impulse response.

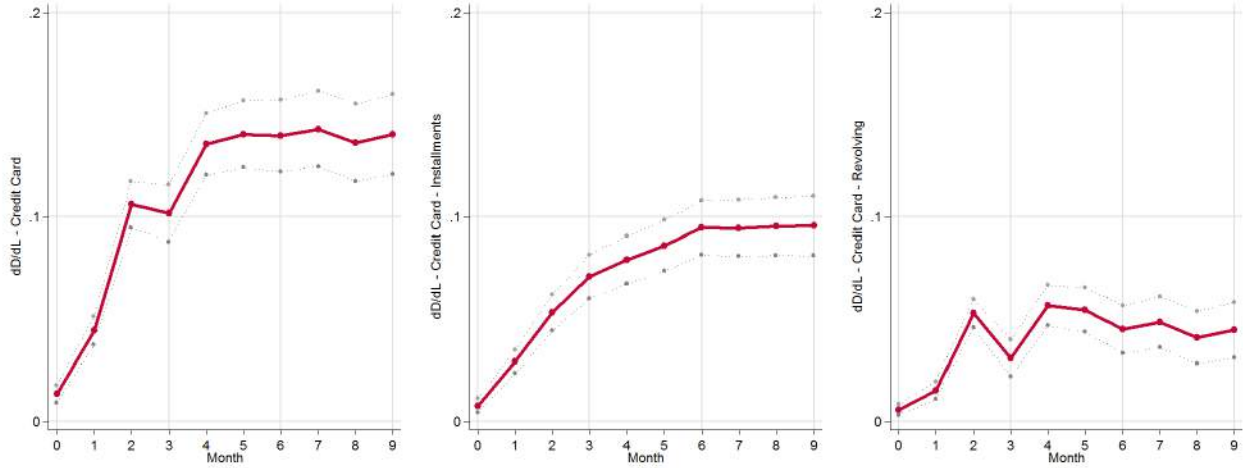
Before discussing spending patterns and heterogeneity, I shortly report results on balance shifting and defaults. To check if the increase in debt represents balance shifting, I use the credit bureau information and estimate the effect on the change in credit card debt outside the financial institution. Appendix 7 reports the results. I verify that borrowing on other cards remain stable, and the results do not represent mere balance shifting. Finally, the credit contract between the financial institution and the consumer contains the option to default, and a high borrowing response may reflect a high risk of default.¹³ In Appendix 7 I report that no detectable difference between the treatment and control group exists with respect to late payments or non-performing loans.

Debt type. Figure 5 reports the response of credit card debt by debt type. I decompose total interest bearing credit card debt to installment debt and revolving debt. The panels in the middle and the right display credit card debt accumulated by direct consumption expenditures in installments, versus end-of-month balances that are revolved. The left figure displays the sum of the two types of debt.

I find that two-thirds of the total debt accumulated comes in the form of installments. Increases in installments represent direct consumption expenditures, used to finance the purchase of durables and services. Therefore, unlike the literature on finance that measures the marginal propensity to *borrow*, I can bound the marginal propensity to *consume* out of liquidity at 0.1. Moreover, three-quarters of the final installment debt is accumulated only after a quarter. Therefore the immediate response of a typical consumer to an increase in credit availability is to finance consumption of durable goods with an investment nature, such as furniture, appliances, health, and education. Installment debt increases throughout the second quarter of the experiment, however there is no evidence of any increases after the second quarter. ($p = 0.77$).

¹³See Chatterjee et al. (2007), Adams et al. (2009), Kaboski and Townsend (2011) and Einav et al. (2012).

Figure 5: Impulse response of credit card debt, by debt type



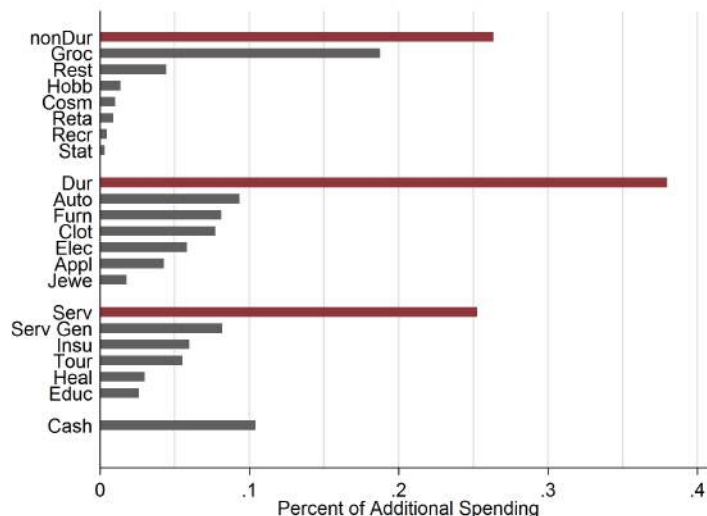
Note. Figures plot the *marginal propensity to consume out of liquidity*. Estimates are obtained using the distributed lag equation (6) in Section 4 on a sample of 54,522 experiment participants. The figure on the left represents total credit card debt. The figures in the middle and on the right represent installment debt and revolving debt respectively.

Note that installment debt and revolving debt are distinct debt contracts with different interactions to the consumer income and balance sheets. In the baseline intertemporal consumption model with a single liquid asset, theory predicts that revolving debt will be used as a *self-insurance* device, comoving *negatively* with income shocks. For example, under the permanent income model, consumers should increase consumption by the annuity value of a transitory increase in income, but reflect permanent shocks one-for-one to consumption. As debt creates the wedge between income and consumption, the permanent income model indicates that consumers should increase (decrease) revolving debt when hit by negative (positive) transitory income shocks and should not borrow with respect to permanent shocks. On the contrary, in an extended model with durables, consumers also incur debt when hit by *positive* income shocks, in order to *invest* in goods with durability, therefore installment debt may comove *positively* with income shocks.

This distinction is important to understand what generates the high private marginal return on borrowed funds, as well making out-of-sample predictions as to if consumers will exhibit sensitivity to credit under various macroeconomic conditions, i.e. recessions. In Appendix 7.4, I provide evidence that revolving balances comove *negatively* with income shocks and installment balances comoves *positively* with income shocks. First, raw correlations between income growth and debt growth provide evidence. Second, I adopt a parsimonious stochastic model of income, and estimate simultaneously the transmission coefficients of permanent and transitory income shocks to credit card debt, in the spirit of [Blundell et al. \(2008\)](#). This approach also verifies the qualitative findings, and provides more structured evidence on the magnitude of the comovement of different types of debt with permanent and transitory income shocks.

Spending patterns. Are particular goods more or less responsive to credit availability? The comprehensive nature of the expenditure data allows me to analyze transaction patterns across 18

Figure 6: Spending patterns



Note. Figure plots the categorical composition of the spending response to liquidity. First, I estimate the response of categorical expenditure for each of 18 spending categories, using the distributed lag equation (6) in Section 4 on a sample of 54,522 experiment participants. The figure then plots the share of each category on the total additional spending done by the treatment group. For example, the groceries bar indicates that 18% of the additional spending done by the treatment group has gone to grocery spending. The red bars represent the total share of spending in nondurables, durables and services respectively.

subcategories of expenditures. In order to estimate the effect on categorical transactions, I replace the left-hand side variable in Equation (6) with categorical spending (in levels). I then calculate the share of spending in each category, as a fraction of total increases in spending.¹⁴ Figure 6 then displays the contribution of each spending category in the total change in spending.

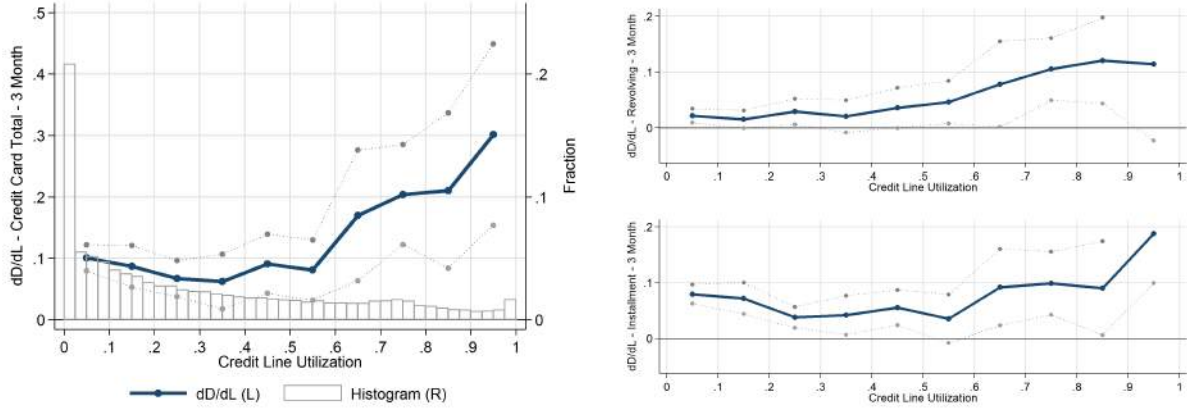
I find that spending on consumer durables (furniture, clothing, electronics, appliances, jewelry), and services (insurance, tourism, health, education) represents two-thirds of the additional spending. Only a quarter of the increase in spending is due to nondurables (groceries, restaurants, hobbies, cosmetics, retail, recreation). Spending on groceries and restaurants constitute almost all of the increase in nondurable spending. Finally another 10% of the additional spending is taken out as cash advances. These findings complement the results that use information in debt type that, expenditures in durables and services represent a large share of the increase in spending.

Commodities usually classified as services have substantial amount of durability, as noted by Hayashi (1985).¹⁵ In addition, consumer durables have some collateral value, give flow utility,

¹⁴I observe that cardholders in the treatment group increase their spending relative to the control group, beyond the increase in their credit card debt. If credit availability entails no wealth effects, the budget constraint implies some credit card transactions are crowded out from cash transactions. Therefore, the interpretation of the spending patterns depends on if spending in all sectors are equally crowded out.

¹⁵Hayashi (1985) runs a distributed lag model of consumption on expenditure, and finds that expenditure in categories such as clothes, recreation, health and education are highly durable.

Figure 7: Heterogeneity by credit line utilization



Note. Graphs plot the cross-sectional distribution of the marginal propensity to consume out of liquidity, after 3 months. Estimates are obtained using the distributed lag Equation (6) on a sample of 54,522 experiment participants. The y-axis reports the cumulative coefficients $\Phi_\tau = \sum_{j=0}^{\tau} \phi_j$ after 3 months. x-axis is credit line utilization, defined as the ratio of interest bearing debt to credit card limit.

and spending on services such as education, health and insurance constitutes investment in human capital, and have substantive effects on well-being and labor market outcomes (Becker, 1964). Therefore the increase in borrowing does not appear to finance a short lived increase in nondurable consumption. Moreover, the spending on consumer durables and services have a lumpy nature and exhibit highly cyclical patterns. This is in contrast to spending in nondurable consumption, for which the consumers have a preference for smoothness.

4.1 Heterogeneity

Average responses mask substantial heterogeneity and does not distinguish whether all consumers respond equally or whether the response is driven by the part of the sample. In this section I investigate the cross-sectional heterogeneity of the response along various dimensions. For brevity, I focus on the state variable of a baseline intertemporal model, disposable resources. In Appendix 7.3, I also analyze structural heterogeneity with respect to income shocks and age, as well as unmodelled aspects of heterogeneity such as education and other demographics.

Heterogeneity by disposable resources. If a consumer is facing a binding credit constraint, or maintains a buffer-stock of disposable resources as precautionary savings, then low level of disposable resources can indicate that a consumer has a higher propensity to spend credit on arrival. I split the sample on the basis of disposable resources, and estimate Equation (6) separately. I use two definitions of disposable resources: (i) credit line utilization, ratio of credit card debt to credit card limits, directly identifies cardholders for whom the credit limit constraint is binding, and yields sharper results. (ii) distance to limit, net liquid assets plus available credit normalized by income, allows me to take the data to the model and calibrate structural parameters. I discuss both in turn.

The left panel of Figure 7 plots the cross-sectional distribution of the responses by credit line utilization bins. Consumers in the first bin utilize less than 10% of their credit lines, and those in the second bin utilize between 10% to 20% of their credit lines and so on. The left axis is the cumulative response of total credit card debt after 3 months. Also displayed is the histogram of credit line utilization. When binning, I use the values in the month prior to the onset of the experiment. This value is pre-determined with respect to decisions taken thereafter.

I verify that consumers respond differentially based on their credit line utilization. Unsurprisingly, consumers closer to the constraint have higher marginal propensities to consume. For example, consumers with credit line utilization exceeding 90% accumulate 30 cents of debt per unit increase in limits, in excess of twice the average response. This finding is consistent with models featuring concave consumption rules, as well as previous research that documents a lack of consumption smoothing, in particular among consumers with low liquidity. However despite appearing at a corner solution to their intertemporal problem, these consumers do not appear to be hand-to-mouth as predicted by the baseline model, and exhibit marginal propensities significantly smaller than unity.

Strikingly, consumers with substantial resources exhibit a statistically significant increase in spending in response to an increase in credit availability. For example, consumers that utilize less than 10% of their credit lines at the onset of the experiment, accumulate 10 cents of debt per unit of credit line increase. Similarly, consumers with utilization rates between 20% and 30% -median utilization lies in this interval- accumulate 7 cents of debt per unit of credit line increase. These findings indicate that adjustment to a new credit regime is borne not only by a small fraction of credit constrained consumers. On the contrary, the average response is due to a substantial precautionary motive through which credit constraints affect the consumption behavior.

In order to better understand what accounts for unconstrained consumers to respond to a change in credit availability, I turn again to data on debt contract type: installments versus revolving debt. I analyze the heterogeneity in spending patterns by credit line utilization. The right panel of Figure 7 decomposes cumulative response of debt type. I find that the increase in revolving debt is mostly driven by consumers at their borrowing constraints. However, consumers at all credit line utilization levels accumulate installment debt. Importantly, the response of unconstrained consumers is due entirely to installment debt.

In the Appendix, I construct a second measure of disposable resources that maps directly to the baseline intertemporal model. I define *distance-to-limit*, the sum of net liquid assets plus available credit. The marginal propensity to consume out of liquidity as a function of this state variable then provides a moment that can be used to calibrate and test a broad set of intertemporal models, as outlined in Section 5. Figure 14 in the Appendix displays the cross-sectional distribution of the responses by distance-to-limit. Similarly, the results indicate that consumers with substantial buffer of liquid assets and credit availability still accumulate economically and statistically significant amounts of debt.

4.2 Dynamics of credit line utilization

In this section I utilize the longitudinal nature of the dataset and bring in novel evidence on the *dynamics* of borrowing decisions. As discussed in Section 2, debt growth creates the wedge between consumption and income, and the underlying preferences generating the sensitivity to credit can be indirectly verified from the dynamics of borrowing behavior.

Consider two motivating examples. First, suppose the consumption rule is linear function of assets, as in the permanent income model. Then consumption is a martingale, and credit line utilization is a unit root process. Therefore ex-ante credit line utilization would be the best predictor of future credit line utilization. On the contrary, if consumption is depressed near the credit constraint in order to insure against uninsurable income shocks, then credit line utilization would exhibit significant predictability near the credit constraint. Second, consider a consumer for whom the borrowing constraint is currently binding. If this consumer is hand-to-mouth, or is very impatient, or has a very high elasticity of intertemporal substitution, then she would be expected to remain at the constraint. If we observe the consumer quickly saving herself out of debt, this information could be used to discipline parameters of the utility function and income process.

In order to analyze the dynamics of borrowing decisions, I use a normalized measure of debt, credit line utilization, defined as the ratio of interest bearing credit card debt to the credit limit. I group experiment participants into ten equal-width non-overlapping bins with respect to credit card utilization. For example, if a cardholder has a credit card utilization between 0 and 0.1, then she is in the first bin, and so on. I bin consumers at $t = 0$, at the first month of the experiment. I then plot the average credit card utilization for each bin in time, in the top panel of Figure 8. The histogram of utilization is displayed in Figure 7.

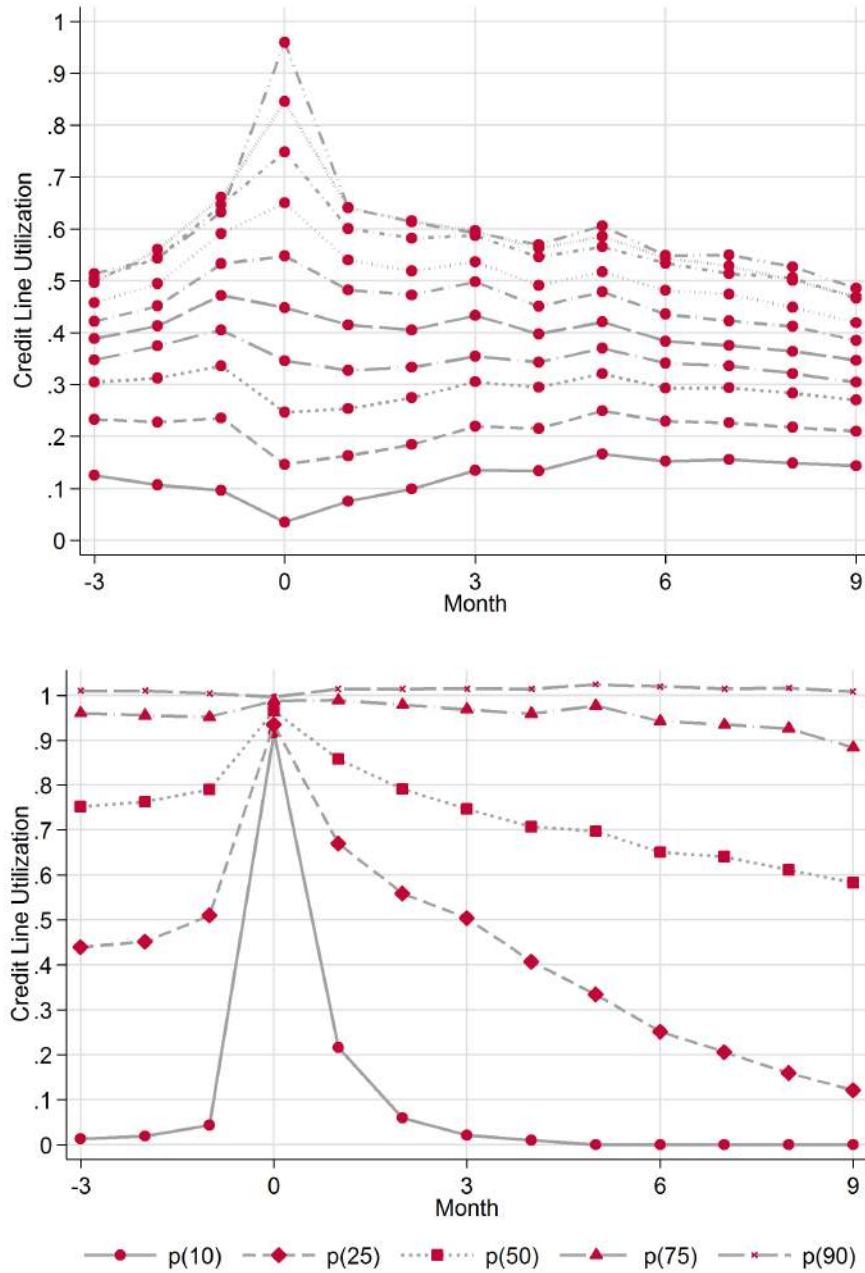
First, I find significant predictability of credit line utilization, in the form of mean-reversion. For example, experiment participants with a utilization rate above 90% at the onset of the experiment, reduce their utilization rate to 60% after 3 months, and 50% after 9 months. Moreover, the same consumers have a utilization rate of 50% three quarters before the onset of the experiment. Therefore, despite holding very little liquid assets, consumers do not appear to borrow as much as they can, and do not appear to be at a corner solution to their intertemporal problem. On the contrary, being strictly constrained appears to be a temporary event, lasting less than a quarter for the *typical* consumer. Most consumers appear to be forward looking with a target utilization rate, and leave a buffer of available credit.

Second, if there was a fraction of rule-of-thumb consumers that set consumption equal to disposable resources, these consumers would have a unique footprint in their credit line utilization: they would remain persistently stuck at the highest utilization bin. Similar conclusions would also apply if the consumers are highly impatient, or are unable to pay back debt due to self-control problems. In order to get a sense of the measure of such *myopic* consumers, I analyze the fraction of consumers at the limit for consecutive months.

Figure 8 uses data on the universe of all cardholders.¹⁶ I focus on cardholders that utilize more

¹⁶I use information from the universe of cardholders, because the bank's credit supply rule may censor hand-to-mouth consumers from receiving limit increases.

Figure 8: Dynamics of credit line utilization



Note. These figures display the dynamics of credit line utilization. The x-axis is time in months, relative to the start of the experiment. The y-axis is credit line utilization, calculated as the ratio of interest bearing credit card debt to credit card limit. In the top figure, 54,522 experiment participants are grouped at $t = 0$ according to their credit line utilization. Consumers in the first bin have credit line utilization between 0.1 and 1, and so on. The figure then plots the average credit line utilization for each bin in time. The bottom figure uses data on a 50,000 random subsample of the universe of all cardholders. I focus on a subset of these consumers that utilize more than 90% of their credit line at $t = 0$. I then plot the 10th, 25th, 50th, 75th and 90th percentiles of credit line utilization for these consumers in each period.

than 90% of their credit lines in the month experiment have started. The figure displays the credit line utilization, given time, for 5 quantiles of these consumers. For example, the triangles correspond to the top 25th percentile of the cardholders that were constrained at $t = 0$. The figure indicates that 90% of all cardholders at the credit constraint save out of debt, putting a bound on strictly hand-to-mouth or very low discount factor consumers. Surprisingly, fewer than 5% of cardholders utilize more than 90% of their credit lines at any point in time, and no more than 2% of cardholders remain at their limits for two consecutive periods. These results are robust to various definitions of cash-on-hand (installment debt, revolving balances, disposable resources), sample selections (experiment participants vs. universe of all cardholders) and time-frames.

This pattern has implications on the heterogeneity of the marginal propensities in the population. Remember that only if the credit constraint is binding, the marginal utility of consuming today exceeds marginal value of saving and consuming tomorrow, and a forward-looking consumer would behave hand-to-mouth, i.e. consumers borrow as much as she can. On the contrary, the findings indicate that most consumers in steady-state have a buffer of credit availability, therefore their marginal propensities to consume out of liquidity should be significantly smaller than unity.

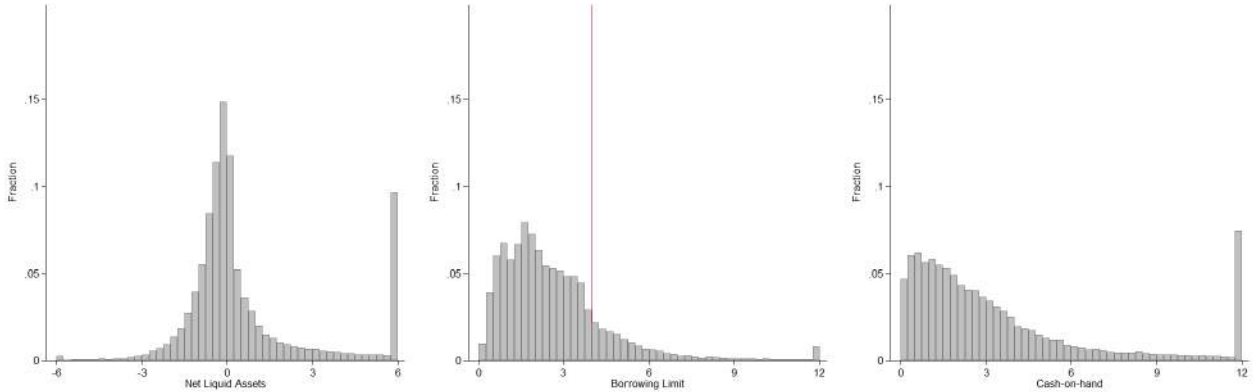
Third, there appears to exist persistent factors that determine long-run levels of credit line utilization. This is evident from how consumers starting off the experiment with different credit line utilizations do not all asymptote to the same credit line utilization. Rather, the long-run utilization levels appear to be monotonically ranked. For example, the typical cardholder who was 90% utilizer 9 months ago has 50% utilization rate, however the population median utilization is 20%. Therefore, the data may call for a deeper model of heterogeneity, with three natural candidates being those in credit card limits, discount rates, and income processes. See [Krusell and Smith Jr \(1998\)](#) and [Guvenen \(2009\)](#). In [Appendix 7.1](#), I discuss evidence for tighter credit lines leading to higher utilization ratios.

Fourth, there exists a substantial velocity in how consumers move within utilization levels. Among consumers at the constraint, the median consumer reduces credit line utilization to 75%, indicating that the consumer saves about 25% of income for three consecutive months. Understanding this velocity is relevant to calculating the costs of credit card borrowing, and predicting the likelihood of a borrowing constraint binding. Quantitatively, draws from the income shock determine the ergodic distribution of liquid assets, as well the velocity with which consumers move across the wealth distribution. I discuss the ability of the structural model in replicating these dynamics in [Section 5](#).

5 Model with Durables

In this section I extend the structural model to jointly rationalize the magnitude and heterogeneity of the marginal propensity to consume out of liquidity, as well as the distribution of state variables. I consider consumers with infinite planning horizons that choose how much to consume, and have motives to save or borrow in order to smooth consumption and invest. I follow [Guerrieri and Lorenzoni \(2015\)](#) and add to the simplified model of [Section 2](#) two important fea-

Figure 9: Histogram of Liquid Assets and Credit Lines.



Note. Figure plots the histograms of (L) net liquid assets (M) credit card limits (R) distance to limit. Net liquid assets are holdings of all liquid wealth minus credit card debt. Liquid assets include checking, savings, money market accounts, stocks, bonds and other mutual funds, net of borrowing from credit cards. Credit line is sum of credit card limits. Distance to limit is the sum of net liquid assets plus available credit. This definition allows the model to be cast in terms of a single state variable. Each unit of observation is an individual in the month before the intervention. The levels are normalized by the average monthly income in the same year. Information only on balances at the particular financial institution. Extreme values folded for display purposes. Red line indicates the cap on credit card limits by the central bank. Overall, the distribution of liquid wealth fares well with the US evidence on [Hall \(2011\)](#), and cross-country evidence on [Kaplan et al. \(2014\)](#).

tures of the environment: illiquid durable goods, and a wedge between borrowing and lending rates. *Durables* in the model correspond to non-residential consumer durables (e.g., appliances, furniture) and services (e.g., health, education).

First, I describe how the consumer allocates disposable resources between liquid and illiquid assets. The presence of liquidation costs lead to lumpy adjustment, and credit constraints make the adjustment bands state-dependent. Under plausible calibrations, consumers hold bulk of their assets in illiquid form, and hold very little liquid assets, which make their behavior sensitive to credit availability. Second, I study heterogenous responses to a shock to credit availability. An increase in credit capacity decreases the precautionary motive for holding liquid assets, and consumers adjust their nondurable and durable consumption. The spending response to increased liquidity comes from two main groups (a) consumers with *low productivity* that borrow to smooth nondurable consumption, and (b) consumers with *high productivity* that borrow in order to invest in the illiquid asset. Finally, I use the model to explore the consumer response to a number of policy shocks in partial equilibrium.

Preferences. Consumers exhibit expected utility form preferences over nondurable consumption C_t , stock of durables and services K_t , with discount factor β , risk aversion γ , share of non-durables in total consumption α ¹⁷

¹⁷Consumption of nondurables and durables are aggregated using a Cobb-Douglas specification. This specification implies (i) a substitution elasticity of 1 between nondurables and durables/services ([Ogaki and Reinhart, 1998](#)); (ii) constant expenditure shares at all asset levels (iii) utility flow from durables and services equal the stock without loss of generality ([Berger and Vavra, 2015](#)).

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \frac{(C_t^\alpha K_t^{1-\alpha})^{1-\gamma}}{1-\gamma} \right] \quad (7)$$

Idiosyncratic earnings. When employed, disposable labor income (in logs) is given by $\log(Y_t) = y_t$, with idiosyncratic shock to earnings given by persistent process

$$y_t = \rho y_{t-1} + \varepsilon_t \text{ with } \varepsilon_t \sim (0, \sigma^2) \quad (8)$$

When unemployed, consumer receives an unemployment benefit equal to v . Transition between employed and unemployed states is determined exogenously by the job finding and separating rates, π_f and π_s .

Assets. Consumers can transfer resources across periods using three assets: (i) a liquid asset for saving; (ii) credit cards for unsecured borrowing; (iii) illiquid durables. The liquid asset pays a gross financial return of R^+ , whereas unsecured borrowing on credit cards is at gross rate R^- .

Durables are divisible, but illiquid. They feature no adjustment cost upwards and can only be liquidated at a per unit cost ζ . They depreciate at rate δ . I assume their relative price is 1. The adjustment function is summarized as,

$$\Lambda(K_{t+1}, K_t) = \begin{cases} K_{t+1} - K_t + \delta K_t & \text{if } K_{t+1} > K_t \\ \delta K_t & \text{if } K_{t+1} = K_t \\ (1 - \zeta)(K_{t+1} - K_t) + \delta K_t & \text{if } K_{t+1} < K_t \end{cases} \quad (9)$$

The intertemporal budget constraint is then given by

$$C_t + \Lambda(K_{t+1}, K_t) \leq Y_t + A_t R^+ - D_t R^- - A_{t+1} + D_{t+1} \quad (10)$$

with an *ad-hoc* limit on borrowing L .¹⁸

Consumer problem. The recursive problem is given by,

¹⁸Such an ad-hoc constraint can be derived endogenously in models with moral hazard or limited commitment. The existence of unemployment benefit, and the calibrated values for L , r and v assure that the *ad-hoc* limit L will be tighter than the *natural limit*. I assume that consumer durables do not require a downpayment, and do not serve as collateral against which consumers can borrow. The credit limit can easily be endogenized by making durables collateralizable. This extended model with endogenous borrowing capacity also captures the heterogeneity in borrowing limits observed in the data.

Table 4: Calibration

Parameter	Definition	Value	Target
β	Discount factor	$0.92^{\frac{1}{4}}$	
γ	Coefficient of relative risk aversion	2	
R^-	Borrowing rate	1.04	16% annual rate on credit cards.
R^+	Lending rate	1.005	2% annual rate on savings account.
L	Borrowing limit	0.9	Median borrowing limit.
ΔL	Change in credit limit	0.4	Median change in borrowing limit.
ρ	Persistence of income shock	.9	
σ^2	Variance of income shock	.03	
π_f	Job finding rate	0.4	Author's calculations.
π_s	Job separation rate	0.04	Author's calculations.
v	Unemployment benefit	0.4	40% of average labor income.
α	Coefficient on non-durables	0.4	Share of non-durables in spending.
δ	Durable depreciation rate	0.03	Service life of 12 years.
ζ	Durables adjustment cost	0.2	

Note. All variables quarterly. See Section 7.7 for details of calibration.

$$V(A, K, Y; L) = \max \left\{ \frac{(C^\alpha K^{1-\alpha})^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}_t \left[V(A', K', Y'; L) | Y \right] \right\}$$

$$C + A' + \Lambda(K, K') \leq Y + AR^+ - DR^-$$

$$D' \leq L$$

$$Y' \in \Pi(Y)$$

I analyze the model by numerical simulations and briefly describe the consumption policy in steady state. Optimality conditions are given in Table 10 in the Appendix. Policy functions are calculated by iterating the Euler equation, using the endogenous gridpoints method of [Carroll \(2006\)](#), as described by [Guerrieri and Lorenzoni \(2015\)](#). See Section 7.7 for details of calibration.

Adjustment of consumer durables. Consumers can now transfer resources to future periods using either liquid assets, or durables. In addition, they can finance current consumption with resources to accrue in the future by borrowing on credit cards. The liquid asset has positive financial return, but is also held for precautionary reasons in order to self-insure against income fluctuations. Durables provide service flow, however their attractiveness as a financial asset is hampered by depreciation and illiquidity. The optimal portfolio composition weighs the financial and precautionary benefits of the liquid asset, versus service flows from the stock of durables.

In the benchmark treatment of durables, the optimal stock of durables K^* is proportional to permanent income. Introduction of liquidation costs, credit constraints and the wedge between borrowing and lending rates, changes the nature of durable adjustment in three important ways. First, consumers adjust their durable holdings on infrequent occasions, due to cost of liquidating. Optimal holdings of durables are then characterized by two adjustment bands, K^+ and K^- , which trigger adjustment towards optimal holdings K^* when reached.¹⁹ If the consumer wealth grows or the stock of durables sufficiently depreciates, and the durable stock falls below the lower band K^- , consumer adjusts durable holdings upwards. If consumer holds too little wealth and the durable stock exceeds the upper band K^+ , then a fraction of durables are liquidated. The optimal holdings of durables K^* lies in the interior region of two bands, determined by the optimality conditions.

Second, credit constraints make the adjustment bands state-dependent. In particular, a tighter credit constraint depresses the adjustment bands near the constraint, due to the precautionary motives for holding liquid assets. When the credit constraint relaxes, the adjustment bands expand upwards. Third, the expensiveness of borrowing compared to lending depresses durable holdings further, at negative holdings of liquid assets.

Figure 10 displays the adjustment bands for the unconditional expectation of labor income. The solid and dashed lines represent the upper and lower adjustment bands respectively. The level of the adjustment bands depend primarily on the income and discount factor. The width of the adjustment bands depend on adjustment costs, uncertainty, risk aversion, and factors that increase the speed of movement within the bands, for example, the rate of return on the liquid asset, and depreciation rate of durables.

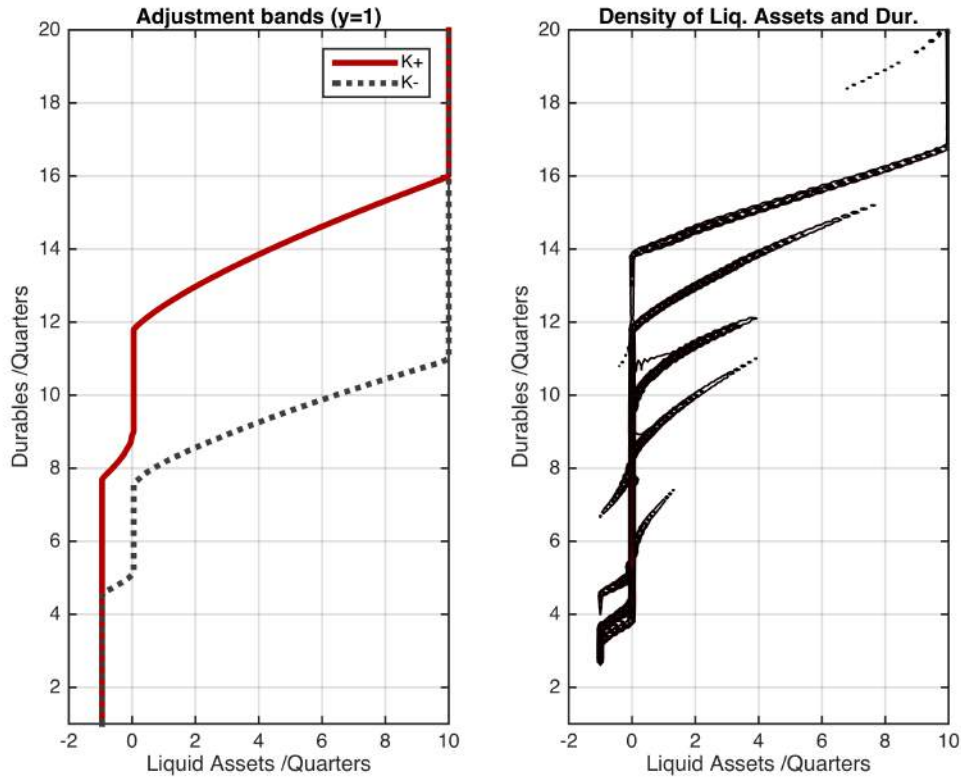
Ergodic distribution of liquid and illiquid assets. The nature of the adjustment bands, and the borrowing lending wedge, deliver an ergodic distribution of liquid assets and durables concentrated within the region of inaction, (K^+, K^-) . The right panel in Figure 10 displays the contours of the joint density of assets, liquid assets and durables. Notice that in this environment, most consumers hold very little liquid assets, despite holding sizeable amount of durables.²⁰

The left panel of Figure 11 displays the marginal densities of liquid assets. The empirical counterpart of this figure is given in Figure 9. The distribution of liquid assets displays a characteristic leptokurtic form with an acute peak at zero, which is determined by three forces. First, high rate of unsecured borrowing leads consumers to pay back debt, pushing consumers from negative holdings towards zero. Second, buffer-stock behavior, and preference for consuming service flow from durables, implies consumers don't hoard liquid assets, but convert them to durables, despite having to bear the cost of transitory income fluctuations, because of a higher long-run utility from optimally holding illiquid assets. Therefore consumers in the tails tend to hit the triggers and adjust to the target in the interior of the distribution, and investment in durable goods that also causes households to be constrained. Third, zero wealth has the largest mass, due to

¹⁹See Grossman and Laroque (1990), Eberly (1994) and Carroll (1997).

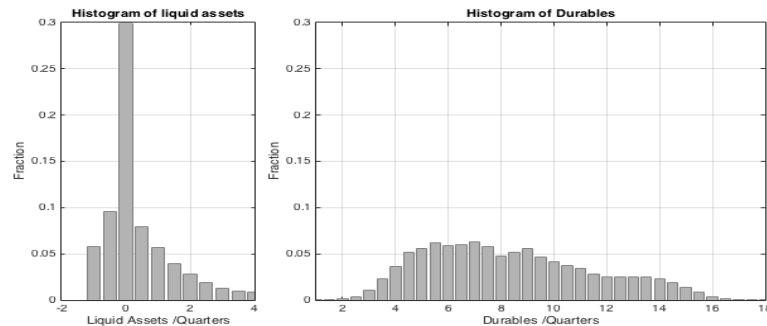
²⁰This prediction of the model is in line with the findings of Kaplan et al. (2014). In my model, the demand for durables is due to its share in the Cobb-Douglas aggregation. Various alternative mechanisms are invoked to explain the empirical tightness of the distribution of liquid assets. First, consumers may have other financial buffers (Blundell et al., 2008). Second, consumers may prefer to *neither a borrower nor a lender be*. See Shakespeare and Hall (2011). Finally, the literature on hyperbolic discounting highlights how sophisticated time-inconsistent consumers may choose to lock up wealth in illiquid forms Angeletos et al. (2001).

Figure 10: Durables adjustment bands and the ergodic distribution of assets.



Note. The figure on the left displays the adjustment bands for durables, when labor income equals for the unconditional expectation of the income shock. The solid red line and the dashed black line represent the upper and lower adjustment bands respectively. If the holdings of durables is larger than the upper adjustment band, the consumer liquidates durables. Similarly for the lower adjustment band. The drop in the bands around zero liquid assets is due to the borrowing and lending wedge. The optimal holding of liquid assets and durables always lies between the two adjustment bands, and satisfies the optimality and complementary slackness conditions in Table 10. See [Guerrieri and Lorenzoni \(2015\)](#) for an extended discussion of the consumer portfolio problem. The figure on the right displays the contours of the joint ergodic density of liquid assets and durables. The left panel of Figure 11 displays the marginal densities.

Figure 11: Ergodic distribution of liquid assets and durables



the wedge between borrowing and lending rates, and because it can be reached from either the triggers or the interior of the distribution.

Consumers convert liquid assets into illiquid forms, and their behavior becomes sensitive to credit both through durables adjustment and the lack of holdings of liquid assets. The ergodic distribution of liquid and illiquid assets determine how many consumers are near the adjustment bands, therefore, how many will adjust their durables stocks in response to a shock to credit availability.

A final distinction of the model with durables pertains to the joint distribution of the income state and liquid assets. In the baseline model, the primary role of liquid debt is to insure against transitory income shocks. Therefore consumers who are near their credit limits are those that have been hit by negative income shocks, which are persistent. In the model with durables, consumers go into debt to invest in durables in the wake of positive income shocks, and some of the consumers at the credit constraint are productive consumers with high permanent income.²¹

6 Discussion and Further Work

In this paper, I have estimated the magnitude, heterogeneity and composition of the consumer spending and debt response to shocks to credit availability. I have emphasized the strengths of longitudinal data on consumer spending, income and balance sheets, as well as identification of the causal effect of credit using variation coming from a randomized trial. Hopefully, this paper will serve as an example of the usefulness of microeconomic data and *test-tube* experiments in answering traditional macroeconomic questions.

The findings of this paper have implications for understanding business cycle dynamics at the macro level, in addition to improving our understanding of household consumption and borrowing dynamics at the micro level. In the micro level, deviations from the permanent income consumption behavior, which assume perfect credit markets, are large for a considerable fraction of the population, not only for a small group of consumers for whom the credit constraint is strictly binding. However the sensitivity to credit does not appear to be driven by short-sighted behavior, with expenditures concentrated in durables at times of idiosyncratic income growth. The consumption and borrowing response of consumers that are not immediately constrained, provides strong support for a precautionary channel and the buffer-stock model. Therefore, dynamics of wealth distribution plays an important role, and models with muted wealth dynamics are likely to miss out on strong precautionary effects. Such models should keep track of liquid assets, durables and credit availability as state variables, otherwise may miss out on important consequences of stabilization policies. My theoretical model parsimoniously incorporates the necessary ingredients to study the effects of aggregate shocks or credit contractions.

I discuss four directions for future research.

Design of credit markets. My findings indicate that consumers use credit for two broad purposes. First, consumers borrow when their income is low in order to smooth consumption. Second,

²¹I confirm this prediction Appendix 7.4, by showing that installment debt comoves *positively* with income shocks of permanent and transitory nature.

consumers borrow when their income is high in order to invest. An important feature of the credit contract under study is allowing purchases using installments, which facilitates financing of large, lumpy purchases, like durables and expenditures in education and health, which fall into the investment category. The installment contract has two features that leads to efficient borrowing dynamics. First, increases in leverage due to increases in installments are more likely to be *good* leverage, i.e. be accompanied by improvements in borrowers' productivity (Sufi, 2011). Second, installment is a commitment to pay back debt. Therefore, it mechanically leads to hump-shaped credit line utilization dynamics: consumers invest and accumulate credit card debt, with the latter being paid gradually. For consumers with low financial literacy with respect to temporal planning and compounding interest, it is often easier to calculate and allocate a fraction of income to installment payments, compared to planning for how long to revolve debt. On the contrary, exploiting naivete about self-control may be easier in an environment where consumers revolve debt (Heidhues and Kőszegi, 2010).

Marginal propensity to consume out of income. The magnitude and heterogeneity of the marginal propensity to consume out of transitory income changes is another important unresolved question in the macroeconomics literature, and have applications to understanding housing wealth effects and evaluating the impact of tax and labor market reforms, and assessing the redistributive effects of monetary policy. In particular, despite the sizeable theoretical work on the concavity of the consumption rule, heterogeneity in marginal propensities had been difficult to document.²² Indeed MPC and MPCL are close cousins, and for a broad class of models, the propensity to spend out of credit bounds below the propensity to spend out of income of same magnitude (Auclert, 2015). In addition, my findings also indicate that a substantial component of the average marginal propensities are driven by unconstrained consumers whom are adjusting their durables holdings. My credit market approach highlights how sharper research designs can be formulated using financial shocks, in order to more precisely estimate the magnitude and heterogeneity of the consumption response.

Behavioral theories. My numerical exercises show that consumers exhibit large spending responses relative to the benchmark model. Behavioral models, such as those featuring hyperbolic discounting, are often invoked to rationalize high levels of observed credit card debt.²³ One conclusion of such models is that consumers borrow excessively and may fail to repay their debt later, despite their earlier intention to do so. My findings indicate that it is important to evaluate the implications of such models on the *dynamics* of asset holdings. For example, is a hyperbolic consumer with reasonably calibrated parameters, sufficiently patient to deliver the mean-reverting utilization dynamics documented in this paper?

Duration of debt. For the short course of the experiment, I find that liquidity does not only have a temporary effect, but consumers use the additional credit to permanently lever up. Periods of steady income growth may encourage such relaxed attitudes towards leverage. However, the budget constraint requires that the cumulative spending out of credit over the life cycle needs to be zero. If, on the contrary, new borrowing exceeds interest payments and repayment of princi-

²²See Carroll and Kimball (1996), Kimball (1990) and Carroll et al. (2013). Two exceptions are Jappelli and Pistaferri (2014) using Italian survey data and Mian and Sufi (2014) looking at shocks to housing wealth.

²³See Laibson et al. (2003). Similarly, consumers may take an increase in credit card limits as a *cue* to consume. Such models of cue-triggered such consumption as Laibson (2001) and Bernheim and Rangel (2004) also predict large marginal propensities.

pal, households are playing a Ponzi game (Hall, 2011). The linkage of the financial crisis is then the *Minsky moment* -sudden reduction in the quantity debt (Eggertsson and Krugman, 2012). What determines the duration to which consumers hold on the debt for, and what ignites the payback of debt remain open questions.

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7 Appendix

7.1 Who is liquidity constrained?

The microeconomic and macroeconomic implications of credit constraints are proportional to individuals effected by them. However since the time of [Hall and Mishkin \(1982\)](#) the literature has not come to a definite conclusion about the fraction of constrained individuals, and the mechanism as to why they are constrained. This is due to both data limitations, and endogeneity of credit availability.

For example, an early study by [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%. More recently, [Hall \(2011\)](#) finds 74% of US households have liquid assets are less than 2 months of income. [Lusardi et al. \(2011\)](#) finds half of survey respondents probably cannot come up with \$2000. In a recent paper, [Kaplan et al. \(2014\)](#) make important progress in identifying constrained households. They find that between 25 to 40 percent of households in the SCF has liquid asset holdings less than half their monthly income. Two-thirds of these constrained households hold sizable amounts of wealth in illiquid assets, but hold very little liquid wealth.

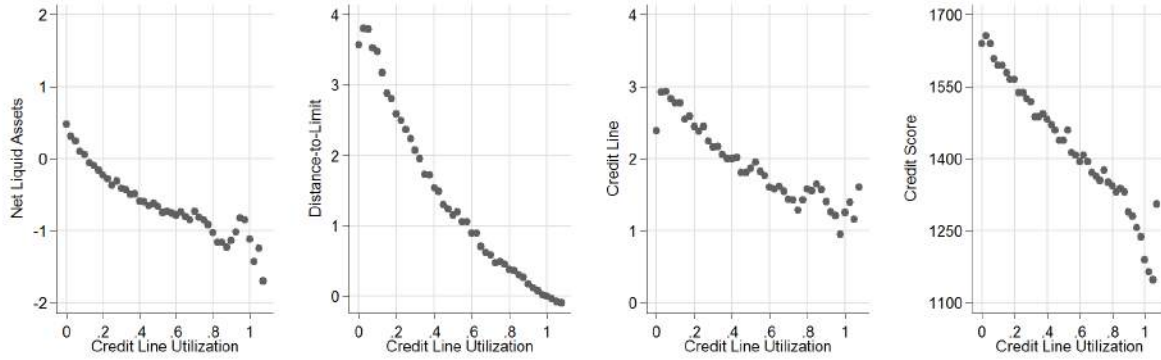
In this section I utilize the high frequency panel information on liquid assets and credit availability to construct two novel metrics of *cash-on-hand*. These metrics for three purposes: (i) In Section 4.1, I analyze the heterogeneity of MPCL with respect to these variables; (ii) In Section 4.2 I analyze *dynamics* of cash-on-hand, to discipline the underlying preferences; Finally, used in conjunction with information on income, demographics and spending patterns, to understand the mechanisms leading to the households being constrained in the first place.

7.2 Sampling and randomization

I select the control group using a two step procedure. First, I group the participants into non-overlapping and exhaustive bins with respect to their end-of-month balances over limits.²⁵ I create two additional bins for consumers with utilization rates less than zero, or larger than one, as cardholders may pay off their balances more than full, or exceed their limits by small amounts. Call these bins $b \in B$. Let N_b indicate the number of cardholders in each bin. Using a random number generator, I then draw a random sample n_b from each 12 bins, totaling up to 26,854 cardholders. In order to maximize statistical power, I set the ratio of the sample sizes n_b proportional to the ratio of the standard deviations of outcomes ([List et al., 2011](#)). This is because the treatment effect becomes more heterogeneous as credit line utilization increases, which I verify before the design of the experiment using observational data.

²⁵In order to minimize endogeneity, I group the consumers according to the ratio of end of month balances, not interest bearing debt, over limits.

Figure 12: Measures of Liquidity Constraints



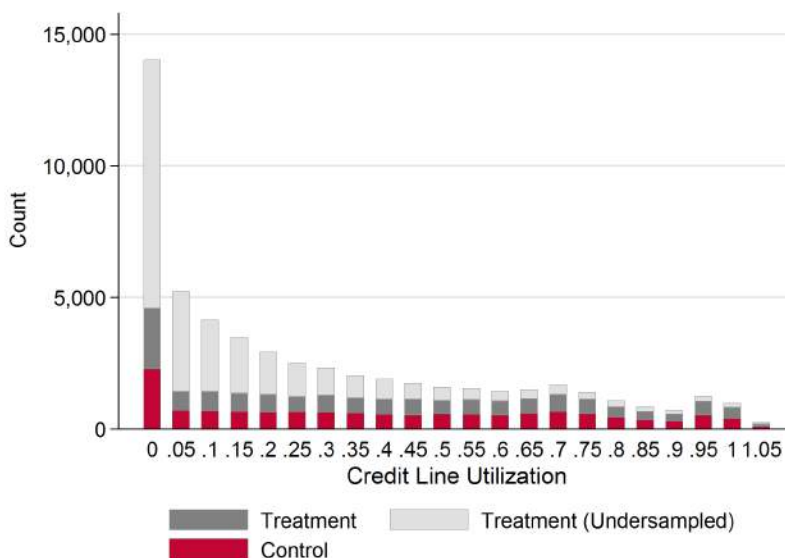
Note. Figures plots the median (1) net liquid assets, (2) distance-to-limit, (3) credit line, (4) credit score, by credit line utilization on the x-axis. Credit line utilization is defined interest bearing credit card debt over credit card limit. Net liquid assets are holdings of all liquid wealth minus credit card debt. Liquid assets include checking, savings, money market accounts, stocks, bonds and other mutual funds, net of borrowing from credit cards. Credit line is sum of credit card limits. Distance to limit is the sum of net liquid assets plus available credit.

Table 5: Credit supply

#	Type	Variable	Range	Cutoff
(1)	Sales	Expected value added	$(-\infty, \infty)$	≥ 0
(2)		Months since limit increase	$[0, \infty)$	> 6
(3)		Months card open	$[0, \infty)$	> 2
(4)	Risk	Customer score	$[100, 800]$	< 180
(5)		Credit card score	$[100, 800]$	< 180
(6)		Behavior score	$[100, 800]$	< 180
(7)		Non-performing loans	$[0, \infty)$	$= 0$
(8)		Late pay days	$[0, \infty)$	$= 0$
(9)	RCT	Control group	$\{0, 1\}$	$= 0$
(10)	Regulatory	Total limit to income	$[0, \infty)$	< 4

Note. Table displays the ten credit eligibility cutoffs. Only cardholders that pass all ten cutoffs are eligible for a credit line extension. Cutoffs (1) to (3) are determined by the credit card *sales* group. Row (1) is a profitability variable, inferred from credit card behavior, by conditioning on a large set of high-frequency variables using non-parametric machine learning methods.²⁴ Rows (2) and (3) are timing rules: cardholders are not considered for a line change if it has been less than two months since the card was originated, or less than six months since the last limit increase. Cutoffs (4) to (8) are determined by the *risk management* group. Row (4) is the customer score, reflecting demographics and affluence; Row (5) is the credit card score, reflecting credit card behavior with respect to payments and delinquencies; Row (6) is behavior score, which incorporates spending patterns and other non-economic predictive variables. Rows (7) and (8) disqualifies cardholders with pre-existing delinquencies from limit extensions. Row (9) indicates the experimental intervention: cardholders assigned to the control group are eliminated from future limit increases. Row (10) is the industry-wide cap on credit card limits imposed by the banking authority.

Figure 13: Sampling of Experiment Participants



Note. In this figure, 54,522 experiment participants are grouped into ‘credit line utilization’ bins based on the ratio of credit card debt to credit card limits in August 2014. The figure then indicates the number of experiment participants of each type in each utilization bin. Definitions of the treatment and control group are given in Section 7.2.

After sampling, I distribute the randomly selected 26,854 cardholders to control and treatment groups using a random number generator. Within each stratification bin, I divide the cardholders 50/50 equally across the two groups. This randomization strategy leads to three classes of participants. The two identical halves of the 26,854 are the control (C) and treatment (T) groups. The control group is withheld from additional credit line increases for 9 months starting June 2015. The treatment group have their limits extended as usual. The remaining 27,938 cardholders, called and treatment-undersampled (T-US), are also in the treatment group, and have their limits extended as well. The distribution of these classes are displayed in Figure 13.

Row 7 of Table 6 shows that there are no detectable differences between the control and treatment groups at 99% confidence level, except a 2% difference in limits in the treatment group ($p = 0.02$). Rows (1) and (2) of Table 6 compares the 54,522 experiment participants to a 50,000 random subsample of cardholders at the bank in August 2014.

As the environment is one of high inflation, real credit card limits are deflated quickly. Issuers, therefore, periodically increase the credit lines of pre-existing cardholders. Focusing on the universe of cardholders, I find that about 4% of credit lines increase every month. I also analyze the time since the last limit increase, and find that the median cardholder at the bank had a limit increase 15 months ago, with more than 95% of the cardholders experiencing a credit line increase in the last 40 months. However, the timing of the credit line increases often correspond to times where credit demand is expected to grow, either due to idiosyncratic or aggregate shocks. Therefore it is difficult to construct a meaningful control group for consumers that are selected for a limit increase in a particular period, as issuers proxy growth in consumer credit using non-

Table 6: Summary Statistics: Selection, Sampling and Randomization

	Group	Count	Age	Income	Limit	Debt	Credit score	Risk score
(1)	All cardholders	>5m	41.3	2,488	8,664	2,261	1,460	428
(2)	Participants	54,522	37.3	2,785	5,452	1,236	1,480	355
	$\mathbb{P}(P = \text{All})$		< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
(3)	Undersampled	27,668	37.9	3,047	6,704	1,044	1,555	338
(4)	Treatment	13,416	36.7	2,434	4,203	1,548	1,402	373
(5)	Control	13,438	36.6	2,494	4,121	1,523	1,401	373
	$\mathbb{P}(T = C)$		0.30	0.29	0.17	0.39	0.78	0.55
	$\mathbb{P}(T + \text{US} = C)$		< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01

Note. Table entries are group means unless otherwise noted. Row (1) based on a 50,000 random sample of all credit card holders in August 2014. Row (2) is based on 54,522 experiment participants in August 2014. Definitions of Rows (3), (4) and (5) are defined in Section 7.2. Income, credit limit and credit card debt variables expressed in local currency. Labor income information for the subset of customers with direct deposit. Risk score represents the sum of three proprietary credit scores, as indicated in Table 5.

economic variables or using non-parametric methods. However, the experiment participants are not a particularly selected group, but appear to be cardholders that are *catching up* with the typical consumer in terms of credit line magnitude. Finally, credit card limits are rarely decreased, with less than 1% of all credit line changes being decreases, therefore the changes in limits can be classified as permanent.

Due to institutional constraints, the credit card limits for the treatment group are not all increased at the same time. 41% of the treatment group is treated at $t = 0$ and an additional 34% is treated at $t = 1$, with 80% of the limits increased by $t = 3$. 16% of the cardholders in the treatment group do not receive the treatment, as they bounce back from the central bank’s credit line clearing system, due to their pre-existing credit line exceeding four times their monthly income. 4% of the consumer in the control group, whom are excluded from limit increases initiated by the bank, request and are granted, a limit increase. Sampling and randomization ensures that selection on the basis these factors are orthogonal to the assignment to treatment, and should have no effect on the magnitude of the treatment effect, but decreases the precision of the estimates. Finally, consumer in the treatment group may have their credit lines increased for a second time after the sixth month of the experiment. I verify in Table that results are robust to exclusion focusing on the first six months of the experiment, as well as excluding consumers in the control group that have requested manual limit increases.

I then obtain a consistent estimator from a standard weighted least squares problem. The weight is the inverse of the probability of being included in the sample due to the sampling, calculated as $\frac{N_b}{n_b}$ where N_b = the number of elements in the population and n_b = the number of elements in the sample. Standard errors are adjusted to allow for arbitrary heteroskedasticity. The asymptotic variance matrix estimator is the White (1980) heteroskedasticity consistent covariance matrix estimator applied to the stratified sample, where all variables for observation are weighted

Table 7: Robustness checks

#	Variable	Criterion	(A) Φ_3	(B) Φ_9
(1)	Credit card debt at bank	Full sample, with month dummies	0.090 (0.007)	0.125 (0.011)
(2)		Full sample, demographic controls	0.094 (0.007)	0.126 (0.012)
(3)		Only cards at bank	0.070 (0.007)	0.098 (0.011)
(4)		Excludes undersampled	0.100 (0.012)	0.139 (0.017)
(5)		Excludes $t > 6$	0.105 (0.007)	
(6)		Excludes manual increases in control	0.095 (0.006)	0.136 (0.009)

Note. Table reports the cumulative response of credit card debt to a dollar change in credit card limits. Unless otherwise noted, estimates are obtained using the distributed lag equation (6), on a sample of 54,522 experiment participants. Columns (A) and (B) report the cumulative coefficients $\Phi_\tau = \sum_{j=0}^{\tau} \phi_j$ after 3 and 9 months respectively. The baseline estimation does not control any cross-sectional or time-series controls, as the dispersion in the explanatory variables are orthogonal to all observables by construction. Row (1) adds to equation (6) a complete set of month dummies. These indicator variables control for aggregate effects, including seasonality, changes in monetary policy, and so forth. Row (2) adds to equation (6) demographic controls, e.g., dummies for age, gender, education level and marital status. These variables control for the persistent characteristics of the account holder. Row (3) restricts sample to consumers without credit cards at other banks. Row (4) excludes undersampled treatment group, and runs the distributed lag model on a sample of 26,854 cardholders, as explained in Appendix 7.2. Row (5) estimates equation (6) for periods $t \in \{0, 1, \dots, 6\}$. Consumers in the treatment group may have their limits extended for a second time, after the first six months of the experiment, and these estimates focus on the treatment effect for the first six months. Row (6) excludes consumers in the control group that requested manual line increases.

by their weights. This estimator also works in the presence of heteroskedasticity of arbitrary and unknown form in the population (Wooldridge, 2010). When estimating Equation (6) on a subpopulation, STATA subpop command is used, and all data are used to calculate the standard errors.

7.3 Additional results

Balance shifting. I examine the response of the experiment participants' debt outside the bank using credit bureau data, in order to ensure that increases in credit card debt does not represent mere balance shifting. First, I replace the left-hand side variable in Equation (6) with credit card debt outside the bank. The financial institution gathers credit bureau information on cardholders on an approximately quarterly basis. Therefore I am unable to plot the full impulse response of debt outside the bank, but I am able to measure the cumulative response after 3 and 9 months. Row 4 of Table 3 displays the result. Consumers do substitute away debt outside the bank, by decreasing their debt outside the bank by 1.7 cents after 3 months and 1.2 cents after

9 months, implying that approximately one-tenth of the cumulative response after 9 months is crowded out from other banks. Second, I focus on consumers without cards at any other bank. 41 % of the experiment participants fall into this category. Row 2 of Table 7 reports the results. Consumers in this selected sample accumulate 10 cents of debt per dollar increase in credit card limits, confirming the results that the increase in debt does not represent mere balance shifting.

Defaults. A credit card account is classified by the bank as non-performing if payments of principal are past due by 90 days or more. As experiment participants are pre-selected according to the risk criterion, they do not have any late payments at the onset of the experiment. After 9 months, 234 of 54,522 subjects fall into non-performing status. Therefore default exists in equilibrium, however at a rate less than 0.5%. Moreover, cardholders in the control group are 0.03% *more likely* to fall into non-performing status, with the difference not being statistically significant. ($p = 0.16$). Similarly, there exists no economically or statistically significant difference between the two groups with respect to late payments. As the number of defaults is too low to make any inference, I do not treat them further theoretically or empirically.

Heterogeneity by age. I analyze the life-cycle profile of the response by estimating Equation (6) separately by age bins. First, I group participants to age bins of width 5, and plot the cross-sectional distribution of the marginal propensity to consume out of liquidity after 3 months. Second, in order to contrast the dynamics of the response, I group participants to age bins of width 10, going from 20 to 60, and plot the full impulse responses.

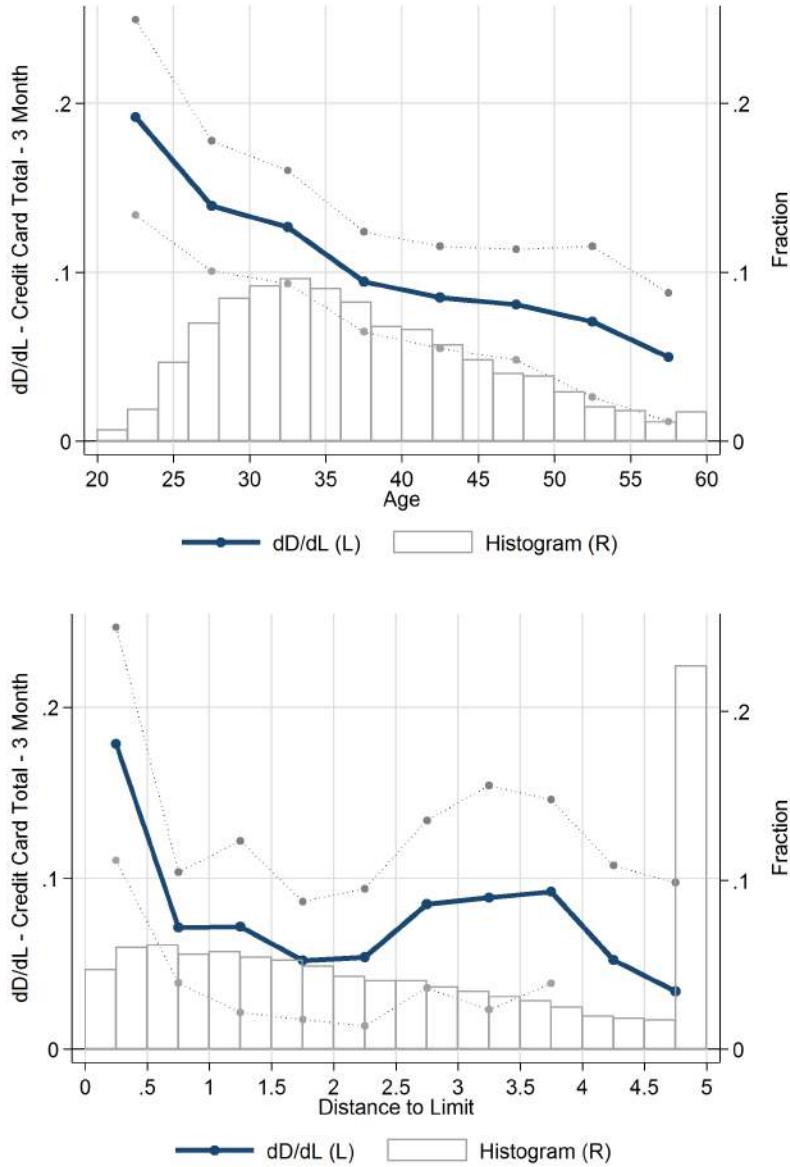
First, Figure 14 plots MPCL(3) by age bins. The life-cycle profile of the marginal propensity to consume out of liquidity declines monotonically with age. For consumers between the ages of 20 to 25 the average MPCL(3) is 0.19. This magnitude is twice as large of a customer in late 30s, and three times as large compared to a customer between the ages of 50 to 55, where the MPCL(3) drops to 0.07. The responses at all age levels are statistically and economically significant.

Second, the *dynamics* of the response also exhibits substantial heterogeneity. Row 1 of Figure 15 plots the full impulse responses of credit card debt for cardholders in their 20s, 30s, 40s, and 50s. Younger consumers not only exhibit larger responses, but also take longer to asymptote to their new target level. Households in their 20s take 5 months to converge their new cash-on-hand target, compared to only 2 months for households in their 50. Finally, although households in their 50s exhibit deaccumulate 2 cents of debt after month 5, the effect is not statistically significant. ($p = 0.16$)

What is the mechanism behind the life-cycle profile of MPCL? Remember that under life-cycle version of the PI, consumption behavior is not effected by a change in liquidity. In models featuring credit constraints and uninsurable income risk, theory predicts the life-cycle profiles of MPCL are determined by two mechanisms:

First, if expected income growth is steep, then younger households consume most disposable resources and hold very little liquid assets. As they age, they save for retirement, and accumulate financial wealth. This financial wealth doubles as a buffer-stock. Thus there would be no additional precautionary saving motive for older consumers and household behavior would be well approximated by PI. The discount factor and income profile is an important determinant of precautionary behavior: absent income growth, households would start saving for retirement early in life. This liquid wealth would double as a buffer-stock. Thus there would be no addi-

Figure 14: Heterogeneity by age and distance to limit.



Note. Graphs plot the cross-sectional heterogeneity of the cumulative response of credit card debt to a dollar increase in limits, after 3 months. The top panel is by age bins of 5. The bottom panel is by distance-to-limit, the sum of net liquid assets plus available credit normalized by average income. Consumers in the first bin have less than half months income of distance to their credit limits, and so on. This variable directly maps to the state variable of the baseline intertemporal model, and can be simulated using the model of Section 5. Consumers with less than five months of distance to limit constitute approximately four-fifths of the population. The theoretical counterpart of this figure is given in the right panel of Figure 3.

tional precautionary saving motive and household behavior would be well approximated by PI. This is the life-cycle buffer-stock model of [Gourinchas and Parker \(2002\)](#).

Second, older consumers have better credit quality and obtain credit on more favorable terms, even conditional on their income. Controlling for limits, there exists no detectable differences in their MPCLs. The two mechanisms based on informational frictions vs life-cycle considerations with respect to income uncertainty have distinct welfare implications. Unfortunately I do not have sufficient power to decompose the two effects.²⁶

Heterogeneity by demographics. I analyze unmodelled heterogeneity by three demographic variables: (i) educational attainment (ii) gender (iii) marital status. In particular, if excess sensitivity of consumption to credit availability is due to a persistent trait, such as that related to time preference and cognition, then demographics may proxy for it. Similarly, household composition is likely to be an important determinant of the response. As family size is not observable, I proxy for it using marital status.

Row 2 of Figure 15 displays the impulse responses of credit card debt by four educational attainments: no high school, high school, college and post-graduate. The variation in the dynamics of MPCL by education resembles very much differences in age. In terms of magnitude, consumers with low educational attainment, those without college degrees, exhibit almost twice the magnitude of the marginal propensity to consume out of liquidity as consumers with college degrees: 0.2 vs 0.1. In terms of dynamics, consumers with college degree converge to new cash-on-hand only after two months, with marginal coefficients ϕ_3, \dots, ϕ_9 jointly insignificant. For the final column, consumers with a post-graduate degree, there is large variation in the response, but the estimates are significant nevertheless.

Row 3 of Figure 15 displays the impulse responses of credit card debt by gender and marital status. I find no significant gender effects in the magnitude or dynamics of MPCL, although the response of women is more variable. I also proxy for having dependents by marital status, but find no detectable differences between consumers that are single or married.

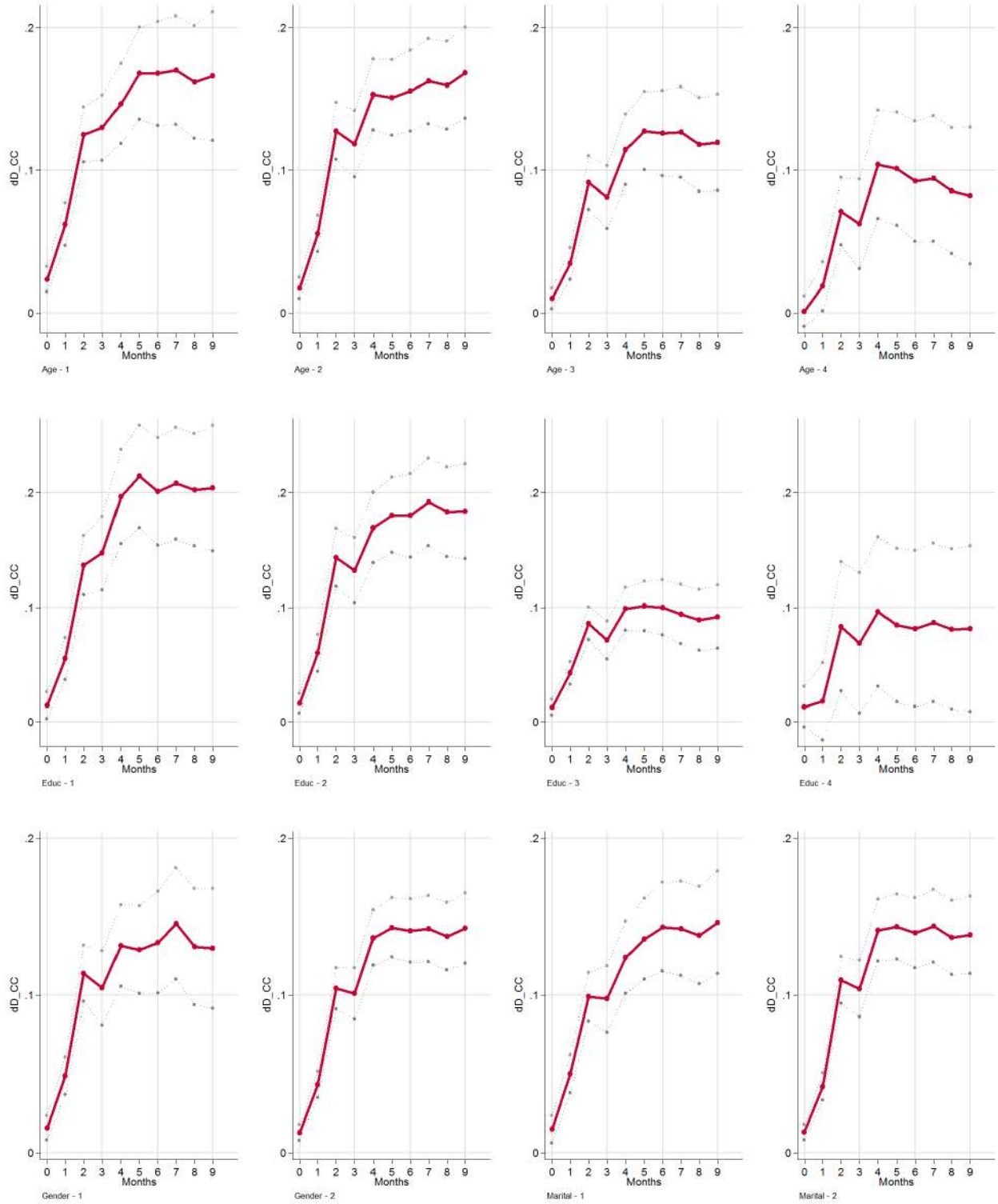
Effects of credit on labor supply. What is the effect of credit availability on labor supply? In models featuring precautionary savings, a relaxation of credit constraints lead households to increase their leverage by also decreasing their labor supply. The reduced form magnitude of this response, and its implications for parameters of the utility function are of particular interest in public economics and labor economics. For example, if increases in disposable resources, such as social insurance, reduce labor supply then optimal unemployment benefits weigh this beneficial liquidity effect to the moral hazard effects ([Chetty, 2008](#)).

I provide preliminary evidence on the labor supply effects of an increase in liquidity. As data on hours worked is not observable, I measure the effect on post-tax labor income. Figure 16 plots the average baseline post-tax labor income for the treatment and control groups between June 2014 and June 2015. I find no evidence of a statistically significant effect of liquidity on baseline wages behavior.

However, most consumers are employed at a fixed monthly salary and may not be able to adjust labor supply on any margin. Therefore, I decompose the overall post-tax labor income into

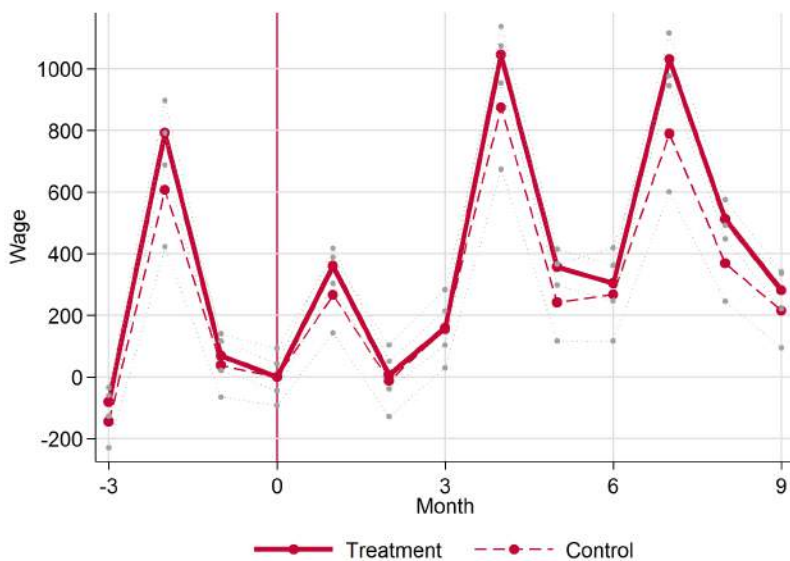
²⁶Due to the short time-frame of the experiment, I am unable to rule out an alternative explanation based on cohort effects. See [Heckman and Robb \(1985\)](#).

Figure 15: Impulse response to credit availability, by demographics



Note. Figure displays the cumulative responses $\Phi_\tau = \sum_{j=0}^{\tau} \phi_j$ of credit card debt to a dollar change in credit card limits, for different demographic groups. Estimates are obtained using the distributed lag equation (6). The first row displays the cumulative responses for consumers in age bins 20-30, 30-40, 40-50 and 50-60. The second row displays the cumulative responses for consumers in education levels bins middle school, high school, college, post-college. The third row displays the cumulative responses for consumers in demographic bins female, male, single, married.

Figure 16: Labor supply response



Note. Figures plots the average post-tax labor income for the treatment and control groups, between June 2014 - June 2015.

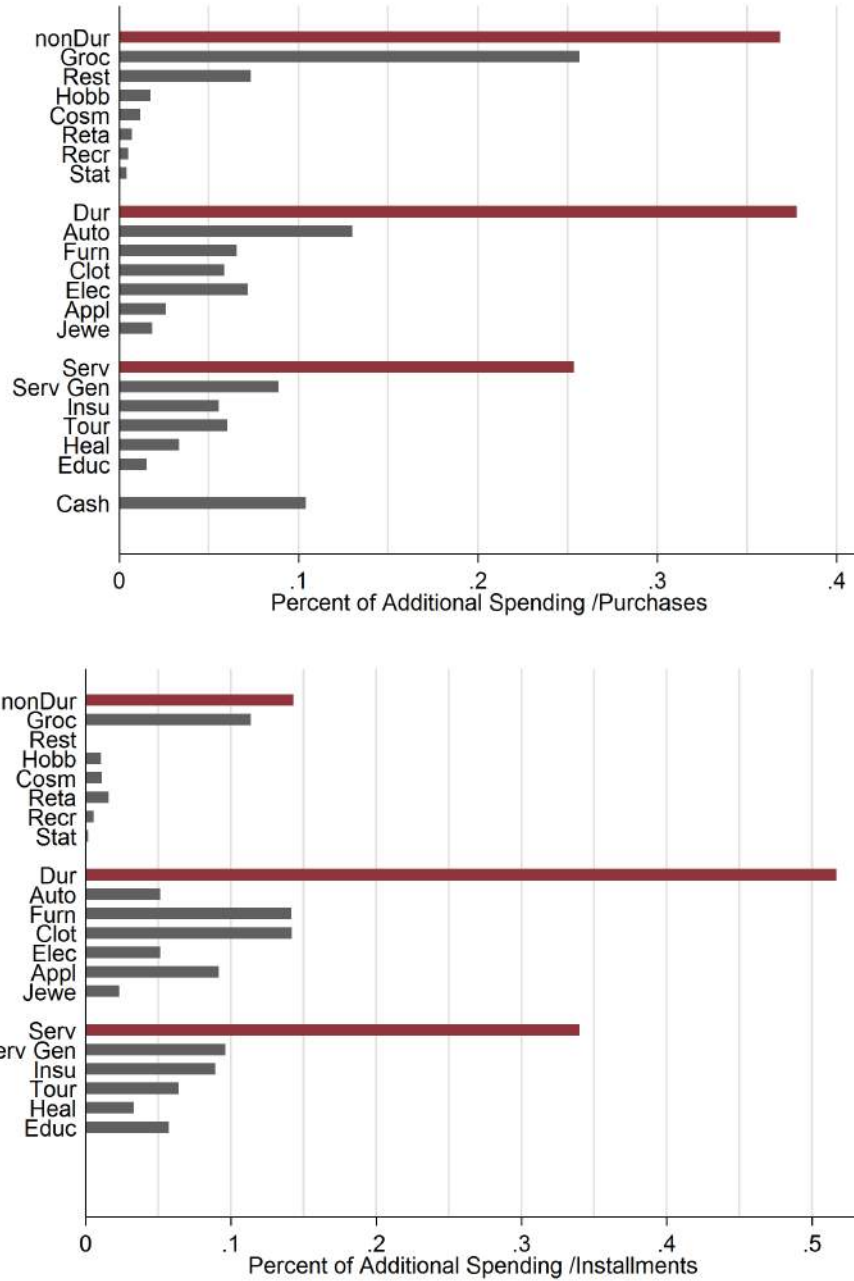
components that better allows to gauge the intensity of work supplied by those in work. I decompose monthly income into four components: (i) baseline salary (ii) overtime pay (iii) individual bonuses (iv) group bonuses. I then pursue an event study, the investigate the effects of credit availability on subcomponents of income. Similarly, I find no evidence of a statistically significant effect of liquidity on labor supply behavior.

7.4 Self-insurance vs investment motives for debt

This section analyzes the comovement of debt with income shocks of various nature, in order to understand the distinct motives for using revolving debt and installment debt. In particular, I show that revolving balances comoves *negatively* with income shocks and installment balances comoves *positively* with income shocks. This section is a condensed version of a companion paper [Aydm et al. \(2015\)](#), which examines the role of liquidity on the transmission of income shocks to consumer spending and debt decisions.

In order to identify the sensitivity of consumption and debt to permanent and transitory income shocks, one needs to identify such shocks, consumer by consumer, from a finite panel of income data. The [Blundell et al. \(2008\)](#) methodology highlights how the sensitivity of behavior to transitory and permanent income shocks can be separately identified. For example, upwards movements in consumption in response to transitory shocks should be followed by mean-reversion to its normal level. This is due to the transitory component of the first differences of income being negatively serially correlated. Therefore next period income growth can be used as an

Figure 17: Spending patterns



Note. Figures plot the categorical composition of the spending response to liquidity. The top panel contains conventional transactions, and the bottom panel contains installment transactions. First, I estimate the response of categorical expenditure for each type of transaction, and each of 18 spending categories (a total of 36 categories), using the distributed lag equation (6) in Section 4 on a sample of 54,522 experiment participants. The figures then plots the share of each category on the total additional spending done by the treatment group. For example, the cash bar indicates that 10% of the additional transactions done by the treatment group has been due to cash withdrawals. The red bars represent the total share of spending in nondurables, durables and services respectively.

instrument for the current period transitory income shock.

I assume a quarterly model of permanent-transitory income to estimate simultaneously the transmission shocks of income shocks to credit card debt. Alongside many advantages, there are two drawbacks of this approach. First, I impose a particular process for income and consumption, therefore it is structural in nature and may suffer from specification bias. Second, the framework does not allow to distinguish between negative and positive income shocks. The latter may be important if liquidity constraints induce an asymmetric response to income shocks with respect to negative and positive shocks.

I restrict sample to experiment participants with wage information. I focus on the 24 month period before the onset of the experiment. I decompose quarterly real (log) income $y_{it} = \log Y_{it}$ to a predictable life-cycle component Ω_{it} , a permanent component y_{it}^P and a stationary transitory component y_{it}^T ,

$$\log(Y_{it}) = y_{it} = \Omega_{it}^Y + y_{it}^P + y_{it}^T \quad (11)$$

I assume that the permanent component is a random walk, $y_{it}^P = y_{i,t-1}^P + \varepsilon_{it}^P$, with $\varepsilon_{it}^P \sim (0, \sigma_P^2)$, and the transitory component $y_{it}^T = \varepsilon_{it}^T$, with $\varepsilon_{it}^T \sim (0, \sigma_T^2)$. Permanent shocks to income may include long-term unemployment, promotions and demotions, health shocks; whereas transitory shocks may include overtime labor supply and bonuses. I assume that the idiosyncratic shocks ε_{it}^P and ε_{it}^T are orthogonal to given information, and their variances are constant over the cross-section. Ω_{it}^C purge business cycle and demographic variation from the data, by conditioning on a set of variables known by the consumers and observable to the econometrician at time t (dummies for age, gender, marital status, region of residence, education, and individual fixed effects.).

I assume that the unpredictable change in credit card debt is a linear function of the permanent and transitory income shocks,

$$\Delta d_{it} = \psi_{it}^P \varepsilon_{it}^P + \psi_{it}^T \varepsilon_{it}^T + \xi_{it} \quad (12)$$

where the effect of the permanent income shock ε_{it}^P and the transitory income shock ε_{it}^T are transmitted with parameters ψ^P and ψ^T respectively. ξ_{it} captures innovations in debt independent of income, such as uncontrolled demographic changes, measurement errors, changes in preferences as well as shocks to higher moments of the income process. The above specification nests a plethora of sensitivity/smoothness specifications.²⁷

I identify the transmission parameters using moments implied by the restrictions on the covariance structure of changes in income and debt. Briefly, sensitivity to transitory shocks shows up as a negative correlation between change in debt and future income, as consumption growth

²⁷At the two extremes are the complete markets benchmark, where consumption is insured against shocks of any nature therefore $\psi^P = \psi^T = 0$, and complete hand-to-mouth existence (autarky) where $\psi^P = \psi^T = 1$. According to the PIH, consumption should respond one-to-one to permanent shocks but transitory shocks should be annuitized, therefore $\psi^P = 1$ and $\psi^T \approx 0$. Models with borrowing constraints or precautionary savings predict only partial insurance against shocks, therefore $\psi \in [0, 1]$.

due to transitory shocks should mean-revert. I use Δy_{it+1} as an instrument for transitory shocks, and $\Delta y_{it-1} + \Delta y_{it} + \Delta y_{it+1}$ as an instrument for permanent shocks.²⁸

Table 8 presents a brief list of estimates of ψ^P and ψ^T , the transmission of permanent and transitory income shocks to revolving and installment debt. The findings confirm that revolving debt comoves negatively with income shocks, and installment debt comoves positively with income shocks.

Table 8: Partial insurance parameter estimates

	Installment	Revolving
Permanent	0.030 (0.027)	-0.083 (0.024)
Transitory	0.006 (0.004)	-0.014 (0.003)

7.5 Policy Applications

Fiscal policy. During the Great Recession, numerous of policy interventions were designed to boost consumption demand, either using fiscal tools (e.g., tax rebates, cash-for-clunkers, first time home buyers credit, unemployment benefits), or by injecting banks with liquidity.²⁹ My results are useful in assessing the feasibility of such stabilization and income maintenance programs. The relative merits and ultimate impact of such programs depend on the form of the stimulus package (cash versus credit, durable versus nondurable), in addition to the state of the consumer income and balance sheets.

My findings provides a natural decomposition of sensitivity to credit availability to a *self-insurance* channel and an *investment channel*, and identifies the aggregate conditions under which each sensitivity would be observed. If aggregate conditions are favorable, then a tightening of credit constraints will lead to a significant drop in consumption and aggregate demand, in particular in durable consumption. On the contrary, if aggregate conditions are not favorable, a relaxation of the credit constraints will not result in be sufficient in boosting durable investment. During downturns, credit will be demanded primarily by consumers at a corner solution to their intertemporal problem, who smooth non-durable consumption, not by unconstrained consumers that adjust their portfolios between durables and credit. These findings are in line with previous studies that attribute the drop in spending between 2007-2009 to the tightening of borrowing constraints, as well as the studies that document the inefficacy of bank-mediated credit expansions in stimulating demand.

²⁸See [Blundell et al. \(2008\)](#) and [Kaplan and Violante \(2010\)](#) for the details of this approach. For an instrument x_{it}^j , the sensitivity of debt growth to income shock ε_{it}^j is given by

$$\psi_{it}^j = \frac{\text{cov}(\Delta d_{it}, \varepsilon_{it}^j)}{\text{var}(\varepsilon_{it}^j)} = \frac{\text{cov}(\Delta d_{it}, x_{it}^j)}{\text{cov}(\Delta y_{it}, x_{it}^j)} \quad (13)$$

²⁹See [Agarwal et al. \(2007\)](#), [Johnson et al. \(2006\)](#), [Mian and Sufi \(2012\)](#) and [Agarwal et al. \(2015\)](#).

A second implication of this distinction pertains to the state-dependence of the heterogeneity of the marginal propensity to consume out liquidity with respect to balance sheet position. As the marginal propensity to consume out of income or liquidity depends both on balance sheet position (liquid asset holdings) and income, understanding the joint ergodic distribution of these state variables is paramount to evaluating policy. During expansions, productive consumers invest in durables by borrowing, therefore consumers with low holdings of liquid assets have high income expectations, and lower marginal propensities. During recessions, consumers at the credit constraint are those that have been borrowing with respect to negative income shocks, and are likely to exhibit higher marginal propensities.

Redistributive monetary policy. The conventional channel through which monetary policy affects aggregate consumption is the intertemporal substitution channel. [Auclert \(2015\)](#) argues that monetary policy can affect aggregate consumption through an additional unhedged interest rate exposure channel: if borrowers (with adjustable rate mortgages) have larger MPCs than the lenders, then a reduction in interest rates will boost consumption of borrowers by more than lenders will cut their consumption. In such a setting, the cross-sectional covariance between MPCs and unhedged interest rate exposures quantifies the effect of redistribution via real interest rates on aggregate demand.

Optimal macroprudential interventions. Household deleveraging episodes can push the economy into a liquidity trap, with depressed consumption and output. Macroprudential policies that restricts leverage could prevent ex-post aggregate demand externalities. [Korinek and Simsek \(2015\)](#) investigate the role of macroprudential policies in mitigating liquidity traps, for example ex-ante macroprudential caps on borrowing. They find that the size of the required intervention depends on the differences in marginal propensity to consume between borrowers and lenders during the deleveraging episode.

Optimal unemployment benefits. A classic empirical results in public finance is that social insurance programs such as unemployment insurance reduce labor supply, interpreted as being due to unemployment benefits distorting the relative price of leisure. However, if an individual cannot smooth consumption perfectly, unemployment benefits affect search intensity through a liquidity effect in addition to the moral hazard effect. [Chetty \(2008\)](#) shows that the optimal unemployment benefit level depends only on the average liquidity and moral hazard elasticities of labor supply.

7.6 Computation

7.7 Calibration

I first calibrate variables for which there exists reliable external evidence. These parameters include variance σ and persistence ρ of the income shocks, employment finding and separating rates π_f and π_s , unemployment benefit v , the gross interest rate for lending R^+ , credit card rate for borrowing R^- , credit limit L and the change in credit limit ΔL , Cobb-Douglas coefficient on nondurables α , durables depreciation rate δ , and cost of adjustment ζ . Their values are reported in Table 4.

Table 9: Job finding and separating rates

Year	Quarter	u_t	u_t^s	π_f	π_s
2014	2	0.102	0.045	0.283	0.043
2014	3	0.105	0.047	0.420	0.041
2014	4	0.109	0.045	0.440	0.040

Borrowing limit and interest rate. The median borrowing limit for experiment participants equals 90% of quarterly income. The median change in the borrowing limit for the treatment group is 40% of quarterly income. The rate on unsecured credit card borrowing is capped by the central bank at 24% APR, and this rate is binding for almost all cardholders. Deflated using the implicit price deflator for personal consumption expenditures, this corresponds to a 16% annual real rate on borrowing. Similarly, the real rate on certificates of deposit is 2% per annum.

Income process and enemployment. I assume a coefficient of autocorrelation of 0.9 and conditional variance of 0.04 for annual wages. I approximate the wage process by a Markov chain, following the approach in [Tauchen \(1986\)](#). For the baseline model in Section 2, I use a 12-state Markov chain. For the extended model in Section 5, I use a 5-state Markov chain.

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.

Let u_{t+1}^s denote the number of short-term unemployed workers, workers unemployed for less than a quarter at period t . Assuming all unemployed workers find a job with probability π_f in the given quarter, the unemployment rate next month is given by the number of unemployed workers that fail to find a job plus the number of the unemployed. Solving this for π_f

$$\pi_f = 1 - \frac{u_{t+1} - u_{t+1}^s}{u_t} \quad (14)$$

In order to calculate the separation rate, I assume that whenever an employed worker loses his job, she becomes unemployed, and has half a quarter to find a job before being recorded as unemployed. The separation rate is then given by the ratio of short-term unemployed workers, to the employed workers this month,

$$\pi_s = \frac{u_{t+1}^s}{(1 - u_t) \left(1 - \frac{1}{2}\pi_f\right)} \quad (15)$$

Table 9 displays the values for the last three quarters of 2014. Finally, I take the state provided unemployment benefit as 40% of monthly income.

Durables. Durables in the model capture consumer durables (e.g., furnitures, appliances) and services (e.g., health, education) I estimate α , the ratio of non-durable consumption to total consumption, from the long-run cost shares, following [Ogaki and Reinhart \(1998\)](#). The average value between January 2008 to September 2014 gives us $\alpha = 0.4$. I assume a quarterly depreciation rate of 3%, which corresponds to a half-life of 24 quarters, and expected service life of 12

years. I set the proportional loss on durables sales to 20%.

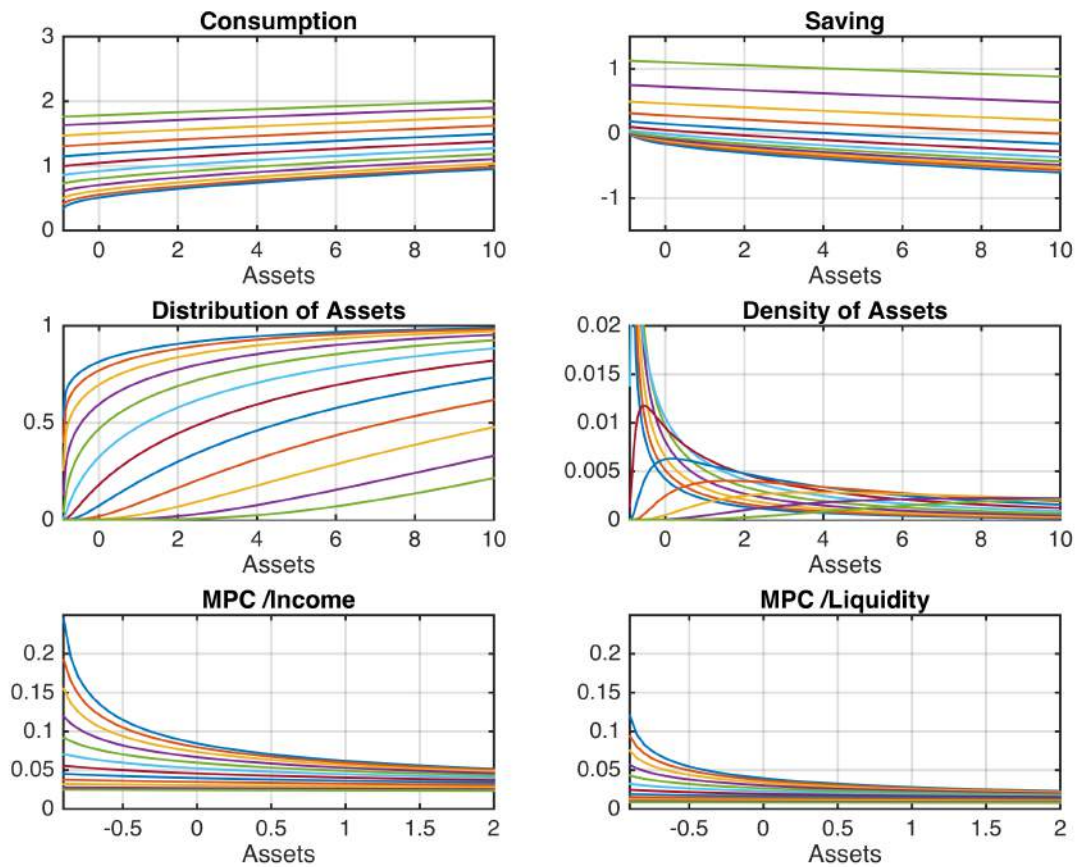
Note that both the chosen depreciation rate, and the adjustment cost parameter are significantly larger than what is commonly used, in order to capture more realistically the further illiquidity of small durables compared to residential investment. For example, when modeling residential housing, the range of commonly used depreciation rates vary between 1% and 1.30% quarterly, leading to a service life of 25 to 36 years.

Table 10: Optimality Conditions for Model with Durables

#		Variable	Condition	
(1)	FOC	C	$U_C(C, K) = \lambda$	
(2)		A'	$\beta \mathbb{E}[V_A(A', K', Y') Y] + \mu = \lambda R^+$	$A' > 0$
(3)			$\beta \mathbb{E}[V_A(A', K', Y') Y] + \mu = \lambda R^-$	$D' > 0$
(4)			$\lambda R^+ \geq \beta \mathbb{E}[V_A(A', K', Y') Y] + \mu \geq \lambda R^-$	$A' = 0$
(5)		K'	$\beta \mathbb{E}[V_K(A', K', Y') Y] + \mu = \lambda$	$K' \geq K$
(6)			$\beta \mathbb{E}[V_K(A', K', Y') Y] + \mu = \lambda(1 - \zeta)$	$K' < K$
(7)			$\lambda \geq \beta \mathbb{E}[V_K(A', K', Y') Y] + \mu \geq \lambda(1 - \zeta)$	$K' = K$
(8)	EC	A	$V_A(A, K, Y) = \lambda$	
(9)		K	$V_K(A, K, Y) = U_K(C, K, N) + \lambda(1 - \zeta)$	$K' > K$
(10)			$V_K(A, K, Y) = U_K(C, K, N) + \lambda(1 - \delta - \zeta)$	$K' < K$
(11)			$V_K(A, K, Y) = U_K(C, K, N) - \delta \lambda$ $+ \beta \mathbb{E}[V_K(A', K', Y') Y] + \mu \Xi$	$K' = K$
(12)	CS	μ	$A' + \Xi K' = 0$	$\mu > 0$
(13)			$A' + \Xi K' > 0$	$\mu = 0$

Note. Table displays the optimality conditions for the extended model with durables and the wedge between borrowing and lending rates. See Section 5 and [Guerrieri and Lorenzoni \(2015\)](#) for details. λ and μ denote Lagrange multipliers associated with the consumer's intertemporal optimization problem. Row (1) is the first order condition for consumption decision. Rows (2) to (4) are the first order conditions for liquid asset decisions, if the consumer is a net saver, net borrower, or hold no liquid assets. Rows (5) to (7) are the first order conditions for durable decisions, for the cases consumer adjusts upwards, downwards, or only covers the depreciation. Row (8) is the envelope condition for liquid asset decisions. Rows (9) to (11) are the envelope conditions durable decisions. Rows (12) and (13) are the complementary slackness conditions for the credit constraint.

Figure 18: Simulation Results: Baseline Model



Note. Figures display the simulation results from the baseline intertemporal model of Section 2. The model is quarterly, and assume a annualized discount factor of 0.92 and a coefficient of relative risk aversion of 2. See Section 7.7 for details of calibration. The x-axis in each graph is assets, the first state variable. Each line corresponds to a distinct realization of the persistent income process, the second state variable. The income process is approximated by a 12-state Markov chain following the approach in Tauchen (1986). Top left panel displays the optimal consumption policy as a function of assets. Policy functions are calculated by iterating the Euler Equation (5) using the endogenous grid-points method of Carroll (2006). Top right panel displays the optimal bond accumulation policy. The middle panels display the ergodic distribution and density of liquid assets. Ergodic distribution of liquid assets is calculated by updating the conditional bond distribution, as discussed in Guerrieri and Lorenzoni (2015). The bottom panels display the MPC out of a shock to disposable resources, of a magnitude equal to 40% of quarterly income (120% of monthly income). The bottom left panel is the MPC out of a transitory change in assets and the bottom right panel is the MPC out of a permanent relaxation of borrowing limits. See Section 2 for details on the calculation of MPC.