NBER WORKING PAPER SERIES

CREDIT CONSTRAINTS IN THE MARKET FOR CONSUMER DURABLES: EVIDENCE FROM MICRO DATA ON CAR LOANS

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Working Paper 7694
http://www.nber.org/papers/w7694

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2000

We would like to thank Richard Blundell, Bo Honoré, Tom MaCurdy, Costas Meghir, Derek Neal, Josef Perktold, and Frank Wolak for useful conversations and suggestions. We also received useful comments from the audiences of the workshop "Aggregate implications of microeconomic consumption behavior" at the Summer Institute of the NBER in July 1996, the SITE workshop "Structural Models in Industrial Organization and Labor Economics" at Stanford in August 1996, the 1999 Econometric Society European Summer Meetings in Santiago de Compostela, Spain, and the 2000 Winter Meetings of the American Economic Association in Boston. Goldberg thanks the NSF (Grant SBR-9731979 through the NBER) and the Sloan Foundation Faculty Research Fellowship Program for financial support. Eduardo Fajnzylber provided excellent research assistance. The views expressed herein are those of the authors and not necessarily those of the National Bureau of Economic Research.

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NBER Working Paper No. 7694
May 2000
JEL No. D0, E0, G2, H0, L0

ABSTRACT

We investigate the empirical significance of borrowing constraints in the market for consumer loans. We set up a theoretical model of consumer loan demand, which in the presence of credit rationing implies restrictions on the elasticities of loan demand with respect to the interest rate and the maturity of the loan. We estimate these elasticities and test the theoretical implications using micro data from the Consumer Expenditure Survey (1984-1995) on auto loan contracts. The econometric specification that we employ accounts for important features of the data: selection, censoring, and simultaneity. Our results suggest that credit constraints are binding for some groups in the population, in particular for young and low-income households.

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1 Introduction

The existence of borrowing constraints in the market for consumer loans has important implications at both the micro and macro levels. At the micro level, credit constraints can affect both the intra- and intertemporal allocations of resources and have important consequences for the effects of various policy measures. At the macro level, liquidity constraints, as borrowing restrictions are often characterized, have been invoked to explain the observed correlation between expected consumption and income growth, and the rejection of the permanent income hypothesis. Moreover, the possibility that individual agents have limited means of smoothing consumption over time has been for a long time considered as a justification for a Keynesian consumption function (see for instance Flemming, 1973). But despite the importance of the topic, and the substantial amount of

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theoretical and empirical research that has been devoted to it, there is still no conclusive evidence on the significance of credit rationing in consumer loan markets.

A potential explanation for this lack of consensus is the fact that most empirical work on the subject has utilized only consumption data, and not data on loans. The majority of this work has been framed in terms of a test of the life cycle - permanent income hypothesis, focusing on the excess sensitivity of consumption to expected labor income (see, for example, Hall and Mishkin (1982), Hansen and Singleton (1982, 1983), Altonji and Siow (1987), Zeldes (1989), Runkle (1991)). The problem with this approach is that the interpretation of the results critically depends on explicit or implicit assumptions about the utility function. In particular, the inference of the existence of credit constraints often rests on the assumption of separability between consumption and leisure, which has been empirically rejected (Browning and Meghir (1991)).

More recently, another set of papers has tried to exploit the idea that in the presence of (at least partly) *collateralizable* loans (this is the case with the financing of durables), liquidity constraints introduce distortions in the intratemporal allocation of resources between durables and non-durables (Brugiavini and Weber (1992), Chah et al. (1995), Alessie et al (1997)). But this idea was again implemented using only data on aggregate or household consumption.

Departing from this tradition, Jappelli (1990) relied on survey questions to identify individuals who have been denied credit, or feel that they would have been denied, had they applied for it. While this approach is direct, and circumvents the interpretation difficulties associated with the previous ones, there is some concern as to the accuracy of the responses to the questions. Given that liquidity constraints are primarily restrictions placed on borrowing, it is rather surprising that none of the above papers have utilized data on borrowing behavior to test for credit rationing.[1]

This paper attempts to fill in this gap by proposing and implementing a novel approach for testing for borrowing constraints that exploits micro data on car loans. Our basic idea is that borrowing restrictions have specific implications for certain features of the demand for loans, and in particular for its interest rate and maturity elasticities. By testing these implications, one can shed some light on the empirical significance of credit restrictions. The strength of this approach is that it does not rely on functional form assumptions concerning the utility function. It is particularly promising if information on loan contracts is combined with data on socioeconomic characteristics to identify households that are likely to face liquidity constraints.

Our focus on the demand for loans forces us to be specific about what we mean by borrowing constraints. Our starting point is Jaffee and Stiglitz's (1990) definition of credit rationing as a situation in which there exists an excess demand for loans at the current interest rates of primary lenders. A strict interpretation of the above definition identifies liquidity constrained consumers as individuals who face an absolute limit in the amount they can borrow against their future income. A weaker interpretation extends the definition to consumers for whom interest rates are not independent of their net asset positions (Pissarides (1978)); of course, the former interpretation can be thought of as a special case of the latter one, if the borrowing rate goes to infinity at the borrowing limit.[2]

[1] To the best of our knowledge, the only studies that have in the past exploited information on borrowing behavior, are Juster and Shay (1964) and Avery (1978), who used experimental data to test for credit constraints.

[2] As shown by Stiglitz and Weiss (1981), such borrowing constraints can arise as an equilibrium phenomenon in the presence of information asymmetries. Modelling these asymmetries is beyond the scope of this paper; instead, we treat borrowing constraints as exogenously given. Our formulation does allow, however, for the borrowing limit

Whatever interpretation one adopts, the implication for the optimization problem facing the consumer is the same; credit constraints introduce kinks and convexities in the intertemporal budget set. Liquidity constrained individuals are the ones who are either at a kink, or in the steeper portion of the budget set. This leads to the following testable implication which will be discussed in the theoretical section below. The demand for loans of unconstrained individuals, consuming at the flatter portion of the budget set, should be a function of the price of the loan (the primary interest rate), but independent of the loan maturity; liquidity constrained consumers, on the other hand, should respond less to changes in the primary interest rates, and more to changes in the borrowing limit. In consumer loan markets, changes in the borrowing limit are primarily achieved through changes in loan maturities; a longer maturity decreases the size of the monthly payment, allowing the consumer to assume a larger amount of debt.[3] [4] Hence, one can test for the presence of credit rationing, by estimating the elasticities of loan demand with respect to interest rate and maturity, and testing the null hypothesis that the maturity elasticity is equal to zero.

Juster and Shay (1964) were the first to stress the implications of borrowing restrictions for the interest rate and maturity elasticities of the demand for loans. It is therefore worth describing the main features of their methodology and results in some detail, and explaining in which major ways our approach differs from theirs. Juster and Shay used experimental data to assess the responsiveness of loan demand to interest rate and maturity. The data were based on a questionnaire that was sent to ca. 16,000 households in 1960, asking them to indicate their preferences among a set of hypothetical financing arrangements. All respondents faced the same problem, namely financing the purchase of a $1,500 automobile. The arrangements, however, differed with respect to finance rates and maturities. Juster and Shay found that, contrary to the widely held view that consumer borrowing did not depend on finance rates, a significant fraction of the households surveyed seemed to respond to interest rates. The response was, however, more pronounced among consumers who, on the basis of various criteria such as age, income, asset holdings, and attitude towards credit, were likely to be unconstrained. Consumers who were likely to be constrained on the basis of the same criteria, were instead shown to be more responsive to changes in the size of monthly payments. The great advantage of the experimental data was that they offered observations on the (hypothetical) loan terms facing individuals who chose not to finance. On the negative side, the results are subject to the usual criticism of survey responses, that the way people talk may not reflect the way they act. Furthermore, the ingenious randomization used by Juster and Shay in the packages offered to different consumers, which allows them to identify interest rate and maturity elasticities of loan demand, yields fairly imprecise estimates given the sample size.

In contrast to Juster and Shay we do not have experimental data, but micro data on auto loan contracts from the Consumer Expenditure Survey (1984-1995). Such contracts are an important, and fast growing component of consumer installment credit - Sullivan (1987), for example, reports

to be a function of observable consumer characteristics, as long as these do not involve actions taken by consumers to maximize intertemporal utility. See also Alessie et al (1997).

[3] The implicit assumption here is that debt repayment, rather than finance charges, dominates the size of the monthly payments. This is probably a realistic assumption for the credit markets for durables which are characterized by short term contracts.

[4] One could argue that downpayment requirements have a similar function, as they effectively limit the amount that can be borrowed. In the U.S., however, anecdotal evidence suggests that downpayment requirements are unlikely to be binding in the automobile loan markets, as most consumers use the receipts from trade-in allowances, to satisfy them. In addition, such requirements have, in many markets, dropped to zero in recent years.

that 39% of consumer credit is auto credit. We see the main strengths of our data set as being threefold: First, there is substantial time variation in interest rates and maturities that we exploit to identify the parameters of the loan demand equation; Sullivan (1987) and recent bank sources document that the average maturity on a loan contract for a new car has increased from 40 months in 1977, to 51 months at the end of 1985, 60 months by the end of 1990, and 72 months in recent years, while interest rate ceilings have been removed. To the extent that this variation is exogenous - and we argue that it is - it offers an ideal experiment for the purpose of identifying credit constraints.[5] Second, our information refers to actual household behavior rather than responses to hypothetical questions. Third, the information on demographics allows us to split the sample into various subgroups, some of which are more likely to be credit rationed than others (for example young households), and test for the presence of credit rationing separately in each of them. We are particularly interested in comparing the relative sizes of interest rate and maturity elasticities across groups.

With all its advantages, however, our data also poses several challenges: First, there is potential selection bias - observations on financing are available only for consumers who purchased a car and decided to finance such a purchase. Second, our data is censored: financing is bounded between 0 and the value of the car. Third, simultaneity issues are likely to be important - both the observed interest rate and maturity of a realized loan are likely to be correlated with unobserved consumer heterogeneity. Finally, normality assumptions often used in the estimation of selectivity models seem particularly inappropriate in our framework. If one considers the loan terms facing an individual consumer to be the results of a search process (this would, for example, be the case if the consumer chooses the lowest interest rate and the maximum maturity among various offered alternatives), then the corresponding loan variables observed in our data would not be distributed normally, even if the original distribution of interest rates and maturities were.

We develop an estimation approach that deals with each of these issues. We first specify an empirical model which - while not directly derived from a full structural model - is informed by a three period model developed in the next section. We next estimate this model by both maximum likelihood (for comparison purposes), and a semiparametric approach that relaxes the joint normality assumption, requiring only that the error terms are independent of the conditioning variables, and that the sampling across households is i.i.d.. We find the employment of the semiparametric method to be a very rewarding exercise indeed, as the results obtained by that method are both significantly different from the ones obtained by maximum likelihood, and consistent with the predictions of the theoretical model. In addition, we believe that the estimation approach we propose represents a methodological contribution. In particular, our method of dealing with endogenous variables in a semi-parametric sample selection model is novel. To the best of our knowledge, this problem has not been considered before in the literature, with the exception of a recent paper by Blundell and Powell (2000), who have proposed an alternative estimator for a binomial model.

[5] A natural question in this context is what is the reason for the increase in maturities in the 1980's and 1990's. The industry wisdom is that this increase occured in response to special financing deals offered by Japanese manufacturers in the late 1980's. In particular, the story in the industry is that a strong yen put upward pressure on the U.S. dollar denominated list prices of Japanese cars in the late 1980's. To offset the negative effect of this price increase on consumer purchases, Japanese manufacturers introduced a system of special financing arrangements (leasing, lower downpayments, longer maturities), which effectively lowered consumers' monthly payments. The rest of the market soon followed.

In terms of empirical results, we find that while the demand for loans is sensitive to the interest rate, the interest rate sensitivity is largest for older rather than younger consumers, and for consumers with relatively large current income. Moreover, we find strong maturity effects, indicating the presence of binding borrowing restrictions. The maturity effects, once again, are more relevant for the groups that one would expect to be liquidity constrained. Interestingly, the only consumer groups for which we do not find significant maturity effects (but do find the strongest interest rate effects) are the middle age group, and the consumer group with the largest current income.

The remainder of the paper is organized as follows: In the next section, we formalize the above discussion by developing an intertemporal utility maximization model that incorporates two sources of budget set kinks: First, there is an upper bound on the amount that can be borrowed in a single period; second, individuals face different interest rates depending on their net asset positions. We use this model to derive the implications of credit rationing for the interest rate and maturity elasticities of loan demand. Section 3 discusses our empirical model and estimation approach; section 4 describes our data and offers some preliminary descriptive results, and section 5 discusses the results from the estimation of the model. Section 6 concludes.

2 A three-period model

To consider the effect of maturity on loan demand, it is necessary to construct a model with at least three periods, so that the effect of extending the maturity from one to two periods can be analyzed. To simplify the algebra and obtain closed form solutions, we introduce some strong assumptions, none of which, however, is essential to our results. The list of assumptions is the following:

(*i*) there are three periods;

(*ii*) there is no uncertainty;

(*iii*) the utility function is intertemporally separable and defined over non-durables and cars; utility is separable between cars and non-durables;

(*iv*) the relative price of cars and non-durables is fixed and equal to 1; the depreciation rate is 0;

(*v*) the income process is exogenous; income is substantially higher in the third period.

(*vi*) cars can only be bought in the first period, and cannot be sold in subsequent periods;

(*vii*) consumers can finance a fraction ϕ of their value, where ϕ is between 0 and 1;

(*viii*) there is a single asset and a single liability; the interest rate on the former is lower than that on the latter; the asset cannot be held in negative quantities; the liability can be used only to finance car purchases;

(*ix*) loans can have maturity (m) equal to 1 or to 2; if the maturity is 2, consumers can choose how much to repay each period. Each payment, however, has to be non-negative, that is consumers cannot borrow more money in subsequent periods.

Assumptions (i) to (iv) are not particularly important and are made only for the purpose of obtaining a closed form solution. The assumption concerning the income process (assumption (v)) serves two purposes. First, by making the income process exogenous we simplify the algebra. Second, the fact that income is much higher in the third period compared to the first two periods makes the problem interesting in that it gives the consumer an incentive to move resources from the future to the present, that is, to borrow.

Assumption (vi) is stronger. By letting consumers buy a car only in the first period, we avoid having to model car purchases in every period, and we can abstract from transaction costs. In addition, assumption (vi) allows us to abstract from the issue of timing in car purchases, that is conceivably affected by credit conditions. As mentioned above, the primary motivation for this rather restrictive assumption is analytical tractability; the fact that our focus in this paper is on the interest rate and maturity sensitivity of loan demand, *conditional* on the decision to buy a car, provides an additional justification.

Assumptions (vii) to (ix) specify the nature of the loans available to the individual consumer. They incorporate our definition of liquidity constraints in the dimensions we mentioned above: the difference between lending and borrowing rates, and the requirement to collateralize the loan with the value of the car. Note also that consumers in this model can only borrow in the first period. If one wants to compare the results of our model to an ideal benchmark in which there are no liquidity constraints, one can relax these constraints; that is one can make the interest rates on loans and assets the same, allow consumers to borrow more than the value of their cars, and give them the possibility of borrowing in the second period to transfer resources from the third to the second period. The assumption that in the two-period maturity case the repayment in each period has to be greater than or equal to zero (assumption (ix)) is consistent with the basic institutional setting in the car loan market.

Given these assumptions, the consumer solves the following maximization problem:

$$\max_{\{C_j\}_{j=1,2,3},K,\phi} U(C_1) + \beta U(C_2) + \beta^2 U(C_3) + V(K)$$

subject to

$$
\begin{array}{ll}
\lambda_1 & C_1 + K(1-\phi) \le y_1 \\
\lambda_2 & C_2 + P - \left(1+r^l\right) \underbrace{\left(y_1 - C_1 - K(1-\phi)\right)}_{A_1} \le y_2 \\
\lambda_3 & C_3 + \underbrace{\left[\phi K \left(1+r^b\right) - P\right]\left(1+r^b\right)}_{P'} - \left(1+r^l\right) \underbrace{\left[y_2 - C_2 - P + \left(1+r^l\right)\left(y_1 - C_1 - K(1-\phi)\right)\right]}_{A_2} \le y_3 \\
\lambda_4 & \phi \le 1 \\
\lambda_5 & -\phi \le 0 \\
\lambda_6 & -P \le 0 \\
\lambda_7 & P - \phi K \left(1+r^b\right) \le 0
\end{array}
$$

and the terminal condition, $A_3 = 0$. Here y_i and C_i are income and non-durable consumption in period i, and A_i is the asset at the end of period i, which pays interest rate r^l. K is the value of the car purchased by the individual in the first period, of which a proportion ϕ is financed, while r^b

is the borrowing rate. Note that by assumption $r^l < r^b$. P is the first payment on the loan in the second period. P' is the second payment on the loan in the third period, which may be non-zero when the maturity equals to two periods. The first three constraints say that net assets cannot be negative. The next two constraints dictate that the financing share has to lie between 0 and 1. The sixth constraint says that the first payment cannot be negative, i.e. the consumer cannot finance more than the value of the car. The last constraint says that the consumer can at most pay back the entire value of the loan. With each one of the constraints above we associate a Kuhn-Tucker multiplier denoted by λ_k $(k = 1, ..., 7)$. Below we discuss certain aspects of the possible equilibria when the maturity of the loan is one or two periods.

2.1 Characterizing the solution

Maximum Maturity=1

When the maximum maturity is one, P is constrained to be equal to $\phi K \left(1 + r^b\right)$. In this case some consumers, depending on the pattern of their income and preferences, will be at corners; that is they will set either $\phi = 1$ or $\phi = 0$. Such points correspond to kinks in the intertemporal budget constraint (IBC). Others, instead, will be on flat parts of the IBC and the equilibrium will be described by a tangency condition relating the ratio of marginal utilities to the relevant intertemporal price. In addition, the presence of liquidity constraints in this model can also distort the allocation between durables and non-durables: for consumers who want to transfer resources from the future to the present, cars will become relatively more attractive as they constitute the only way consumers can borrow.[6]

Note that given the difference between lending and borrowing rates, no consumer will simultaneously choose $A_1 > 0$ and $\phi > 0$.[7] Hence, if $A_1 > 0$, the optimal finance share is zero, and the Euler equation links the consumption in periods 1 and 2 to the interest rate r^l:

$$U_{C_1} = \beta U_{C_2}(1 + r^l)$$

A second case to consider is one in which the finance share is zero but the first period assets A_1 are also zero. The Euler equation for these consumers is characterized by a slack term:

$$U_{C_1} = \lambda_1 + \beta U_{C_2}(1 + r^l)$$

In other words, these consumers face a shadow interest rate that lies between the borrowing and the lending rates.

In either case, since the maximum maturity is one period, consumers with $\phi = 0$ will not have a chance to borrow in period 2 and move resources from period 3 to period 2. The equilibrium condition will therefore be either an Euler equation involving r^l (if $A_1 > 0$), or an Euler equation involving a notional (but unobservable) interest rate that is higher than the lending rate (if $A_1 = 0$).

[6] This point was made by Brugiavini and Weber (1992) and Chah, Ramey and Starr (1995). For consumers who are saving instead, the allocation between durables and non-durables is given by the standard intratemporal first order condition that relates relative prices (assumed here to be one) to the ratio of marginal utilities.

[7] This and subsequent claims are proven in an Appendix available at http://www.econ.ucla.edu/kyria.

For consumers who borrow a positive amount (but less than K), so that $0 < \phi < 1$, the interest rate that enters the Euler equation is r^b. Their Euler equation is:

$$U_{C_1} = \left(1 + r^b\right) \beta U_{C_2}$$

Consumers who want to borrow more than K, will not be able to do so. These consumers will set $\phi = 1$, and will have a Kuhn-Tucker multiplier entering the intertemporal first order condition:

$$U_{C_1} = \lambda_4 + \left(1 + r^b\right) \beta U_{C_2}$$

Since these consumers will not be able to increase their finance share even if maturity is extended to two periods, we focus on consumers with interior values of the finance share.

Consumers with $0 < \phi < 1$ will set $A_1 = 0$ and may have A_2 equal or greater than zero. Although we cannot solve for the optimal finance shares for these consumers without further assumptions on the form of the utility function, we can characterize the optimal car value. If the optimal ϕ is less that one we can show that in equilibrium $U_{C_1} = V_K$. When the optimal ϕ is one, however, the equilibrium condition for K involves a Kuhn-Tucker multiplier:

$$\left(1 + r^l\right) V_K = \left(1 + r^b\right) U_{C_1} - \lambda_1$$

If $V'' < 0$, this implies that the optimal K increases when the liquidity constraint is binding.

Maximum Maturity=2

The case of the two-period maturity is more complex, as we have to consider both the allocation between periods 1 and 2, and the allocation between periods 2 and 3. Given our assumptions, consumers can now choose how much to repay in each period, as long as the repayment amounts are non-negative. This structure assumes more flexibility in the repayment schedule than what is actually observed in practice,[8] but by focusing on the least constraining case, we avoid making specific assumptions about the repayment schedules and obtain more general results.

In characterizing the equilibrium when maturity is equal to two periods, it is useful to make the following observations. First, $\phi A_1 A_2 = 0$. Thus, if $A_1 > 0$ and $A_2 > 0$, then $\phi = 0$. This means that, to the extent that we are interested in interior values of the finance share (i.e. in $0 < \phi < 1$), we can concentrate on cases where the assets are zero in at least one period. We next summarize our findings for this case under different repayment schedules.

If the repayment amount in period 2 is zero (i.e. $P = 0$), then it is possible that the consumer finances a fraction of the car purchase even if the first period or second period assets are positive. Hence, there are three conceivable subcases: (a) $A_1 = A_2 = 0$, (b) $A_1 > 0, A_2 = 0$, and (c) $A_1 = 0, A_2 > 0$. However, given the difference in the borrowing and lending rates, it is not possible to have simultaneously $P = 0$ and $A_2 > 0$.

If the repayment in period 2 is positive but less than the entire value of the loan ($0 < P < \phi K(1 + r^b)$), then it is not possible to have $0 < \phi < 1$, $A_1 = 0$ and $A_2 > 0$ at the equilibrium, nor can we have $0 < \phi < 1$, $A_1 > 0$ and $A_2 = 0$. For a positive repayment amount in period 2 and interior values of the finance share, the only relevant case is thus the one in which both $A_1 = 0$ and

[8] In practice consumers face fixed repayment schedules; even though they may have some choice among schedules, they usually face more stringent constraints than the non-negativity constraint imposed here.

$A_2 = 0$. The consumer is here trying to move resources from the last period of his/her life to the earlier ones.

Finally, we allow consumers to repay the entire loan in the first period ($P = \phi K(1 + r^b)$). In this case the optimal finance shares when $A_1 = A_2 = 0$ or $A_1 = 0, A_2 > 0$ coincide with those obtained when the maximum maturity is equal to 1, while, as in the one-period maturity case, it is not possible to simultaneously have $0 < \phi < 1$ and $A_1 > 0$.

Similar to the one-period maturity case, we can show that for consumers with $0 < \phi < 1$ and $P > 0$, the Euler equation is:

$$U_{C_1} = \left(1 + r^b\right) \beta U_{C_2}$$

while if $P = 0$, it is $U_{C_1} = \left(1 + r^b\right)^2 \beta^2 U_{C_3}$. And as before, we can characterize the optimal K for consumers with $0 < \phi < 1$ through the relationship, $V_K = U_{C_1}$.

In short, our discussion of the solution of the model for the cases in which the financing share is an interior point may be summarized in the following Table:

$0 < \phi < 1$	$A_1 = A_2 = 0$	$A_1 = 0, A_2 > 0$	$A_1 > 0, A_2 = 0$
$m = 1$:	ϕ_{11}^*	ϕ_{12}^*	NA
$m = 2$:			
$P = 0$	ϕ_{21}^*	NA	ϕ_{22}^*
$0 < P < \phi K\left(1 + r^b\right)$	ϕ_{23}^*	NA	NA
$P = \phi K\left(1 + r^b\right)$	ϕ_{11}^*	ϕ_{12}^*	NA

NA means that the optimal share is not a feasible solution. To derive an explicit expression for the optimal ϕ's, and compare the effects that the interest rate has in the various cases, we have to be specific about the form of the utility functions for non-durable consumption $U(C)$, and durable consumption $V(K)$. In the Appendix we give the expressions for the optimal ϕ's in the table assuming isoelastic functions,[9] that is, $U(C) = C^{1-\gamma}/1 - \gamma$, and $V(K) = K^{1-\gamma}/1 - \gamma$. Which of the entries is relevant, depends on the particular assumptions one makes about the income process, the interest rates and the parameters of the utility function. We should point out that these assumptions are not used in the empirical part. They are only made in this section to help us study the effects of a maturity increase on the finance share.

2.2 Liquidity Constraints and the Effects of a Maturity Increase

To study the effects that an increase in the maximum maturity has on the loan demand of liquidity constrained consumers, one has to compare the optimal finance share in the one-period maturity case to the optimal finance share in the two-period case. The discussion in the previous subsection

[9] For the derivation of the optimal ϕ's, see the additional Appendix.

should immediately make clear that this is a very difficult task. Even when one assumes specific functional forms, the expressions for the optimal finance shares depend on which specific constraint is binding in each case; depending on the particular values of the multipliers and the values of each period's assets (which of course are endogenously determined in the model) one can obtain a variety of optima, and an evaluation of the effects of a maturity increase requires a large set of bilateral comparisons.

In analyzing the effects of maturity, it is useful to distinguish between two cases: the case where the optimal finance share takes interior values, and the case where the consumer is at a corner (this corresponds to $\phi = 0$, or $\phi = 1$). As mentioned above, for consumers who are at an interior and decide to pay off the entire amount of the loan in the second period, maturity has no effect on loan demand. These consumers are obviously not constrained in the sense considered in this paper. However, in many cases consumers at an interior solution will have different optimal shares depending on whether the maximum maturity is one or two periods. To show how the optimal finance shares change as a function of maturity, we look at some specific numerical examples below.

For consumers at a corner, the argument is less clear cut. Suppose that the consumer's preferences and income path are such that he/she sets $\phi = 0$ in both the case where the maximum maturity is one, and the case where the maximum maturity is two. Then a maturity extension obviously has no effects on the fraction financed, even though the consumer may very well be liquidity constrained. The same applies to the case $\phi = 1$. Hence the experiment of a maturity increase will not be very useful in identifying liquidity constrained consumers who are at corners. To the extent of course that a consumer switches from $\phi = 0$ in the one-period maturity case to $\phi > 0$ in the two period case, the maturity increase experiment can be informative. The former cases show that our test could have, under certain circumstances, limited power.

Now consider the case $0 < \phi < 1$. To get an idea of how loan demand responds to interest rate and maturity changes, we use the formulas given in the Appendix to compute the optimal finance shares for alternative income paths and interest rates. The results from such a numerical example are depicted in Figure 1. We assume that $\beta = 0.9$, and $\gamma = 0.8$. To make the problem interesting, we assume a rising income path with a relatively high income in the last period; in particular, we set $y_1 = 1.5$, $y_2 = 2$, and $y_3 = 4$. We then compute the optimal finance shares, as well as each period's consumption and assets, for each possible equilibrium scenario and for 80 different values of the borrowing interest rate r_b. As required by the theoretical model, r^b is specified to be greater than r^l, the latter being set equal to 10 percent. To characterize the optimal financing shares, we compute all the quantities in the Table and check which, among those that do not violate any of the constraints imposed by the model, correspond to the highest value of utility. [10]

Comparing the utility levels at each borrowing rate, we find that the consumer would choose $A_1 = A_2 = 0$, $0 < P < \phi K \left(1 + r^b\right)$, $0 < \phi < 1$, if a two period loan is available, and $A_1 = A_2 = 0$, $0 < \phi < 1$ if maximum maturity is equal to one period. In Figure 1 we plot the optimal finance shares for each one of these two cases as a function of the borrowing rate. The graph exhibits three interesting features. First, in both cases the lines are downward sloping indicating that loan

[10] For the specific parameterization of the model, most of the possible equilibria are ruled out as one or more of the constraints are violated. For example, in the case $m = 2$, $P = 0$, $A_1 > 0$, and $A_2 = 0$, and $0 < \phi < 1$, using the formulas for the optimal finance share and the income values listed above, we obtain negative values for the first period's assets for all values of the interest rate; this implies that for this specific income path, the consumer would like to borrow at the – cheaper – lending rate.

demand is negatively related to the interest rate. Second, the line corresponding to a longer maturity ($m = 2$) lies above the line for the one-period maturity case. Hence, the graph suggests that for the consumers with the assume features, longer maturities are associated with higher finance shares. Third, the slopes of the lines depicting the finance share as a function of interest rate depend on whether the maximum maturity is one or two periods. This indicates that maturities affect loan demand interactively with the interest rate (this is also evident in the formulas for the optimal finance share in the Appendix).

Finally, the implications of the model described by assumptions (i)-(ix) can be compared to an ideal benchmark in which there are no liquidity constraints. Suppose that the borrowing rate r^b is equal to the lending rate r^l, that borrowing is not restricted to the first period only (or, equivalently, that buyers can roll over car loans), and that consumers can borrow an amount that exceeds the value of their car (that is ϕ is unconstrained). Then it is easy to see that the length of the maturity is irrelevant for consumers' decisions. Given that there are no constraints on ϕ, consumers can borrow as much as they want in the first period; and given that they can also borrow in the second period, longer maturities are no longer the only way by which resources can be transferred from the third to the second period.

In summary, the simple model considered in this section has the following empirical implications:

(1) In the absence of credit rationing, loan demand is independent of maturity. When liquidity constraints are binding, however, loan demand will – in most cases – be an increasing function of maturity.

(2) In the presence of binding liquidity constraints, maturity affects loan demand interactively with the interest rate.

It is important to note that, while these general implications form the basis of our empirical tests, we do not take the exact results or functional forms at face value. The empirical investigation of these implications will have to deal with several challenges, ranging from the endogeneity of interest rate and maturity, to issues associated with sample selection bias and corner solutions. We discuss these issues extensively in the next section.

3 Empirical specification and econometric issues

The main goal of our paper can be described as estimating the elasticities of automobile loan demand with respect to interest rate and maturity, and testing the hypothesis that different population groups have different elasticities, with the group least likely to be liquidity constrained exhibiting higher interest rate elasticity, and zero maturity elasticity. Unlike Juster and Shay (1964), we do not rely on an experiment, but use data on individual car purchases and the loans associated with them. The simple model sketched in Section 2 constitutes the basis for the specification of the empirical equations we estimate below.

Using actual data on auto financing rather than responses to survey questions, poses, however, several challenges. First, credit constraints may affect the decision to purchase a car; consumers who do not enter the automobile market may do so because they do not wish to buy a car, or because they cannot obtain the necessary loan to finance the purchase. Second, the amount which is borrowed may depend on the size of the car that is bought which in turn may depend on the availability and cost of credit. Third, information on the loan terms facing the buyer, interest rate and maturity in particular, is available only for the subset of consumers who finance their purchase; the notional interest rate faced by those who do not finance is not observed (neither is the rate of return they earn on their savings). Fourth, consumers who finance 100% of their car, are also at a corner, even though the interest rate and the maturity of their loans are observed.[11] Fifth, the interest rate and maturity of those who finance may be endogenous, since consumers generally choose the combinations of interest rates and maturities that best fit their needs. In addition, as documented below, different consumers may face different interest rates and maturities depending on how much they borrow, what type of car they buy (new vs. used), etc.. This implies that interest rates and maturities (as well as their interactions) should be treated as endogenous. We discuss these issues below.

3.1 The empirical model

The equation we want to estimate can be written as follows:[12]

$$f_i^* = \ln(\phi_i^*) = x_i\theta + \gamma_1 r_i + \gamma_2 rm_i + \varepsilon_i^f \tag{1}$$

where ϕ * is defined as the desired ratio of the car loan to the value of the car, that is, the share of the car value which is financed. The dependent variable is expressed in logarithmic form to take into account the fact that the finance share cannot be negative. x is a vector of variables that capture demographics, and life cycle effects on the decision to finance. Examples of variables included in this vector are a polynomial in age, family size, and education dummies. r is the interest rate of the loan and $rm \equiv r \times m$ is the interaction of the interest rate with the maturity of the loan. Both r and rm are considered endogenous. How the estimation procedure deals with this issue is discussed below. Finally, ε^f is a residual term.

When trying to estimate the financing share equation (1), we are faced with a number of sample selection issues. First, finance shares are observed only for those individuals who decide to buy and finance a car. Since the decision to buy is most likely affected by the availability and cost of credit, one has to correct for the sample selection bias induced by the nature of our data. The two decisions, "buy vs. not buy", and "finance vs. not finance", can be either treated separately, or collapsed into one estimating equation in which the dependent variable is 1 if the individual buys and finances, and zero otherwise. Since we could not think of any exclusion restrictions that would allow us to identify the coefficients of two separate equations (that is we could not find variables that would affect the decision to buy but not to finance) we chose the second approach.

[11] It is also possible that individuals financing a high proportion of their car value are also at a corner, in that they might be financing the maximum percentage allowed. Unfortunately, we have no easy way to identify these consumers, as the data do not contain information on downpayment requirements.

[12] Given that equation (1) is interpreted as an approximation to a possibly complex structural relationship, it is advisable to experiment with further functional forms considering the interest rate and maturity interactions; one could, for example, model the effect of these variables as a polynomial in interest rate and maturity. The main problem with this approach is that, as will be shown below, one needs to introduce an additional equation for each endogenous term entering equation (1); this would complicate the estimation considerably.

We model the decision to buy and finance as a binary threshold crossing model (from now on we drop the subscript i for notational simplicity):

$$I_1 = 1\{Z\beta + u_1 \geq 0\} \tag{2}$$

where Z includes demographic information (age, family size, education level, gender, race, etc.) and regional and time (year) dummies.

Second, financing shares ϕ^* cannot exceed unity (and hence their logarithms, f^*, cannot exceed zero). Dealing with censoring at 1 is quite important, as individuals financing the full amount of their purchase are probably the ones facing a binding credit constraint. We define the indicator variable I_2 to be 1 if $\phi^* < 1$ (or equivalently if $f^* < 0$) and 0 otherwise. In other words,

$$I_2 = 1\{f^* < 0\} \tag{3}$$

Hence we only observe:

$$f = I_1 \times I_2 \times f^* \tag{4}$$

Finally, interest rate and maturity are only observed for consumers who finance. In this respect, the problem we are facing is similar to the standard labor supply problem where wages are only observed for participants. Furthermore, as discussed above, since different individuals have access to different financing sources that provide with different interest rates and maturities, these variables should be treated as endogenous variables. This presents the problem of finding instruments with enough variation to identify the coefficients of interest. The main identification assumption used in this paper is that time and regional dummies affect loan demand only through their effect on interest rates, maturities, and their interactions. Furthermore, we hope that there is enough time and regional variation in interest rates and maturities, so that the effect of these variables on loan demand can be identified. The reduced form equations for the interest rate and the interest rate - maturity interactions are:

$$r^* = W\delta_r + u_3 \tag{5}$$

$$rm^* = W\delta_{rm} + u_4 \tag{6}$$

The vector W denotes the instrumental variables. The instruments we use in practice, are year-quarter, and regional dummies. As documented below, much of the observed interest rate and maturity variability is explained by the finance source. We do not, however, include finance source in the instrument set, as this variable is likely to be correlated with individual heterogeneity in loan demand.

The variables r^* and rm^* denote the interest rate and interest rate - maturity interaction facing the consumer. These are observed only if the consumer actually takes a loan. The observed interest rate, r, and the observed interest rate - maturity interaction, rm, are therefore given by:

$$r = I_1 \times r^* \tag{7}$$

$$rm = I_1 \times rm^* \tag{8}$$

Equations (5)-(8) can be substituted into equation (1) to obtain the following reduced form finance share equation:

$$f^* = X\delta_f + u_2 \tag{9}$$

where

$$X \equiv \begin{bmatrix} x & W \end{bmatrix} \qquad \delta_f \equiv \begin{bmatrix} \theta \\ \gamma_1\delta_r + \gamma_2\delta_{rm} \end{bmatrix} \qquad \text{and} \qquad u_2 \equiv \varepsilon^f + \gamma_1 u_3 + \gamma_2 u_4$$

3.2 Estimation Approach

Equations (2)-(9) constitute a reduced form system with unknown parameters of interest β, δ_r, δ_{rm}, and δ_f. Below we summarize our estimation approaches.

3.2.1 A parametric approach

Assuming a zero-mean joint normal distribution for the reduced form error vector (u_1, u_2, u_3, u_4) with variance-covariance matrix Σ we can estimate the reduced form parameters $(\beta, \delta_f, \delta_r, \delta_{rm}, \Sigma)$ by maximum likelihood. The likelihood for the reduced form model is:

$$L(\beta, \delta_f, \delta_r, \delta_{rm}, \Sigma) = \prod_{I_{1i}=0} P_{1i}(\beta) \times \prod_{\substack{I_{1i}=1 \\ I_{2i}=0}} P_{2i}(\beta, \delta_f, \delta_r, \delta_{rm}, \Sigma) \times \prod_{\substack{I_{1i}=1 \\ I_{2i}=1}} P_{3i}(\beta, \delta_f, \delta_r, \delta_{rm}, \Sigma)$$

where

$$\begin{aligned}
P_{1i}(\beta) &= \Pr(I_{1i} = 0) \\
&= \Pr(u_{1i} \leq -Z_i\beta) \\
P_{2i}(\beta, \delta_f, \delta_r, \delta_{rm}, \Sigma) &= \Pr(I_{1i} = 1, f_i^* \geq 0 | r_i, rm_i) f(r_i, rm_i) \\
&= \Pr(u_{1i} \geq -Z_i\beta, u_{2i} \geq -X\delta_f | r_i, rm_i) f(r_i, rm_i) \\
P_{3i}(\beta, \delta_f, \delta_r, \delta_{rm}, \Sigma) &= \Pr(I_{1i} = 1 | r_i, rm_i, f_i) f(r_i, rm_i, f_i) \\
&= \Pr(u_{1i} \geq -Z_i\beta | f_i, r_i, rm_i) f(f_i, r_i, rm_i)
\end{aligned}$$

Having obtained consistent estimates of the δ's, and the variance covariance matrix of the parameter estimates, we apply a minimum distance estimator to estimate the structural parameters γ_1 and γ_2. Let π be the vector that stacks the reduced form parameters, $h(.)$ the function that maps the structural parameters into the parameters of the reduced form equations (this mapping includes the identifying restriction $\delta_f = \gamma_1\delta_r + \gamma_2\delta_{rm}$), and V the variance-covariance matrix of the reduced form parameters. The structural parameters γ_1 and γ_2 are estimated by minimizing the quadratic form:

$$Q = (\hat{\pi} - h(\theta, \gamma_1, \gamma_2, \delta_r, \delta_{rm}))' \, \widehat{V}^{-1} \, (\hat{\pi} - h(\theta, \gamma_1, \gamma_2, \delta_r, \delta_{rm}))$$

This estimator is consistent and asymptotically normal; its variance covariance matrix is obtained from the Hessian of Q. Under the null of correct specification, the minimand is asymptotically distributed as a χ^2 with $q-l-2$ degrees of freedom.

3.2.2 A semiparametric approach

The approach described above relies on the joint normality of the unobservable error terms. As we discuss here it is possible to relax this assumption while maintaining the weaker assumption that the errors are independent of the conditioning variables and that sampling across individuals is i.i.d.. Note that the reduced form equations constitute a non-standard Tobit-type model with simultaneous presence of sample selection and censoring which also contains endogenous regressors. Our estimation approach combines elements of the semiparametric literature on standard Tobit-type models.

Under the assumption that the errors are independent of the conditioning variables and that sampling across individuals is i.i.d. it is possible to estimate β in the binary response model (2) using the maximum rank correlation estimator (MRC) of Han (1987) or any of the rank estimators of Cavanagh and Sherman (1998). However, for computational convenience we will estimate β by probit, maintaining the assumptions that the error in (2) is a standard normal variate.

Next, note that the equations (5)-(8) constitute two standard sample selection (Type 2 Tobit) models. Under the assumption that the errors in (5)-(6) are independent of the instruments W, and that sampling across individuals is i.i.d, each one of the equations may be estimated separately using Powell's (1987) weighted pairwise approach. The idea of this estimation method is the following. In a standard sample selection model, Least Squares (LS) is inconsistent due to the presence of a selection correction term that arises because of the presence of correlation between the unobservables in the selection and the continuous outcome equations. Under independence of regressors and unobservables, this term is only a function of the linear index determining selection (here $Z_i\beta$). The idea then is that, under some smoothness assumptions, for two individuals that have approximately equal selection indices, i.e. $Z_i\beta \approx Z_j\beta$, the magnitude of the selection bias terms are also approximately equal. Hence pairwise differencing eliminates the sample selection bias. Since β is not known it is estimated from the selection equation in a first step. In the second step the parameters of the continuous outcome equation are estimated by weighted LS on the pairwise differenced selected sample, where the weight per pair varies inversely with the magnitude of the difference in the estimated selection indices for the pair.[13]

Formally, we estimate δ_r and δ_{rm} by minimizing:

$$\sum_{i<j} I_{1i} I_{1j} K\left(\frac{(Z_i - Z_j)\hat{\beta}}{h_n}\right)\left[(r_i - r_j) - (W_i - W_j)\, d_r\right]^2$$

and

$$\sum_{i<j} I_{1i} I_{1j} K\left(\frac{(Z_i - Z_j)\hat{\beta}}{h_n}\right)\left[(rm_i - rm_j) - (W_i - W_j)\, d_{rm}\right]^2$$

[13] Alternatively, one could use the estimator proposed by Ahn and Powell (1993), which does not impose the linear structure in the selection equation. The difference with the method described above is that Ahn and Powell use the difference in the (nonparametrically estimated) selection probabilities (propensity scores) to form the appropriate weights instead of the selection indices.

where $\hat{\beta}$ is a root-n consistent estimator of β. Here $K(\cdot)$ is a kernel density function, for example a normal density, and h_n is a bandwidth constant which is required to converge to 0 as sample size increases. The effect of this weighting scheme is that, asymptotically, only individuals with the same selection indices (for which the selection biases exactly offset each other) contribute to the estimation.

We now turn to the estimation of the reduced form financing equation (9). Note that in the absence of sample selection the dependent variable f^* is censored from above at zero. For two individuals i and j, the error terms, u_{2i} and u_{2j}, are therefore no longer identically distributed since they are censored at different points. The idea then is to trim them so that they become identically distributed and that their difference is distributed symmetrically around zero (Honoré and Powell (1994)). However, the presence of sample selection destroys once more the identical distributions. The idea then is that the selection indices $z_i\beta$ and $z_j\beta$ are equal, the two trimmed residuals are once again identically distributed and their difference is still symmetrically distributed around zero (see also Honoré and Powell (1998)). This last idea is operationalized by weighting each pair of observations with a weight that depends inversely on the magnitude of the difference in the estimated selection indices. We therefore propose to estimate δ_f by minimizing:

$$\sum_{i<j} I_i I_j K\left(\frac{(Z_i - Z_j)\hat{\beta}}{h_n}\right)\left\{[(f_i - f_j) - (X_i - X_j)d_f]^2 1\{-f_j > (X_i - X_j)d_f > f_i\} + \right.$$
$$\left[{f_i}^2 - 2f_i\left[f_j + (X_i - X_j)d_f\right]\right] 1\{-f_j \leq (X_i - X_j)d_f\} +$$
$$\left.\left[{f_j}^2 + 2f_j\left[-f_i + (X_i - X_j)d_f\right]\right] 1\{f_i \geq (X_i - X_j)d_f\}\right\}$$

Having obtained β, δ_f, δ_r and δ_{rm} it is in principle possible to obtain an analytic form for the variance-covariance matrix of the estimators and proceed to apply minimum distance to estimate γ_1 and γ_2. This variance matrix may be also obtained by bootsrapping the reduced form system above. We will follow the second approach.

4 Data Description

4.1 The CES Data

The data used in the estimation are provided by the Consumer Expenditure Survey (CES), 1984-95. The CES is collected by the Bureau of Labor Statistics to compute the Consumer Price Index. It is a rotating panel in which each household is interviewed four consecutive times over a one year period. Each quarter 25% of the sample are replaced by new households.

The data provided by the CES include an extensive number of socioeconomic characteristics and information on the vehicle stock holdings of each household each quarter. In particular, for each vehicle the household owns, the BLS collects data on the purchase date and source, various vehicle characteristics, including whether the car was purchased as new or used, the purchase price, the trade-in allowance, and detailed information on the financing of the purchase. The latter includes the source of financing (dealer, bank, credit union, other financial institution, or other private source), the downpayment, the amount of the principal, the size of the monthly payments, the maturity of the loan, and the effective interest rate, computed by the direct ratio formula financial institutions use. A household enters our sample as one that bought a car only if the car purchase occurred during the interview period, or in the three months prior to the first interview. In principle we have information about the finance of the car whenever the purchase has occurred in the 12 months preceding the interview, *provided that the loan has not been fully repaid*. The reason we do not use the information on cars purchased between 12 and 3 months before the first interview is that in this case we would miss all households that took a loan with very short maturity, and repaid it before the first interview.

Our estimation approach uses three loan variables: the real interest rate, the maturity and the finance share. The maturity is directly given by the CES. To compute the real interest rate, we subtract the inflation rate in the consumer price index from the effective interest rate. The financing share is computed as the ratio of the principal to the sum of the downpayment, principal and trade-in allowance; this definition reflects the fact that the role of the trade-in allowance in auto financing is essentially equivalent to that of the downpayment. The finance share of households who bought more than one vehicle during the interview period is computed as the ratio of the total auto debt taken by the household during the year, to the total value of the cars purchased; the interest rate and maturity are computed as weighted averages of the interest rates and maturities referring to the individual loans, with the loan amounts used as weights. This way, each household appears in our sample only once.

Tables 1 and 2 provide some descriptive statistics and Table 3 contains a list with the acronyms of the variables used in the estimation. From the 11666 households who bought at least one car during our sample period, 46% took auto loans; the average finance share for these households is 0.78. Among those who financed, approximately 18% financed 100% of the car value, while 33% financed more than 90% of the car price. These numbers suggest that a substantial portion of the households who take car loans may be at a corner of the IBC. The most popular finance source appears to be the banking sector with 44%, followed by dealers with 22%, and credit unions with 17%. The means of the interest rate and maturity are consistent with common wisdom, as the average interest rate for new cars is slightly lower than the one for used cars, while the opposite holds for the average maturity. As indicated by Table 2, both interest rate and maturity exhibit substantial variation in our sample (note that the interest rates are negative for some observations, because of inflation). But while most of the interest rate variation comes from the cross-sectional dimension of our data, maturities also exhibit substantial time series variation. Figure 2 plots the average maturities and interest rates in each quarter. Interest rates exhibit a slight downward trend during our sample period; maturities rise substantially from approximately 45 months for new, and 28 months for used cars at the beginning of 1984, to 55 (38 for used) months towards the end of the sample.

4.2 Preliminary Data Analysis

To summarize the main features of our data set, we related auto loan variables (such as interest rates, maturities, sources of financing, etc.) to various socioeconomic characteristics. This preliminary data analysis is purely descriptive and does not correct either for sample selection bias, or for the potential endogeneity of some of the variables appearing on the right hand side. Some interesting patterns, however, are evident. We use some of these facts to justify the modelling choices we make in the following section in which we estimate the structural parameters of the demand for loans.

To draw the profile of the car buyers who finance their purchases, we started by estimating probit equations relating the existence of auto loans to a set of demographics. But the results (omitted here for brevity), while intuitive, are not informative regarding the question of credit constraints. This is hardly surprising; the absence of auto financing may indicate the presence of credit constraints, or alternatively, reflect the car buyer's ability to pay in cash.

A perhaps more informative exercise is to characterize the individuals who have credit contracts with long maturities and the individuals that have finance shares higher than 90% of the car value. Note that two of the empirical implications of the theoretical model described above were that liquidity constrained consumers would prefer longer maturities, and that some liquidity constrained consumers will be at the corner of $\varphi = 1$.[14] The maximum maturity term was 60 months for the early years of our sample; in later years the maximum was increased to 72 months. A few observations in our sample have loans with maturities in excess of 100 months; such cases are, however, very rare and probably reflect loans obtained from special sources. In Table 4 we report the results from the estimation of probit equations, in which the dependent variable is 1 for observations taking loans with maturities greater than or equal to 60 months. While the sign of some of the coefficients is hard to interpret (e.g. education dummies, income), other parameter estimates are consistent with the presence of credit constraints; for example, young households are more likely to finance at long maturities. Note also that long maturities seem to be used more by households financing through dealers.

Table 5 characterizes the households with large finance shares (in the reported probits the dependent variable is 1 if the household financed more than 90% of the car value). The results here are very intuitive. Households with large finance shares are young, have little education, low income and low financial assets. To the extent that one interprets large finance shares as an indicator of credit constraints, one can use these results to identify consumer groups that are likely to be liquidity constrained. We exploit this idea in the next section, where we split our sample into various subgroups according to the criteria of age, income, and education, and test for the existence of liquidity constraints separately in each case.

As mentioned in the previous section, our approach for identifying liquidity constraints exploits exogenous variation in interest rates and maturities. Before we discuss the estimation of the structural model, it is therefore useful to take a look at the main determinants of the variability (both cross sectional and over time) of interest rate and maturity. To this end, we regressed these variables on various household characteristics, credit source dummies, and dummies for new vs. used car. We conducted this exercise without correcting for sample selection, or potential endogeneity of some of the regressors, but experimented with a variety of specifications. Two patterns clearly emerge out of these regressions: First, a large fraction of both interest rate and maturity variability is accounted for by the new vs. used dummy. Second, both interest rates and maturities are highly correlated with credit source dummies (e.g., credit unions are associated with lower interest rates and shorter maturities). The choice of credit source is itself highly correlated with socioeconomic characteristics; estimation of a simple multinomial logit on the choice of finance source points to age, education, race and gender as the main determinants of this choice.[15]

[14] Note that in our theoretical model downpayments are not required. In reality, however, downpayment requirements of 10% are quite common; financing shares of 90% could be indicating corner solutions in such cases.

[15] For brevity we do not include the tables with these results in the paper, but they are available from the authors upon request.

We use these descriptive results to justify two important choices we make in the specification of the empirical model. First, we do not use the source of financing as an instrument, even though this variable captures a substantial amount of the cross sectional variability of interest rates. The reason is that it is likely to be correlated with unobserved heterogeneity. Perhaps a preferable treatment of the credit source would explicitly model the decision where to obtain credit from; this, however, would complicate our model considerably. Second, for the same reason, that is the likely endogeneity of such a variable, we do not use the choice between new vs. used as an instrument. Instead we solely rely on the time variation of interest rates and maturities. To the extent that this time variation is induced by factors unrelated to the loan markets (as indicated in the Introduction, the industry wisdom is that the maturity increases were primarily due to fluctuations in the Yen/$ exchange rate and the effect that these had on Japanese car sales), time dummies are valid instruments. A potential criticism of this identification assumption is that time dummies could be capturing business cycle effects on loan demand, if such effects have not been adequately controlled for in the estimation. To preclude this criticism we experiment with including current income as a proxy for business cycle effects in one of the specifications (see next section for more detail).

5 Results from the Estimation of the Empirical Model

In section 3 we laid out our estimation strategy, which involves first estimating the reduced form of the model, by both maximum likelihood and the semiparametric method, and then applying a minimum distance estimator to obtain the structural parameters. The reduced form system (2)-(9) is specified as follows. The vector Z of variables that enter the selection equation includes, in addition to the exogenous variables that enter the other equations, a quadratic in the average age of the existing cars, the number of cars per drivers at the beginning of the sample, dummies for minorities and females, a dummy for consumers with no cars at the beginning of the interview period, and dummies for the population size of the city of residence.

The vector W consisting of the exogenous variables that enter the reduced form equations for r and rm, includes a constant, year dummies, and regional dummies. The vector X includes, in addition to the exogenous variables entering the interest rate and maturity equations, a quadratic in the age of the household head, and three educational dummies: one for household heads who did not graduate from high school, one for high school graduates, and one for individuals who have received some college education but without receiving a college degree. These variables capture life cycle effects that are likely to affect the demand for loans; in addition, they can be thought of as the determinants of the value of the car purchased by the consumer in a reduced form specification.

We also experimented with a second specification in which current income was included in both the vectors X and Z. Current income captures, among other things, business cycle effects on loan demand. As mentioned above, our basic identification assumption is that time dummies affect loan demand only through interest rates and maturities; but this assumption is problematic if the effects of the business cycle on loan demand have not been accounted for, especially if the business cycle affects the various age, education, income, etc. groups in different ways. By including income in the specification we attempt to at least partially control for such effects. The potential problem is that income could itself be endogenous; this would be for example the case if consumers took a second job or worked overtime in order to purchase a car. To examine how sensitive our conclusions are to the inclusion of income in the estimation we report results from both specifications.

Our sample includes 70184 households, of which 16.6% bought a car (new or used) during the completed interview period. The maximum number of completed interviews in the CES is four. Because households who have completed four interviews are naturally more likely to have bought a car than households who have completed a smaller number of interviews, we also included the number of completed interviews as an explanatory variable in the estimation of the sample selection equation. Among those who bought a car, about 47% used auto financing. In the following discussion we focus on the coefficients of the finance equation; we do not report the results of the reduced form equations, since these are not interesting per se.

5.1 The financing share equation

The results from the estimation of the finance share equation are reported in Tables 6 to 10. All results are divided into two columns. The first is based on the maximum likelihood estimation, and the second one is based on the semiparametric method. Before we discuss our results in detail, we should note that a-priori we have more confidence in the results obtained by the semiparametric method. The reason is that we have no justification for the assumption that the residuals are distributed as jointly normal. On the contrary, we have good reason to believe that the assumption of normality is inappropriate in the context of our empirical model: if the interest rates and maturities facing individual consumers are themselves the results of a search process, then it is unlikely that they are distributed as normal. Accordingly, we will base our subsequent discussion primarily on the semiparametric method; we still report the MLE results for comparison purposes, since the normality assumption - however inappropriate - is still standard in the literature.

Table 6 reports the results from a specification which uses all observations in our sample. The total number of households who finance is 4324.[16] There are some notable differences between the point estimates and standard errors obtained with MLE versus semiparametrics, but the signs and statistical significance of the two main parameters of interest, the parameter on the interest rate, and the parameter on the product of interest rate and maturity, seem robust to the alternative estimation methods.

The joint significance of the variables included in the vector x indicates that life cycle effects are indeed important. The individual coefficients, are however hard to interpret, especially since they are not robust to the use of the semiparametric method. Among them, the coefficient on income in the second specification (that includes income on the right hand side of both the probit and the finance share equations) is perhaps noteworthy; the coefficient is positive, and statistically significant in the maximum likelihood estimation. A possible interpretation – that would be reinforced by the descriptive statistics of section 5 indicating that consumers with higher income are more likely to finance – is that consumers with lower income have a harder time obtaining car loans, and

[16] Note that this number is significantly lower than the number of observations associated with a positive finance share in Tables 1-5 (5407). The reason is that we now use regional dummies as instruments, and are therefore forced to drop all observations with missing values for region. Unfortunately, the BLS blanks out information on region in certain cases, in order to preserve confidentiality. Given the information on population size, the CES user would be able to infer the exact residence of households in particular areas if the regional information were available (e.g., if the population size is greater than 4 million, and the region is West, one knows that the household lives in Los Angeles).

even when they do, they finance a smaller fraction.

The coefficients on r and $r \times m$ both have the expected signs, (the first one negative, the second one positive), and are highly significant. Even though the point estimates differ in the MLE and semiparametric specifications, the robustness of the signs indicates that loan demand is sensitive to both interest rate and maturity. This is consistent with the existence of binding liquidity constraints in the population.

To get a better idea as to who is most affected by the presence of liquidity constraints, we next split the sample into three age groups. Age group 1 consists of households with head 35 years and younger, age group 2 includes household heads in the age range of 35-55, and age group 3 consists of all households with heads 55 years and older. A-priori we would expect the younger households to be the ones being most constrained by the existence of liquidity constraints. This should be particularly the case with the more educated among them; such households face a steep income profile and are thus most likely to be affected by constraints that prevent them from transferring expected future wealth to the present.

Table 7 reports results for each age group. Again, we experimented with two specifications, one without income on the right hand side, and one with income, and in each case we estimated our system using both MLE and semiparametrics. The coefficients on r and $r \times m$ exhibit the same robustness as before. In all cases the coefficient on the interest rate is negative, and the coefficient on the product of interest rate and maturity is positive; in most cases both coefficients are statistically significant. It is also interesting to note that the point estimates for the interest rate coefficient seem to be increasing in absolute value as we move from the younger to the older group. Note, however, that this coefficient does not capture the interest rate sensitivity of loan demand, as the interest rate is also part of the second term, the product $r \times m$.

To show how the effect of interest rates varies with different maturities, in Figure 3 we plot the derivative of the loan demand with respect to the interest rate against the maturities used by the car buyers in our sample. The derivatives are plotted separately for each age group; on each graph, there are two dotted lines, one corresponding to the derivatives we computed using the results from the specification without income, and one corresponding to the derivatives we computed based on the results of the specification with income. As can be seen from the graph, the two lines overlap almost entirely, indicating that our conclusions are indeed robust to the use of income in the specification. The horizontal line indicates a zero interest rate derivative.

Several interesting patterns emerge out of Figure 3. First note that for all three groups interest rate derivatives are increasing in maturities; liquidity constrained consumers are less likely to respond to interest rate changes. Second, the interest rate derivatives for the first and third age groups are positive for almost the entire range of the maturity distribution. Only the consumers with very low maturities in these groups exhibit interest rate sensitivity. In contrast, a significant percentage of car buyers in the middle age group exhibit negative interest rate derivatives; consistent with our expectations, these are again the buyers with the lowest maturities within the group.

While the graphs in Figure 3 illustrate how the interest rate elasticity is affected by maturity for the different groups, they are not informative about the average effect that interest rates have on the demand for loans in the different groups. To get at these effects, in the third and fourth rows of Table 7, we report the partial derivatives of the finance share with respect to interest rate and maturity. Before we discuss their values, two notes on their computation are necessary. First, we are interested in the average derivatives of the latent finance share with respect to interest rate and maturity, and not those of the observed finance share. We believe that these are the derivatives that capture the existence of binding liquidity constraints. These derivatives are estimated as $E_n\left(\frac{\partial f^*}{\partial r}\right) = \hat{\gamma}_1 + \hat{\gamma}_2\bar{m}$ and $E_n\left(\frac{\partial f^*}{\partial m}\right) = \hat{\gamma}_2\bar{r}$, respectively, where E_n denotes expectation with respect to the empirical distribution of m and r, respectively. Second, the derivatives computed in Tables 7 to 9 are conditioned on the sample with positive finance shares.

The derivatives in Table 7 indicate some important differences between the derivatives obtained using the coefficients estimated by MLE, and the derivatives based on the coefficients obtained by the semiparametric method. These differences are most pronounced in the interest rate derivatives, which often have opposite signs in the two methods. Five of the MLE interest rate derivatives have the wrong sign (positive), even though three out of them are not statistically significant. The semiparametric results look more reasonable.

These derivatives exhibit the same pattern in the two specifications with and without income. For the first and third age groups the interest rate derivatives are positive but not statistically different from zero. It is only the second age group (35-55 year olds) that exhibits a negative interest rate derivative. With respect to the maturity derivatives on the other hand, both the first and third groups exhibit positive and statistically significant maturity derivatives. The second group on the other hand has a positive maturity derivative, but it is not statistically significant.

In light of the theoretical discussion of section 2, one can interpret these results as suggesting that the second age group is not liquidity constrained, while the other two age groups are. The second group seems responsive to the price of the loan, the interest rate, but is not sensitive to maturity changes. The opposite is true for the other two groups. For the first group (the younger households) these results are quite intuitive and consistent with our expectations. As noted earlier, younger consumers may be the most liquidity constrained as they expect higher income in the future, but market imperfections may prevent them from borrowing against it in the present. Our results are perhaps more surprising in the case of the third group, the consumers who are older than 55 years. One possible interpretation is that this group includes consumers who are retired and may therefore face more constraints in the credit markets.

Table 5 of the descriptive section suggests that households with low income are more likely to have finance shares in excess of 90% and hence be at a corner. This empirical finding motivates our next experiment, in which we group households into three income groups: the first one consists of households with annual after-tax income below \$25,000; the second group includes all households with incomes between \$25,000 and \$50,000 per year; and the third group is the 'high income' group, including households with \$50,000 and above after-tax income. Just as with the previous grouping, we considered two specifications, one in which income is included as an explanatory variable in both the probit and finance share equations, and one in which income is omitted. Table 8 reports the estimates along with the interest rate and maturity derivatives associated with these specifications.

Once again the semiparametric results provide strong support for the hypothesis that some households are liquidity constrained, in a pattern that is consistent with our intuition. Among the three groups, only the third (high income) group exhibits interest rate sensitivity. In contrast, the point estimates for the interest rate derivatives of the lower income groups are positive, and we cannot reject the hypothesis that they are zero. Moreover, both lower income groups exhibit high and statistically significant derivatives with respect to maturity; for the third group, on the other hand, there is no evidence that its loan demand responds to maturity increases. Overall, the picture that emerges from these results strongly suggests that the lower income groups are liquidity constrained, while the high income group is not. This is again shown explicitly in Figure 4, that plots the interest rate derivatives for each income group against the maturity. The perhaps most striking feature of this figure is that the high income group (incgroup=4) is characterized by negative interest rate derivatives over the entire range of the maturity distribution. Moreover, the interest rate derivative in this group does not appear to be increasing in maturity; this is consistent with the aforementioned finding that this group does not respond to maturity changes and is not liquidity constrained. In contrast, interest rate derivatives in the other two, lower income groups are increasing in maturity; as expected, the majority of car buyers in the lowest income groups do not respond to interest rates, while the interest rate sensitivity of the middle income group lies somewhere between the other two.

Finally, we also considered an alternative grouping in which age and education dummies were interacted to form four groups: young households with low education, young households with high education, older households with low education, and older households with high education. This grouping is rather coarse as the threshold for young vs. old was set at 35 years of age, and 'having attended some college' was the defining criterion for higher education. Ideally, we would have liked to consider finer groups, for example young households (less than 30 years old) with college degrees, etc. But such groups contain very few observations that financed a car purchase, so that estimation is not feasible. These problems associated with cell definitions are reflected in the results of Table 9, which seem less informative compared to the results of the previous tables. The table reports interest rate and maturity derivatives for each age/education group. There seems to be no clear pattern emerging from this table, except from the fact that the group with young households and low education consistently exhibits high sensitivity to maturity. In light of the results of Table 9 on the income groups, this is probably due to the fact that younger households with little education have lower income.

As a further check on our results we also estimated an alternative specification in which only interest rate was included as a regressor in the financing share equation. The results reported in Table 10[17] reveal the same pattern as the results of the previous tables: only the groups that we would a-priori expect not to be liquidity constrained (middle aged, high income, high education) exhibit negative and significant interest rate derivatives. For the other groups, the hypothesis that they are not responsive to interest rate changes cannot be rejected. The only difference compared to our previous results that included maturity in the estimation refers to the older group (age group 3) that now appears to be sensitive to interest rate changes.

6 Conclusion

To summarize our results, we find strong evidence that liquidity constraints exist, particularly among younger, and lower income households. This conclusion is based on a test that makes direct use of loan data for new car purchases. While we demonstrated the main idea behind the

[17] Since the results were very similar across specifications, we only report the results based on the semiparametric method, with income in the probit and financing share equations here.

test in the context of a simple theoretical model, the test itself is very general as it does not rely on specific functional forms of the utility function. The idea is simply that for consumers who are not liquidity constrained, loan demand is solely a function of the price of the loan (the interest rate), while liquidity constrained consumers also respond to maturity changes. To implement this test we exploited exogenous variation in interest rates and maturities and developed an estimation approach that dealt with the main challenges posed by our data: selection bias, censoring, and endogeneity of interest rates and maturities faced by car buyers.

The specific empirical results are consistent with the predictions of the theoretical model in that we find: (1) Consumer groups that we would a-priori consider more likely to be liquidity constrained (e.g., young, low income households) do not respond to interest rates but are sensitive to maturity changes; (2) consumer groups that do not seem likely candidates for liquidity constraints (e.g., high income, middle-age consumers) exhibit interest rate, but not maturity sensitivity; and (3) the higher the chosen loan maturity is, the lower the interest rate sensitivity appears to be.

A drawback of the test we propose is that it only works for interior values of the financing share, but fails to identify liquidity constrained consumers who are trapped at corners; in other words, we can identify the intensive, but not extensive margin. In this sense, we can think of our approach as potentially underestimating the importance of liquidity constraints; but this problem would have been more severe if we had failed to find any evidence in favor of liquidity constraints. Given that despite the above limitation we still find strong evidence for liquidity constraints, we believe that our conclusion that such constraints exist, in particular among young and low income households, is fairly robust.

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APPENDIX

Optimal Finance Shares, $0 < \phi < 1$

	$A_1 = A_2 = 0$
$m = 1$	$\phi_{11}^{*} = \frac{2y_2\left(1+r^b\right)^{-1/\gamma}\beta^{-1/\gamma}-y_1}{\left(1+r^b\right)^{-1/\gamma}\beta^{-1/\gamma}\left(y_2+y_1\left(1+r^b\right)\right)}$
$m = 2$	
$P = 0$	$\phi_{21}^{*} = \frac{2y_3\left(1+r^b\right)^{-2/\gamma}\beta^{-2/\gamma}-y_1}{\left(1+r^b\right)^{-2/\gamma}\beta^{-2/\gamma}\left(y_3+y_1\left(1+r^b\right)^2\right)}$
$0 < P < \phi K\left(1+r^b\right)$	$\phi_{23}^{*} = \frac{2\left[y_2\left(1+r^b\right)+y_3\right]\left(1+r^b\right)^{-2/\gamma}\beta^{-2/\gamma}-y_1\left[1+\beta^{-1/\gamma}\left(1+r^b\right)^{1-1/\gamma}\right]}{\left(1+r^b\right)^{-1/\gamma}\beta^{-1/\gamma}\left[y_1\left(1+r^b\right)^{2-1/\gamma}\beta^{-1/\gamma}+\left(y_2\left(1+r^b\right)+y_3\right)\left(1+r^b\right)^{-1/\gamma}\beta^{-1/\gamma}\right]}$

	$A_1 = 0, A_2 > 0$
$m = 1$	$\phi_{12}^{*} = \frac{2\left[y_3+\left(1+r^l\right)y_2\right]\left(1+r^b\right)^{-1/\gamma}\beta^{-2/\gamma}\left(1+r^l\right)^{-1/\gamma}-y_1\left(1+\beta^{-1/\gamma}\left(1+r^l\right)^{1-1/\gamma}\right)}{\left(1+r^b\right)^{-1/\gamma}\beta^{-2/\gamma}\left(1+r^l\right)^{-1/\gamma}\left[y_3+\left(1+r^l\right)y_2+\left(1+r^b\right)\left(1+r^l\right)y_1\right]}$
$m = 2$	
$P = 0$	NA
$0 < P < \phi K\left(1+r^b\right)$	NA

	$A_1 > 0, A_2 = 0$
$m = 1$	NA
$m = 2$	
$P = 0$	NA
$0 < P < \phi K\left(1+r^b\right)$	$\phi_{22}^{*} = \frac{y_3+2y_3\beta^{-1/\gamma}\left(1+r^l\right)^{1-1/\gamma}-\beta^{1/\gamma}\left(1+r^b\right)^{2/\gamma}\left(1+r^l\right)^{-1/\gamma}\left[y_2+\left(1+r^l\right)y_1\right]}{\beta^{-1/\gamma}\left(1+r^l\right)^{1-1/\gamma}y_3+\beta^{-1/\gamma}\left(1+r^b\right)^2\left(1+r^l\right)^{-1/\gamma}\left[y_2+\left(1+r^l\right)y_1\right]}$

Table 1: Descriptive statistics of households

Variable	Number of Obs.	Mean	Std. Dev.	Min	Max
Age of household head	70184	47.0	17.8	16	90
Family size	70184	2.6	1.5	1	18
Adults	70184	1.96	0.94	1	14
Number of interviews	70184	3.4	0.81	2	4
Avg number of cars	70184	1.96	0.94	0	22
% of households with 0 cars	70184	14.7	-	-	-
Mean age of the stock of cars	69829	6.76	5.03	0	27
Financial assets	57057	11763	29836	0.	364500
% of households buying a car	16.6	-	-	-	-

Table 2: Descriptive statistics of recently bought cars

Variable	Number of Obs.	Mean	Std. Dev.	Min	Max
Fraction financing	11666	0.464	0.500	0	1
Fraction financing 100%	5409	0.180	0.384	0	1
Fraction financing >90%	5409	0.326	0.469	0	1
Finance share	5407	0.783	0.188	.02	1
Interest rate	5409	0.089	0.044	-0.053	0.229
Int. rate on new cars	2460	0.076	0.040	-0.053	0.224
Int. rate on used cars	2949	0.101	0.050	-0.053	0.229
Int.rate on finan >90%	1764	0.090	0.045	-0.053	0.214
Maturity (in months)	5409	41.4	17.7	2	252
Mat. on new cars	2460	49.6	15.8	2	252
Mat. on used cars	2949	34.6	16.3	2	180
Mat. on finan. >90%	1764	40.5	18.2	2	252

Finance Source	Frequency	Percent
Dealer	1178	22.3
Bank	2348	44.4
Credit union	914	17.30
Finance company	477	9.03
Other (including missing)	492	6.70

Table 3: List of Variables Used in the Estimation

AGE2	Dummy, 1 if age of household head is between 35 and 55
AGE3	Dummy, 1 if age of household head is greater than 55
EDUC3	Dummy, 1 if household head is a high school graduate
EDUC4	Dummy, 1 if household head attended (but not completed) college
EDUC56	Dummy, 1 if household head is college graduate or has higher education

Table 4: Choice of Long Maturity

Dependent variable: 1: If long maturity is used; 0: Otherwise
Method of estimation: Probit
Number of observations: 5409
Number of positive observations: 1305

Parameter (Std. Error)	Spec. 1	Spec. 2	Spec. 3
C	-0.82	-0.91	-0.73
	(0.06)	(0.06)	(0.06)
AGE2	-0.10	-0.13	-0.10
	(0.04)	(0.04)	(0.04)
AGE3	-0.12	-0.12	-0.15
	(0.06)	(0.06)	(0.06)
EDUC3	0.16	0.12	0.16
	(0.06)	(0.06)	(0.06)
EDUC4	0.29	0.23	0.29
	(0.06)	(0.07)	(0.06)
EDUC56	0.16	0.05	0.16
	(0.06)	(0.07)	(0.06)
FEMALE	0.00	0.03	0.01
	(0.05)	(0.05)	(0.05)
MINOR	-0.02	-0.02	-0.04
	(0.06)	(0.07)	(0.06)
INCOME	—	.46 E–05	—
	(NA)	(.82 E–06)	(NA)
ASSET	—	-.93 E–06	—
	(NA)	(.94 E–06)	(NA)
BANK	—	—	-0.05
	(NA)	(NA)	(0.04)
CREDIT UNION	—	—	-0.19
	(NA)	(NA)	(0.06)
FINANCIAL COMPANY	—	—	-0.02
	(NA)	(NA)	(0.07)
OTHER	—	—	-0.88
	(NA)	(NA)	(0.14)

Table 5: Who Finances more than 90%

Dependent variable: 1: If fin. share>0.9; 0: Otherwise
Method of estimation: Probit
Number of observations: 5409
Number of positive observations: 1894

Parameter (Std. Error)	Spec. 1	Spec. 2
C	-0.18	-0.14
	(0.05)	(0.06)
AGE2	0.01	0.04
	(0.04)	(0.04)
AGE3	-0.28	-0.23
	(0.05)	(0.06)
EDUC3	-0.16	-0.12
	(0.05)	(0.06)
EDUC4	-0.21	-0.16
	(0.06)	(0.06)
EDUC56	-0.37	-0.29
	(0.06)	(0.06)
FEMALE	0.12	0.09
	(0.04)	(0.05)
MINOR	0.05	0.04
	(0.06)	(0.06)
INCOME	—	-.16 E–05
	(NA)	(.80 E–06)
ASSET	—	-.38 E–05
	(NA)	(.96 E–06)

Table 6: The demand for car loans

All Groups

Dependent variable: Log of Financing Share
Number of Obs. Financing: 4324

Without income in either probit or f equation

Variable	MLE		Semiparametric	
AGE	-0.015	(0.006)	-0.013	(0.006)
AGESQ	0.019	(0.003)	-0.005	(0.004)
EDUC2	0.039	(0.020)	0.088	(0.023)
EDUC3	-0.029	(0.016)	0.002	(0.017)
EDUC4	-0.017	(0.017)	0.043	(0.017)
r	-0.814	(0.131)	-0.376	(0.093)
$r \times m$	2.677	(0.290)	0.818	(0.267)

With income in both probit and f equation

Variable	MLE		Semiparametric	
AGE	0.000	(0.006)	-0.010	(0.007)
AGESQ	0.015	(0.003)	-0.005	(0.004)
EDUC2	-0.023	(0.020)	0.065	(0.026)
EDUC3	-0.075	(0.016)	-0.013	(0.019)
EDUC4	-0.053	(0.017)	0.030	(0.018)
INCOM	0.052	(0.018)	0.033	(0.056)
r	-1.211	(0.170)	-0.414	(0.099)
$r \times m$	3.857	(0.370)	0.897	(0.290)

Acronym Explanation:

AGESQ: Square of household head age
EDUC2: Dummy, 1 if household head has not completed high school
EDUC3: Dummy, 1 if household head is a high school graduate, but has not attended college
EDUC4: Dummy, 1 if household head attended (but not completed) college

Table 7: The demand for car loans

By Age Group

Dependent variable: Log of Financing Share

Without income in either probit or f equation

	MLE			Semiparametric		
Variable	Age Gr.1	Age Gr.2	Age Gr.3	Age Gr.1	Age Gr.2	Age Gr.3
r	-0.338	-0.776	-1.293	-0.217	-0.240	-1.520
	(0.145)	(0.193)	(0.431)	(0.142)	(0.156)	(0.403)
$r \times m$	0.766	2.735	3.864	0.683	0.284	4.605
	(0.380)	(0.410)	(1.073)	(0.347)	(0.378)	(1.358)
$\frac{\partial f^*}{\partial r}$	-0.018	0.389	0.306	0.069	-0.119	0.385
	(0.069)	(0.049)	(0.160)	(0.119)	(0.097)	(0.242)
$\frac{\partial f^*}{\partial m}$	0.694	2.425	3.336	0.619	0.252	3.975
	(0.345)	(0.363)	(0.926)	(0.315)	(0.335)	(1.172)
Number of obs. financing	1393	2195	736	1393	2195	736

With income in both probit and f equation

	MLE			Semiparametric		
Variable	Age Gr.1	Age Gr.2	Age Gr.3	Age Gr.1	Age Gr.2	Age Gr.3
r	-0.375	-1.197	-1.469	-0.252	-0.369	-1.616
	(0.148)	(0.254)	(0.469)	(0.145)	(0.145)	(0.447)
$r \times m$	0.968	3.872	4.528	0.667	0.570	4.929
	(0.391)	(0.533)	(1.139)	(0.369)	(0.366)	(1.502)
$\frac{\partial f^*}{\partial r}$	0.030	0.452	0.404	0.028	-0.126	0.424
	(0.072)	(0.065)	(0.173)	(0.114)	(0.087)	(0.257)
$\frac{\partial f^*}{\partial m}$	0.878	3.433	3.909	0.605	0.505	4.255
	(0.355)	(0.472)	(0.983)	(0.335)	(0.325)	(1.297)
Number of obs. financing	1393	2195	736	1393	2195	736

Table 8: The demand for car loans

By Income Group

Dependent variable: Log of Financing Share

Without income in either probit or f equation

	MLE			Semiparametric		
Variable	Inc Gr.1	Inc Gr.2	Inc Gr.3	Inc Gr.1	Inc Gr.2	Inc Gr.3
r	-1.035	-1.586	-1.146	-0.252	-0.862	-0.189
	(0.437)	(0.352)	0.384)	(0.120)	(0.275)	(0.154)
$r \times m$	3.748	4.375	3.362	1.050	2.043	-0.137
	(1.238)	(0.739)	0.726)	(0.348)	0.706)	(0.343)
$\frac{\partial f^*}{\partial r}$	0.394	0.273	0.422	0.148	0.006	-0.253
	(0.091)	(0.073)	(0.079)	(0.112)	(0.109)	(0.112)
$\frac{\partial f^*}{\partial m}$	3.527	3.948	2.720	0.988	1.844	-0.111
	(1.165)	(0.667)	(0.587)	(0.328)	(0.637)	(0.277)
Number of obs. financing	1362	1648	1031	1362	1648	1031

With income in both probit and f equation

	MLE			Semiparametric		
Variable	Inc Gr.1	Inc Gr.2	Inc Gr.3	Inc Gr.1	Inc Gr.2	Inc Gr.3
r	-1.406	-1.843	-1.517	-0.227	-0.855	-0.205
	(0.606)	(0.419)	(0.504)	(0.120)	(0.271)	(0.156)
$r \times m$	5.070	5.187	4.225	0.958	2.057	-0.143
	(1.700)	(0.894)	(0.983)	(0.402)	(0.689)	(0.346)
$\frac{\partial f^*}{\partial r}$	0.528	0.362	0.453	0.138	0.020	-0.272
	(0.116)	(0.092)	(0.101)	(0.107)	(0.111)	(0.112)
$\frac{\partial f^*}{\partial m}$	4.771	4.681	3.418	0.902	1.856	-0.116
	(1.600)	(0.807)	(0.796)	(0.378)	(0.622)	(0.280)
Number of obs. financing	1362	1648	1031	1362	1648	1031

Table 9: The demand for car loans

By Age-Education Group

Dependent variable: Log of Financing Share

Without income in either probit or f equation

	MLE				Semiparametric			
Variable	Old low	Old high	Young low	Young high	Old low	Old high	Young low	Young high
r	-0.683	-1.492	-0.237	-0.339	-0.272	-3.723	0.007	-0.290
	(0.248)	(0.334)	(0.217)	(0.169)	(0.146)	(2.499)	(0.189)	(0.161)
$r \times m$	2.714	3.880	1.684	0.316	0.731	12.273	1.180	0.481
	(0.564)	(0.694)	(0.495)	(0.438)	(0.456)	(8.758)	(0.509)	(0.442)
$\frac{\partial f^*}{\partial r}$	0.430	0.191	0.431	-0.200	0.027	1.601	0.475	-0.078
	(0.058)	(0.079)	(0.096)	(0.087)	(0.105)	(1.376)	(0.179)	(0.121)
$\frac{\partial f^*}{\partial m}$	2.479	3.273	1.584	0.278	0.667	10.351	1.110	0.423
	(0.515)	(0.586)	(0.466)	(0.385)	(0.416)	(7.387)	(0.479)	(0.389)
Number of obs. financing	1414	1375	687	848	1414	1375	687	848

With income in both probit and f equation

	MLE				Semiparametric			
Variable	Old low	Old high	Young low	Young high	Old low	Old high	Young low	Young high
r	-1.268	-1.761	-0.438	-0.416	-0.582	-4.347	-0.083	-0.367
	(0.350)	(0.377)	(0.266)	(0.171)	(0.204)	(3.372)	(0.219)	(0.164)
$r \times m$	4.323	4.548	2.491	0.582	1.645	14.160	1.395	0.617
	(0.770)	(0.777)	(0.596)	(0.440)	(0.658)	(11.676)	(0.594)	(0.436)
$\frac{\partial f^*}{\partial r}$	0.506	0.212	0.550	-0.160	0.093	1.795	0.470	-0.095
	(0.086)	(0.091)	(0.116)	(0.087)	(0.142)	(1.773)	(0.197)	(0.120)
$\frac{\partial f^*}{\partial m}$	3.949	3.836	2.343	0.512	1.502	11.943	1.312	0.543
	(0.703)	(0.655)	(0.561)	(0.387)	(0.601)	(9.848)	(0.559)	(0.384)
Number of obs. financing	1414	1375	687	848	1414	1375	687	848

Table 10: The sensitivity of loan demand with respect to interest rate
An alternative specification: Only r in finance equation

With income in both probit and f equation

By Age Group

	Semiparametric		
	Age Gr.1	Age Gr.2	Age Gr.3
r	-0.058	-0.172	-0.275
	(0.092)	(0.078)	(0.117)
Number of obs financing	1393	2195	736

By Income Group

	Semiparametric		
	Inc Gr.1	Inc Gr.2	Inc Gr.3
r	-0.034	-0.106	-0.251
	(0.073)	(0.081)	(0.103)
Number of obs financing	1362	1648	1031

By Age-Education Group

	Semiparametric			
	Old Low	Old High	Young Low	Young High
r	-0.127	-0.563	0.193	-0.195
	(0.076)	(0.105)	(0.155)	(0.095)
Number of obs financing	1414	1375	687	848

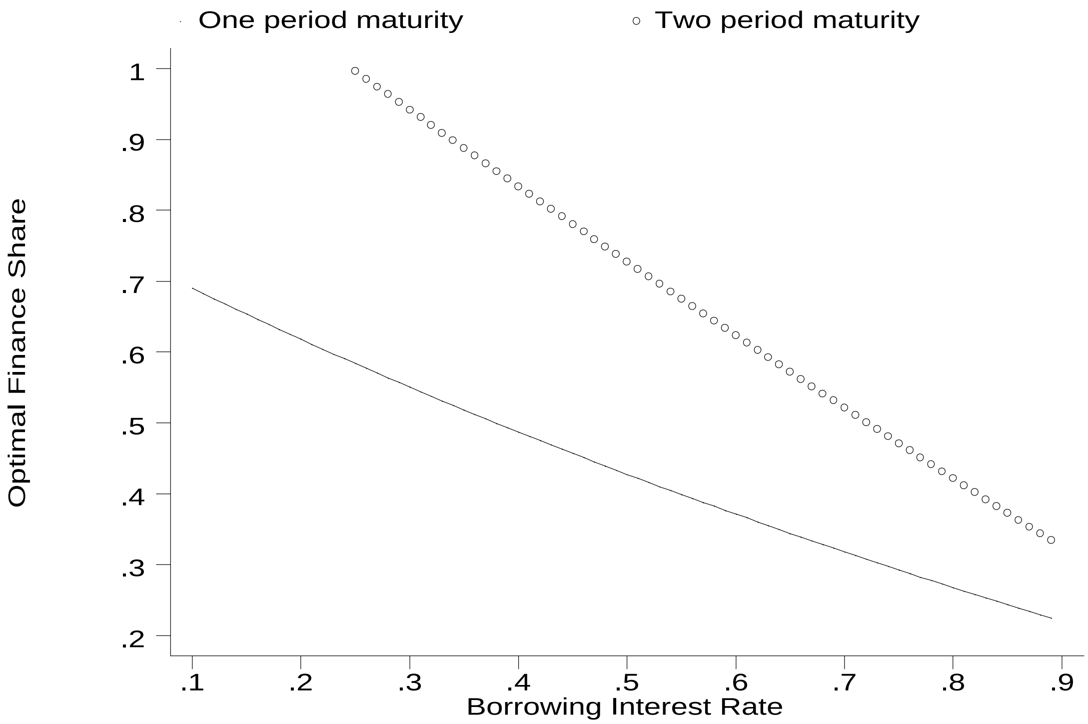

Figure 1: Optimal Finance Shares: $y_1 = 1.5$, $y_2 = 2$, $y_3 = 4$, $\beta = 0.9$, $\gamma = 0.8$, $r_l = 10\%$; solid line: $m = 1$, $A_1 = A_2 = 0$; dashed line: $m = 2$, $A_1 = A_2 = 0$, $0 < P < \phi * K * (1 + r_b)$

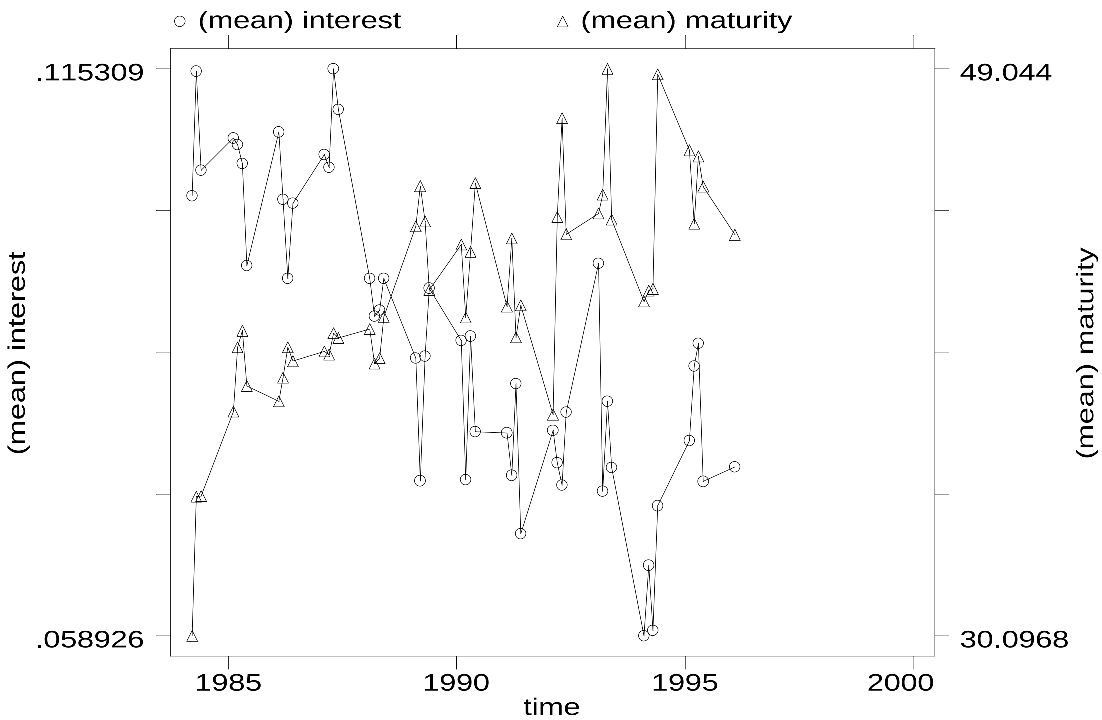

Figure 2: Interest Rate and Maturity

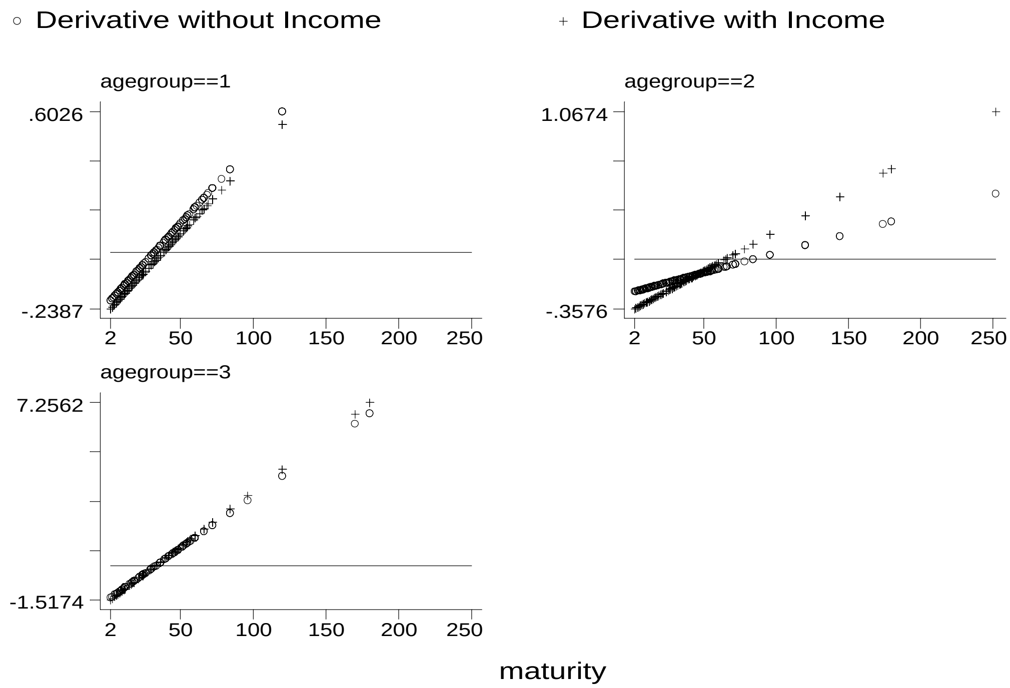

Figure 3: Sensitivity of Loan Demand with respect to Interest Rate by Age Group - with/without Income

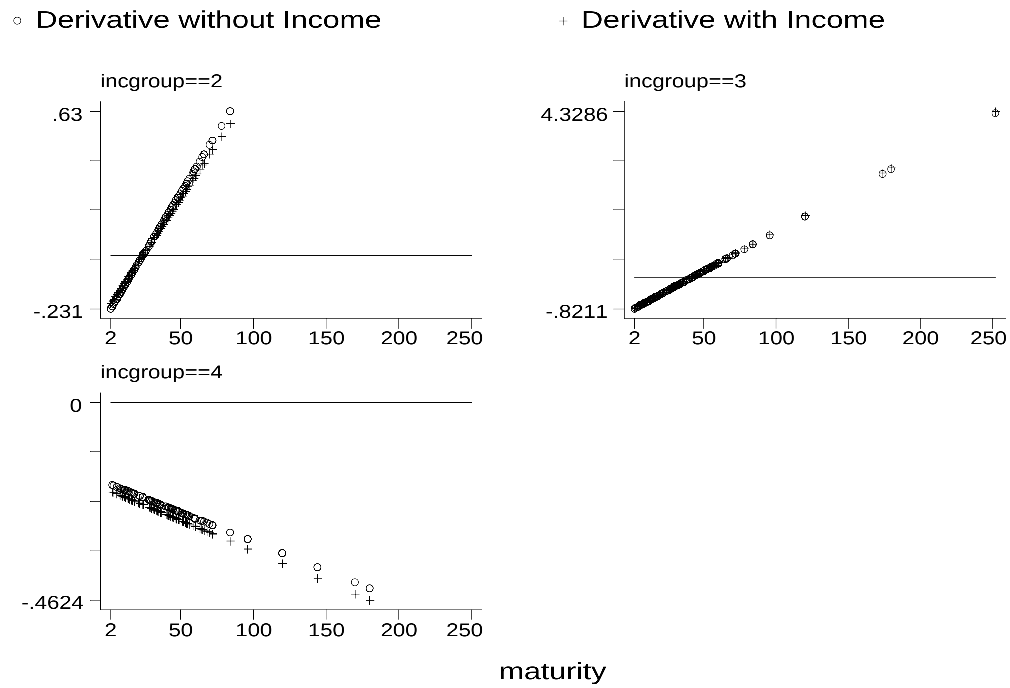

Figure 4: Sensitivity of Loan Demand with respect to Interest Rate by Income Group - with/without Income