TESTING FOR LIQUIDITY CONSTRAINTS IN EULER EQUATIONS WITH COMPLEMENTARY DATA SOURCES

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Abstract—Previous tests for liquidity constraints using consumption Euler equations have frequently split the sample on the basis of wealth, arguing that low-wealth consumers are more likely to be constrained. We propose alternative tests using different and more direct information on borrowing constraints obtained from the 1983 Survey of Consumer Finances. In a first stage we estimate probabilities of being constrained, which are then utilized in a second sample, the Panel Study of Income Dynamics, to estimate switching regression models of the Euler equation. Our estimates indicate stronger excess sensitivity associated with the possibility of liquidity constraints than the sample splitting approach.

I. Introduction

IT IS NOW widely believed by applied economists that the rational expectations–permanent income model of consumption in its most simple form is inconsistent with the data. There is much less agreement as to why we observe the empirical failure of the model. Is it just that preferences are in fact more complicated than in the simplest model? Or is the failure due to other features of the model, like the assumption of perfect credit markets? The existence of liquidity constraints, in particular, has important policy implications, for example, with regard to taxation, financial market liberalization, growth, and welfare (Hubbard and Judd (1986), Jappelli and Pagano (1995)). It is therefore important to distinguish whether the rejection of the model results from borrowing constraints or from some other source.

The most influential microeconomic tests addressing the issue of liquidity constraints have relied on sample separation rules based on household assets. However, assets alone are a rather imperfect predictor of binding constraints; and sample splitting does not explicitly reflect uncertainty about who is constrained. Unfortunately the U.S. surveys with consumption data do not have direct indicators of credit constraints, and the surveys with such indicators lack information on consumption. In this paper we combine data from the Survey of Consumer Finances (SCF) with data from the Michigan Panel Study of Income Dynamics (PSID) using two-sample instrumental-variables techniques. We identify liquidity constraints with direct indicators of credit constraints available only in the SCF: self-reported indicators of whether people were turned down for loans, and of credit card ownership and the availability of a credit line. These indicators are used to impute the probability of being liquidity constrained for households in the PSID. We then estimate the Euler equation for consumption in the PSID as a switching regression using the stochastic sample separation information provided by the imputed probabilities. Thus our paper also makes a methodological contribution in extending recently developed two-sample instrumental-variables techniques (Angrist and Krueger (1992)) to a switching regression setting.

Compared to the asset-based sample splitting procedure of Zeldes (1989) and Runkle (1991), our approach relies on different and more direct information to assess the likelihood of a constraint. It therefore complements this earlier work. Furthermore, our econometric methodology explicitly takes into account the uncertainty about regime classification, that is, the fact that any indicator is bound to be only an imperfect predictor of credit constraints. The empirical evidence suggests that liquidity constraints affect the consumption growth rate more strongly than suggested by earlier sample splitting approaches. This is particularly true during the periods in which the SCF indicators of credit constraints are most reliable.

In section II we review the recent literature on liquidity constraints and Euler equations, motivate our methodology, and compare it with previous studies. In section III we describe the data used in the analysis and compare the indicators of liquidity constraints available in the SCF to asset-based sample separation rules previously used in testing for liquidity constraints in the PSID. Section IV presents the results of estimating the consumption Euler equation using switching regressions. Section V concludes.

II. Literature Review and Motivation

While the central implication of Hall's (1978) rational expectations–permanent income hypothesis is simple and powerful, there has been ample research documenting its empirical failure. The model has failed strongly in aggregate time-series studies (e.g., Campbell and Mankiw (1989)) but much, if not all, of this failure can be explained by aggregation issues.[1] Studies relying on microeconomic data have not had as clear results. For example, Hall and Mishkin (1982) found excess sensitivity in the PSID, whereas Altonji and Siow (1987) did not.

The tests that reject the permanent income model do not point directly to the reason why the model fails. In the early literature following Hall, excess sensitivity was generally held to be due to the presence of credit market imperfec-

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[1] See Galí (1990), Attanasio and Weber (1993), Goodfriend (1992), and Pischke (1995).

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tions, in the form of interest rate differentials or credit rationing (Flavin (1985), Hubbard and Judd (1986), Hayashi (1987)). In fact, credit constraints break the powerful implication of Hall's model: current consumption is no longer a sufficient statistic for everything the consumer knows about the future. This leads to an intertemporal dependence in the Euler equation for consumption. However, as more recent literature has emphasized, such dependence would not have to stem from the budget constraint. Similar dependence could be generated by nonseparable preferences, durability of goods, or slow adjustment of consumers. While the empirical implications for the Euler equation of all these extensions are rather similar to liquidity constraints (Browning (1991); see also Attanasio (1995) for discussion)[2] intertemporal dependence originating from the preference side has vastly different policy implications than do credit constraints.

A. Previous Tests Using Sample Splits

Recent empirical work has therefore tried to incorporate additional information to detect the presence of liquidity constraints. One such approach, pioneered by Juster and Shay (1964) and used by Zeldes (1989) and Runkle (1991), relies on an asset-based sample separation rule. Suppose that the level of assets separates households that are likely to be liquidity constrained (low-wealth group) from those that have access to credit markets or have no need to borrow (high-wealth group). If the only violation of the model is due to the existence of liquidity constraints, excess sensitivity should arise only in the low-asset group. If instead excess sensitivity is due to some other source, there is no reason to believe that the results for the two groups should differ. Zeldes indeed finds a violation of the theory in the low-asset group: the coefficient of lagged income in the Euler equation is significant and twice as large (in absolute value) as for the high-asset group. Runkle, on the other hand, does not find significant effects of lagged income in the Euler equations for either of the two groups.

While adding outside information improves the power of the test for liquidity constraints and ties potential rejections more clearly to a specific alternative, splitting the sample on the basis of wealth has a number of drawbacks.[3] First of all, wealth is a good indicator of liquidity constraints only if there is a roughly monotonic relation between the two. But poor households are not necessarily identical to constrained households. Some households face a nonzero limit on borrowing, and observing zero or even negative wealth does not necessarily imply that they have reached the limit. Some households with negative wealth may have been able to take out their optimal, unconstrained amount of debt subject only to their intertemporal budget constraint. According to Wolff (1994), about 15% of the SCF sample has negative net worth (including housing, real estate, and pension wealth as part of the assets). Even considering measurement errors, this indicates that a significant fraction of the population has been able to borrow without full collateral, and many if not most of these may not be at a borrowing limit.[4]

Second, sample splits based on wealth are bound to be highly imperfect because assets and asset income are often poorly measured. For instance, Zeldes' and Runkle's sample split is based only in part on a direct question in the PSID, asking whether households currently have liquid assets in excess of two months' income. For other survey years, lacking this question, a corresponding variable is created based on information on asset income. We show below that this measure systematically overstates the number of low-asset households. Apart from such systematic misclassification, survey measurement error may further obscure the relationship. As a result of all these biases, the low-asset group is contaminated by the presence of unconstrained households, and the high-asset sample may also contain constrained households. These errors reduce the power of the statistical test since they move the excess sensitivity coefficients closer together for the two groups. As will be seen, we instead classify a household as liquidity constrained if it was refused loans or discouraged from borrowing, or if it has no credit cards or other lines of credit. Even though these criteria are subject to problems of their own, they use more direct information on liquidity constraints than the sample split based on assets and should be less subject to misclassification errors.[5]

B. Empirical Model

To contrast the asset-based sample splitting technique to related work, including our own, consider the two separate Euler equations as a switching regression model,

$$\Delta \ln c_{it+1} = \alpha_1 + \beta'_1 X_{it+1} + \gamma_1 \ln y_{it} + \epsilon^1_{it}, \qquad \text{if } \pi' Z_{it} \geq u_{it}$$

[2] Meghir and Weber (1996) circumvent this problem in a clever fashion. They exploit the fact that liquidity constraints should affect all commodities similarly while the same is not true if preferences are nonseparable. Comparing within-period marginal rates of substitution and intertemporal Euler conditions, they find no evidence for the existence of liquidity constraints.

[3] Zeldes' results have also been criticized by Keane and Runkle (1992) on econometric grounds.

[4] Asset-based splits can lead to false positives as well as false negatives in classifying the constrained. As an example of the former, consider a household with high wealth, but whose assets are "committed," for example, set aside to pay for college tuition or a mortgage. Such assets might not be available to be used to smooth nondurable consumption.

[5] A further problem, inherent to most tests for liquidity constraints, is that in empirical work the Euler equation is usually linearized, and so omits second- and higher order terms of the conditional distribution of consumption growth. As was pointed out by Zeldes (1989) and Carroll (1992), this could create a correlation between consumption growth, lagged income, and assets, leading to spurious evidence in favor of constraints. Our indicators of constraints do not completely avoid this problem either. However, the problem might be less severe if the correlation of the omitted terms with our indicators is smaller than that with the asset-based indicators.

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$$\Delta \ln c_{it+1} = \alpha_2 + \beta'_2 X_{it+1} + \gamma_2 \ln y_{it} + \epsilon^2_{it+1}, \qquad \text{if } \pi' Z_{it} < u_{it} \tag{1}$$

the first equation referring to constrained households and the second to unconstrained households. The vector X_{it} includes preference shifters and, possibly, the interest rate; y_{it} is disposable income. The instruments Z_{it} and the random variable u_{it} indicate whether a household is constrained or not in period t. The approach of Zeldes and Runkle may be thought of as the special case with binding liquidity constraints indicated by $L_{it} = I(\pi' Z_{it} \geq 0)$, where $I(\cdot)$ is an indicator function, Z_{it} contains only the asset–income ratio and the cutoff point (two months' income), and $\sigma^2_u = 0$. If the permanent income model holds and the Euler equation is correctly specified, γ_1 and γ_2 should be zero; if the only violation of the theory is liquidity constraints, then only γ_1 should be significantly different from zero.

There are two problems associated with this test: (1) assets are an imperfect indicator of liquidity constraints as discussed above; (2) the test does not take into account uncertainty about regime classification. To address the measurement problems associated with the asset–income ratio, one should recognize explicitly that L_{it} is only an imperfect predictor of liquidity constraints and estimate a switching regression model analogous to that proposed by Lee and Porter (1984) in a different context. Hajivassiliou and Ioannides (1991) extend this idea one step further. They consider not only uncertainty about regime classification, but also relate to demographic characteristics the cutoff of the asset–income ratio below which the liquidity constraint is assumed to be binding. In terms of the formulation above, these variables become part of the Z_{it} vector. They estimate the Euler equations both with a two-step procedure and with full information maximum likelihood. Both cases involve a binary regression of the asset–income ratio on demographic variables and lagged values of the dependent variable. While their approach acknowledges the fact that the sample separation rule is an imperfect indicator of liquidity constraints, it nonetheless retains the assumption that liquidity constraints vary monotonically with the asset–income ratio. As we pointed out, this rules out the possibility that individuals can borrow without full collateral and therefore have negative net worth.

This problem is circumvented by the approach of Garcia et al. (1997). They proceed in a similar fashion to Hajivassiliou and Ioannides, but apply a switching regression model with unknown sample separation to data drawn from the Consumer Expenditure Survey. The instruments Z_{it} are again demographic variables; however, the instruments are not related to any extraneous indicator of liquidity constraints. Instead, the instruments Z_{it} are used directly to find differentials in the slope coefficients of the Euler equations for the two regimes. There are various problems with this approach. First, it is not clear which regime should be labeled as the constrained regime and which one as the unconstrained. Garcia et al. propose to identify the two regimes by comparing the signs of the coefficients of the Z_{it} vector with the logit coefficients of Jappelli (1990), relating the indicator of liquidity constraints in the SCF to demographic variables. We incorporate this eye-balling procedure formally into our estimation method. A second shortcoming is that, when the sample separation is unknown, the switching regression model's demands on the data are extremely high. Nevertheless, Garcia et al. find significant excess sensitivity in one regime but not in the other.[6]

As in Zeldes and Runkle, we use extraneous information to identify liquidity constrained households, but our measures of liquidity constraints differ from those of the previous literature. We use a direct question on liquidity constraints and alternatively information on credit cards and credit lines available in the SCF (see section IIC). If this information were also available in the PSID, we could easily apply a switching regression model in one sample. Since our direct information on liquidity constraints is only available in the SCF, our approach is best thought of as an application of two-sample instrumental-variables techniques,[7] although here instrumental-variables estimation is not necessary for consistency but just serves to link the two samples. Rewrite the switching regression model in equations (1) in a single equation as

$$\Delta \ln c_{it+1} = \theta'_2 W_{it+1} + (\theta'_1 - \theta'_2) W_{it+1} L_{it} + \epsilon_{it+1} \tag{2}$$

where $\theta'_j W_{it+1} = \alpha_j + \beta'_j X_{it+1} + \gamma_j \ln y_{it}$, and L_{it} is an indicator of a binding liquidity constraint. Next take expectations conditional on Z_{it}, the instruments used to predict liquidity constraints, including the variables in W_{it+1}. Therefore

$$E(\Delta \ln c_{it+1} | Z_{it}) = \theta'_2 W_{it+1} + (\theta'_1 - \theta'_2) \times W_{it+1} E(L_{it} | Z_{it}) + E(\epsilon_{it+1} | Z_{it}). \tag{3}$$

The orthogonality condition implied by the permanent income hypothesis is $E(\epsilon_{it+1} | Z_{it}) = 0$, that is, all variables in Z_{it}—and not just those in W_{it+1}—need to be orthogonal to the Euler equation error. Since L_{it} is not available in the PSID, we need to add a first stage to the model of the form $E(L_{it} | Z_{it}) = \pi' Z_{it}$. The parameters of this equation will be estimated in the SCF by regressing the indicator of liquidity constraints on the demographic variables Z_{it} to get $\hat{\pi}$. While the assumption that the conditional expectation of L_{it} is linear in Z_{it} is a strong one, we found that using a probit or logit function to estimate $\hat{\pi}$ gave very similar results. In a

[6] Maddala (1986) reports that disequilibrium studies without extraneous information on regime classification have also frequently found surprisingly good results, whereas Monte Carlo experiments reveal that such results are not likely to be expected.

[7] See Angrist and Krueger (1992) and Arellano and Meghir (1992). In consumption studies with microeconomic data Carroll and Weil (1994), Lusardi (1996), and Garcia et al. (1997) provide applications of two-sample techniques. Carroll and Weil also use the PSID and SCF in conjunction.

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second stage equation (2) will then be estimated in the PSID by replacing L_{it} by $\hat{\pi}'Z_{it}$. In the appendix we demonstrate consistency of the estimator and show how we construct standard errors.

W_{it+1} will include variables such as age and changes in family size to proxy for changes in preferences over the lifecycle. Since Z_{it} must include all W_{it+1} variables, our estimator requires us to construct change in family size also in the SCF. The only way of accomplishing this is to exploit the panel section of the 1983 and 1986 waves of the SCF, using it to calculate the three-year change in family size. This in turn requires that we use three-year differences in consumption in the PSID as well. Thus the equation we are actually estimating in the second stage is

$$\ln c_{it+3} - \ln c_{it} = \theta'_2 W_{it+3} + (\theta'_1 - \theta'_2) W_{it+3}(\hat{\pi}' Z_{it}) + \epsilon_{it+3}. \quad (4)$$

C. Definition of Liquidity Constraints

We use three different indicators of liquidity constraints, available only in the 1983 SCF.[8] The first indicator defines a liquidity-constrained household as one that gave an affirmative answer to the following question: ''In the past few years has a particular lender or creditor turned down any request you (or your husband/wife) made for credit or have you been unable to get as much credit as you applied for?'' In addition, some consumers may not apply for credit because they think that, if they did, they would be turned down. So we add to the group of liquidity constrained these ''discouraged borrowers,'' that is, households who reported an affirmative answer to the question: ''Was there any time in the past few years that you (or your husband/wife) thought of applying for credit at a particular place but changed your mind because you thought you might be turned down?'' Excluding from the group of credit constrained those who reapplied for a loan and received the desired amount results in 233 households out of a total of 1615 (14.4% of the sample) who reported themselves as being liquidity constrained.[9]

Even households who have been turned down for a loan may not be truly constrained. Many of these households report they possess credit cards or credit lines, so they may be able to borrow at least some amount. Therefore we also constructed a second, more stringent indicator, where we exclude from the constrained group using the first indicator all households that report that they have a credit card or a line of credit. According to this definition only 5.8% of the sample is constrained.

Another objection to either of these first two indicators of liquidity constraints is that the questions about being turned down for loans may pertain mostly to consumers who intend to borrow for the purchase of a house, car, or other durable which serves as collateral. The Euler equation, however, concerns nondurable consumption. Since banks look at similar variables for any type of loan application, whether collateralized or not, our first-stage regressions should still give a good picture of who is likely to be constrained. In fact, our first-stage results qualitatively resemble those reported by Boyes et al. (1989) using data on applications made to a particular credit card company.[10]

Nevertheless, in order to address any remaining objection that our constrained consumers include those seeking collateralized loans we also use as a third indicator of liquidity constraints only those households that have neither a credit card nor a line of credit. According to this indicator, 23.7% of the households are constrained. This indicator has its own shortcomings in turn. Some households might have already borrowed up to their credit limit on their credit card or credit line, so they are constrained even if they have a credit card; others do not have credit cards simply because they do not want to borrow. Unfortunately the 1983 SCF does not allow us to distinguish between these households. The 1989 SCF does provide some information for bank credit cards. Of households with a positive balance on their main bank credit card, less than 6% were at its credit limit.

The information on liquidity constraints comes from a single cross section, while we impute the constraint probabilities in the PSID for 1971 to 1984.[11] The probability of liquidity constraints depends on the behavior of both households and lenders. Our assumption is that both depend on a set of observable household characteristics (demographic and employment-related variables, our first-stage variables) in a way that is stable over time. This assumption may be open to question; in particular, the supply of credit responds to a variety of factors, such as the monetary and regulatory regimes and institutional developments in the credit market. Insofar as the relationship between household characteristics and borrowing constraints changed over time, the precision of the predicted probabilities of constraints is reduced, and our test is biased against detecting liquidity constraints.

In order to check the stability of the first-stage coefficients, we perform a number of experiments. We restrict the second-stage sample to PSID waves 1979 to 1984, a period that is closer to the reference periods of the SCF indicators of constraints, which either refer to the early 1980s (the

[8] See Avery and Kennickell (1988) for a description of the SCF.

[9] Several studies have adopted this definition of liquidity constraints. Jappelli (1990) describes the characteristics of households for which they are binding. With some identifying assumptions, Perraudin and Sorensen (1992) use this indicator to estimate the separate determinants of the supply and demand for loans. Cox and Jappelli (1993) and Duca and Rosenthal (1993) estimate that desired debt for those who reported themselves as liquidity constrained exceeds actual debt. Gale and Scholz (1994) find that constrained households contribute less to IRAs. Gropp et al. (1997) find that there is a greater probability of being constrained in states with unlimited bankruptcy exemptions. Eberly (1994) splits the sample according to the constraint indicator and tests for excess sensitivity in Euler equations for the stock of automobiles.

[10] Since it is expensive to repossess collateral, creditors care about the same features—determining the ability to repay debt obligations—for both collateralized and uncollateralized loans (Gropp et al. (1997)).

[11] Recall that we are using three-year changes between year $t + 3$ and year t in our estimation. In referring to sample periods, we always refer to the base year t; for example, the last change in the sample is $c_{1987} - c_{1984}$.

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question on being turned down for loans) or just 1983 (the questions on credit cards and lines). These results are reported in section IV.

No survey data with information on credit constraints exist for the 1970s. However, the question about being turned down for loans was also asked in the 1989 SCF. We experimented with calculating the first-stage coefficients from the 1989 SCF as well. The survey differs enough from the 1983 SCF that this procedure is not fully comparable to our estimates for 1983, which we report below.[12] Nevertheless, the patterns that we find in the data indicate that the assumption of coefficient stability is not a bad one, at least for the 1980s. First of all, the fraction of constrained households is about the same in 1983 and 1989 according to each of the three constraint indicators. Also, the coefficients of the first-stage regressions are very similar, in terms of both size and significance, using either the 1983 or the 1989 SCF. Further, the resulting probabilities of constraints imputed in the PSID are highly correlated, with a correlation coefficient of 0.85. Thus we conclude that using the estimated coefficients from the SCF in years other than the early 1980s is a reasonable assumption, particularly in the later part of the sample.

III. Data and Measures of Liquidity Constraints

A. Data Description

This section describes the broad characteristics of the data. Details are available from the authors upon request. The main drawback of the PSID is that the only consistently available measure of nondurable consumption is food expenditures. In order to estimate the Euler equation we must therefore invoke separability between food and other expenditures. The validity of this assumption is questionable. Meghir and Weber (1996), using data from the Consumer Expenditure Survey, find that expenditures on food at home, transport, and services are not weakly separable either from each other or from food out of home, clothing, and fuel. On the other hand, using the same data set, Lusardi (1996) finds that the Euler equations are very similar for food and for broader aggregates of nondurable expenditures. In both cases she rejects the Euler equation.

In the construction of the PSID sample and of the relevant variables we follow Zeldes (1989) closely. Zeldes uses data from the PSID from 1971 up to 1982, while our sample extends to 1987. The final sample contains three-year consumption changes for 1974–1971, 1975–1972, and 1977–1974 to 1987–1984.[13] Defining an ‘‘observation’’ as a consumption change, each household has 13 potential observations. The total number of observations is 35,280. Income and wealth measures in the PSID are deflated by the price index of personal consumption expenditures (base year 1982–1984); food expenditures are deflated by the price indexes for food at home and away from home. Unlike Zeldes we include the low-income subsample in our analysis and provide weighted estimates. Poorer households may be more likely to be affected by binding liquidity constraints, so it seems wise to exploit this additional part of the sample.

We construct the SCF sample and variables to conform as closely as possible to the PSID counterparts. The high-income subsample in the SCF is excluded. We only use households who were reinterviewed in 1986 and exclude households with changes in marital status in the intervening period. The final SCF sample includes 1615 observations.

In order to compare the direct indicator of liquidity constraints with the previous literature, we recreated the sample splits used by Zeldes based on the ratio of assets to disposable income. In most years the PSID does not ask directly about the level of assets. In some years a question is available asking ‘‘Do you have any savings [that] amount to as much as two months' income or more?’’ This cutoff is the basis for one of Zeldes' sample splits: everyone with liquid assets worth less than two months' income is included in the constrained group. The question is not available in some years. In these years the level of assets is estimated by dividing asset income by the interest rate, that is, by ‘‘blowing up’’ asset income.[14]

Of the years in our sample, only in 1984 does the PSID contain information on the actual level of liquid assets, in addition to asset income. For 1984 we compared the distributions of actual asset levels with the estimate of assets blown up from asset income. Up to the median, the blown-up asset distribution lies below that of actual assets.[15] This suggests that asset income is underreported at low levels of assets. The underestimation of assets in the left tail of the distribution can result in substantial misclassification of unconstrained households, because the cutoff point separating low and high-wealth groups occurs at fairly low levels of assets. This implies that splits that use asset income to impute wealth will tend to overstate the size of the constrained group, not only because low wealth may be an imperfect predictor of constraints, but also because imputation of liquid assets from asset income results in considerable measurement errors.[16]

[12] For instance, in 1989 we cannot relate the constraint probability to changes in family size since there is no follow-up interview. Also, the variable recording region is not publicly available.

[13] The food expenditure question was not asked in 1973.

[14] Zeldes also constructs other sample splits. In a second, more stringent split the constrained group consists only of households with no asset income, and the unconstrained sample of those with assets worth more than six months' income. The intermediate part of the sample is discarded. A third split adds a measure of net housing wealth to liquid assets; otherwise it is similar to the first split described in the text, also using the two months' income cutoff. For brevity we concentrate here on the first split. We have also analyzed how the other splits compare with our indicators of constraints, and found similar results.

[15] The median is $1469 for actual liquid assets and 0 for blown-up liquid assets.

[16] The comparison between blown-up assets and actual asset levels is similar when performed in the SCF and if liquid assets are defined to include or exclude bonds, stocks, and IRAs.

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TABLE 1.—SAMPLE MEANS

Variable	PSID 1983 (1)	SCF Full Sample (2)	SCF Turned Down for Loan (3)	SCF No Credit Card or Line (4)	SCF Low Assets (5)
Demographics					
Age of head	48.7	47.5	37.9	49.5	44.0
Married	0.663	0.664	0.553	0.484	0.664
Divorced	0.114	0.132	0.227	0.194	0.157
Black	0.109	0.125	0.300	0.228	0.177
Male head	0.732	0.745	0.673	0.613	0.748
One adult	0.280	0.250	0.330	0.380	0.236
Two adults	0.575	0.567	0.515	0.471	0.573
Three or more adults	0.144	0.183	0.154	0.149	0.190
No kid	0.575	0.554	0.403	0.579	0.475
One kid	0.163	0.176	0.210	0.178	0.205
Two kids	0.168	0.181	0.266	0.131	0.209
Three or more kids	0.093	0.089	0.120	0.113	0.111
Region					
North East	0.227	0.210	0.249	0.178	0.184
North Central	0.291	0.300	0.215	0.275	0.292
South	0.305	0.342	0.356	0.429	0.375
West	0.177	0.148	0.180	0.118	0.149
Schooling					
No high school	0.127	0.158	0.116	0.351	0.188
Some high school	0.157	0.145	0.180	0.199	0.163
High school graduate	0.356	0.333	0.318	0.312	0.339
Some college	0.164	0.185	0.236	0.110	0.188
College graduate	0.126	0.094	0.060	0.024	0.078
Post graduate	0.058	0.084	0.090	0.005	0.044
Income and employment					
Disposable income	26,488	24,282	18,768	13,699	21,185
Head employed	0.670	0.710	0.721	0.497	0.744
Homeowner	0.710	0.730	0.433	0.547	0.672
Number of observations	3114	1615	233	382	1003

Notes: PSID samples include the poverty subsample; means are weighted by family weights. SCF means are unweighted. Column (3) refers only to households who report being denied credit or discouraged from borrowing. Column (4) refers to households who have no credit card or credit line. Households in column (5) have liquid assets below two months' income.

B. *Comparing Liquidity Constraint Indicators*

Table 1 reports sample means for income and various demographic variables for both the PSID and the SCF. Because the SCF was conducted in 1983, we present means for the PSID for the same year in column (1). The SCF sample means are displayed in column (2). The means in the two data sets are reasonably similar, and the existing differences do not seem to follow any systematic pattern. This is comforting, as the two samples used in the estimation need to stem from the same population.

The next three columns compare sample means for constrained households in the SCF using various indicators of liquidity constraints: turned down for loan, no credit card or credit line, and low assets (liquid assets less than two months' income).[17] The low-asset indicator classifies a much larger fraction of households as constrained than either of the two other splits. Consumers turned down for loans are, on average, considerably younger and earn less income than the unconstrained households or those with low assets.

[17] The turned-down, no credit card indicator is a strict subset of the turned-down indicator, and is not reported for brevity.

TABLE 2.—COMPARISON OF SAMPLE SPLITS BASED ON BLOWN-UP ASSETS AND ALTERNATIVE INDICATORS FOR LIQUIDITY CONSTRAINTS

Alternative Split	Constrained in Both Splits (1)	Constrained in Zeldes' Split Only (2)	Constrained in Alternative Split Only (3)	Unconstrained in Both Splits (4)	Correlation of Predicted Probabilities (5)
Split based on asset stocks	803 (50%)	200 (12%)	105 (5%)	507 (32%)	0.964
Turned down for loan	192 (12%)	811 (50%)	41 (3%)	571 (35%)	0.678
Turned down, no credit card	88 (5%)	915 (57%)	6 (0%)	606 (38%)	0.719
No credit card or credit line	298 (18%)	705 (44%)	84 (5%)	528 (33%)	0.535

Notes: All cross tabulations are based on the SCF. The sample size is 1615. Those constrained according to the Zeldes split have assets less than two months' worth of income; assets are derived from asset income. The stock-based split defines constrained individuals analogously but is based on asset stocks. Turned down for loans refers to the self-reported indicator for those who were denied loans or discouraged from borrowing. Turned down, no credit card excludes those with a credit card or credit line from the constrained group in the previous split. No credit card or credit line refers to those individuals who report having neither a credit card nor a credit line. The correlation coefficients in column (5) refer to the predicted probabilities obtained using the blown-up asset split and the alternative splits reported in each row. The prediction equation is estimated in the SCF and the predicted probabilities are calculated in the PSID. The PSID sample includes the poverty subsample and correlations are weighted. The sample size is 35,280.

Households who were denied loans have higher education than unconstrained households, whereas low-asset households typically have less schooling. This suggests that permanent income is above current income for the households who were turned down for loans. The likely source of their constraint is therefore their inability to borrow against their human capital. Blacks and those households living in the north east are far more likely to be constrained according to the turned-down indicator.

The group with no credit card or credit lines is rather different from both those turned down for loans and the low-asset group. Households without credit cards are often unmarried and headed by females, predominantly older, and with relatively little education. They have current income substantially below average, and often lack a job. The lack of a credit card for these households may indicate that they could face borrowing constraints because they have unfavorable demographic characteristics.

Most of these relationships between constraints and demographics persist in a multivariate regression. The most important exception is that the role of female headship disappears for the credit card indicator. In addition, the regional patterns change somewhat.[18]

Thus our indicators of liquidity constraints classify different households as constrained than do the usual asset-based splits. These alternative classifications seem consistent with sensible notions of liquidity constraints. We further investigate the differences across the various indicators in table 2. It refers to the SCF and contrasts the sizes of the constrained and unconstrained groups resulting from splitting the sample in different ways. In particular it compares the classification

[18] The first-stage regression results, which we use below to predict the probability of constraints, are available from the authors upon request.

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using the blown-up measure of liquid assets used by Zeldes with that resulting from splitting according to actual asset stocks and to the direct indicators of credit constraints. The rows in table 2 report the number and fraction of households that are constrained according to both sample splits, constrained only according to Zeldes' split, constrained only according to the alternative split, and unconstrained in both cases. The percentages in each row therefore sum to 100. The last column reports the correlation coefficient between the predicted probabilities in our first-stage regression; we comment on them at the end of the section.

The first row shows the extent of sample contamination deriving from using blown-up assets instead of asset stocks: overall, 17% of households are misclassified (12% are predicted to have low liquid assets while in fact they have assets greater than two months' income, and 5% are predicted to have high assets while in fact they report them to be low). This confirms our previous discussion that using asset income to predict asset stocks, as one is forced to do when using the PSID sample, leads to classifying too many households as constrained. In addition, the comparison reveals that the split based on asset income produces both false positives and false negatives.

The rest of table 2 concentrates on the direct indicators of liquidity constraints. The interesting columns are (2) and (3). Column (2) indicates that Zeldes' constrained group is contaminated by people who do not report themselves being turned down for credit, or have a credit card or line, or both. The extent of this contamination is substantial: for instance, 50% of the sample has access to loans or is not interested in borrowing but is in fact included in the low-asset group. On the other hand, column (4) shows that the contamination of Zeldes' unconstrained group is not as severe: only 3% of households that were turned down for credit have liquid assets exceeding two months' income (only 5% of those without credit cards or lines, and less than 1% of those both turned down and lacking credit cards and lines).

Assuming credit status is a good indicator of liquidity constraints, then tests of liquidity constraints using the asset-based indicator are rather inefficient. Only about one-fifth of the observations with low assets are really unable to borrow (0.12/(0.12 + 0.50)); about one-third using the no credit card or credit line indicator. This implies that the "true" coefficient for lagged income in Zeldes' regression for the constrained group should be three or five times as large, in absolute value, than what he finds in the data. Of course, since our proxies are also bound to be somewhat imperfect indicators of liquidity constraints as well, we do not expect the difference in the results to be necessarily quite as large. Nevertheless, the size of the coefficients should be larger than in asset-based estimates if our proxies are better able to discriminate between constrained and unconstrained households.

We next estimate in the SCF the probability of binding liquidity constraints using the asset split and the three alternative constraint indicators, which will later be used to impute the probability of being constrained in the PSID. The linear probability model includes demographics (age, age squared, dummies for sex of the head, married, divorced, two dummies for the number of adults, three dummies for the number of kids, the change in the number of adults, and the change in the number of kids, and a dummy for black), three regional dummies, five dummies for education, and the log of household disposable income and its square, a dummy for the head's employment status, the employment status interacted with the education dummies, and a dummy for whether the household owns its home. The regressors are levels of demographics or lagged behavioral variables which do not belong in the Euler equation independently. For most regressors the definitions in the SCF and in the PSID are basically the same.[19]

The first-stage coefficients from the SCF can be used to impute the probability of constraints in the PSID for each of the various indicators of constraints. One convenient way of comparing the different indicators is to compute the correlations between the resulting probabilities of constraints. Column (5) of table 2 shows the correlation between the probabilities using the Zeldes split (blown-up assets less than two months' income) and the probabilities using the other indicators. The correlation between the probabilities estimated using actual versus blown-up assets is 0.96. This indicates that the households with low assets and with low-asset income have very similar characteristics. The correlations between the predicted probabilities based on Zeldes' split and our alternative measures are substantially less than 1. The correlation is highest excluding from the group that was turned down those with a credit card (0.72), and lowest using the indicator based simply on credit cards or credit lines (0.54), with the turned-down indicator falling in between (0.68). The size of the correlations confirms the descriptive analysis: not only do the survey questions about credit status predict a different fraction of households constrained, but also the characteristics of the constrained group are different.

IV. Euler Equation Estimates

In this section we present estimates of the Euler equation in the PSID. The specification and the estimation strategy differ somewhat from Zeldes'. Unlike Zeldes, we do not perform fixed-effects estimation. The reason is that there is not enough variability in the imputed probabilities of liquidity constraints within individual households over time. We must therefore rely on the variability of the constraint

[19] There is a slight problem with the timing of the constraint indicators. In the Euler equation for changes between year t and year $t + 3$, the variables about the constraint should refer to year t. This would be 1983 in the SCF. Recall that the question about being denied credit was asked in 1983 but refers to the past few years. It therefore does not strictly correspond to the same year as other variables which are measured at a point in time, such as employment or income. While this is less of a problem for the demographic variables that do not change or only change slowly, we do need to include income in the first-stage equation because it is also a regressor in the second stage.

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probabilities across households, and assume that individual effects, like differential discount rates or differences in the expected variability of consumption, are uncorrelated with the probability of being liquidity constrained. While this is a strong assumption, it is unlikely that these demographic differences follow the same pattern as liquidity constraints.[20]

We also do not include time dummies in the estimated Euler equation. The reason for this is mainly due to computational difficulties in constructing the variance–covariance matrix of the estimates with many covariates. However, given that we have 13 years of data, including two recessions and recoveries, macro effects should largely average out in the estimation. We reestimated our main specifications including time dummies and found that this did not change the coefficient point estimates much.

A further difference with respect to Zeldes concerns the variables included in the Euler equation. Instead of using his measure of changes in food needs (capturing changes in family composition), we directly control for the change in the number of adults and the change in the number of children. We found these variables to be superior indicators for the food consumption profile. To control for changes in preferences, we include age and age squared in the Euler equation, which are also included in the first stage. Finally, we include lagged disposable income to test for excess sensitivity.

As mentioned, we use three-year changes in food consumption in the PSID to maintain comparability with the 1983–1986 SCF. Given that consumption follows a martingale, using overlapping three-year changes of consumption will introduce serial correlation in the Euler equation errors up to the second lag (abstracting from additional within-year time aggregation). Because there are missing data so that not all households are present for the same years, the autocorrelation in the errors will be household-specific. We adjust the covariance matrix for this household-specific autocorrelation pattern. Since the pattern is known given the years for which we have data for a specific household, we also computed generalized least-squares (GLS) estimates, but these turned out to be almost identical to the ordinary least-squares (OLS) estimates. We present OLS estimates in the tables below.

We included the poverty subsample of the PSID in the estimation since it will contain many households which are likely to be liquidity constrained. To adjust for the oversampling and to achieve comparability with the SCF we weighted the second-stage estimates by the PSID family weights. Since it did not affect our results, we do not weight the estimates in the SCF, which is a representative data set. Unlike Zeldes we omit the interest rate from the Euler equation. This avoids the need to use instrumental variables in the estimation of the Euler equation since all regressors are part of the household information set. Similarly, but like Zeldes, we do not condition on other variables such as labor supply, which might be nonseparable from food consumption. We would also need instruments in the SCF for the conditioning variables.[21]

In order to compare our results to the previous literature, we present in column (5) of table 3 the coefficients of an Euler equation estimated in the PSID separately for the low- and high-wealth samples, using Zeldes' blown-up asset split. We find no evidence of excess sensitivity in the high-wealth group, whereas for the low-wealth group the coefficient on lagged income is small, significantly different from zero but not significantly different from the income coefficient in the

TABLE 3.—EULER EQUATION ESTIMATES

	Two-Sample Switching Regression Model				Sample Split
Constraint Indicator	Turned Down for Loan (1)	Turned Down, No Credit Card (2)	No Credit Card or Credit Line (3)	Asset-to-Income Ratio (4)	Asset-to-Income Ratio (5)
Unconstrained Regime					
Constant	0.403	0.386	0.425	0.505	0.290
	(0.067)	(0.070)	(0.095)	(0.128)	(0.097)
Change in number of adults	0.112	0.109	0.106	0.141	0.120
	(0.006)	(0.005)	(0.006)	(0.014)	(0.010)
Change in number of children	0.100	0.100	0.102	0.124	0.105
	(0.007)	(0.006)	(0.007)	(0.015)	(0.010)
Age	−0.0095	−0.0087	−0.0108	−0.0126	−0.0086
	(0.0018)	(0.0015)	(0.0021)	(0.0032)	(0.0023)
Age squared/100	0.0062	0.0056	0.0080	0.0073	0.0057
	(0.0016)	(0.0014)	(0.0021)	(0.0029)	(0.0022)
Lagged disposable income	−0.011	−0.012	−0.011	−0.012	−0.003
	(0.005)	(0.006)	(0.008)	(0.011)	(0.008)
Constrained Regime					
Constant	0.208	0.069	0.221	0.338	0.285
	(0.228)	(0.415)	(0.117)	(0.084)	(0.052)
Change in number of adults	0.067	0.067	0.115	0.087	0.103
	(0.030)	(0.048)	(0.017)	(0.009)	(0.005)
Change in number of children	0.072	0.024	0.057	0.078	0.091
	(0.023)	(0.042)	(0.015)	(0.007)	(0.005)
Age	0.0052	0.0197	0.0023	−0.0029	−0.0050
	(0.0071)	(0.0132)	(0.0036)	(0.0023)	(0.0014)
Age squared/100	−0.0070	−0.0209	−0.0039	−0.0001	0.0024
	(0.0074)	(0.0135)	(0.0034)	(0.0024)	(0.0015)
Lagged disposable income	−0.035	−0.060	−0.028	−0.024	−0.012
	(0.023)	(0.040)	(0.011)	(0.008)	(0.005)
Percent constrained in the SCF	14.4	5.8	23.7	62.1	62.1

Notes: Dependent variable is the three-year change in log of food consumption. All regressions include the poverty subsample of the PSID, and PSID regressions are weighted using the family weight. Number of observations in the PSID is 35,280. In column (1) a household is constrained if it reported being denied credit or discouraged from borrowing; in column (2) if it also does not have a credit card or credit line. In column (3) a household is constrained if it does not have a credit card or credit line. In columns (4) and (5) the household is constrained if liquid assets are below two months' income. Columns (1) to (4) use the two-sample estimator described in text; standard errors are adjusted for two-sample estimation and for the overlapping data structure. Column (5) reports OLS estimates based on splitting the PSID sample.

[20] Hajivassiliou and Ioannides (1991) and Garcia et al. (1997) also do not control for fixed effects in the Euler equation for consumption.

[21] Since a natural instrument for a variable like the change in employment status of the head is its lag, this is not feasible. Such nonseparabilities, as long as they affect both the constrained and the unconstrained consumers alike, will not affect the difference of the excess sensitivity coefficients in the two regimes. Our results are unchanged if we include the household interest rate uninstrumented in the second stage.

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unconstrained group at the 5% level. The evidence for excess sensitivity is weaker than in Zeldes' original work, but more pronounced than in Runkle (1991). Some of the difference with Zeldes' results stems from the differences in the sample periods. As Mariger and Shaw (1988) pointed out, the income–consumption correlation in the PSID varies substantially from year to year. In particular, consumption growth is characterized by excess sensitivity in the 1970s; inclusion of the 1980s tends to weaken the results.[22]

The other columns in table 3 report the coefficients of the switching regression model described in section II. In addition to the three direct indicators of liquidity constraints in columns (1) to (3), we also apply the two sample procedures to Zeldes' asset-based split to produce the results in column (4).[23] We find again stronger evidence for excess sensitivity in the low-asset group. Using the indicator for being turned down for loans in column (1), the point estimate on lagged income for the constrained group is -0.035, about three times as large in absolute value than the corresponding estimate obtained with splitting the sample according to wealth in column (5). This coefficient is significant at the 10% level. As in columns (4) and (5), the coefficient is not significantly different from the coefficient on lagged income in the unconstrained group. While our point estimates are consistent with a stronger role for liquidity constraints than found with Zeldes' methodology, our estimates are not very precise.

One possible interpretation of the imprecision of the results is that the larger standard errors result from our two-sample methodology. However, this is not the case. The standard error for the constrained group increases from 0.005 in column (5) to 0.008 in column (4) (an increase of about 60%), indicating that some, but not much, information is lost by applying the two-sample instrumental-variables estimator. In comparison, using the indicator for being turned down for a loan in column (1) yields a standard error of 0.023, which is almost three times as large as for the asset split. Notice also that all the coefficients in column (1) for the constrained group are estimated much less precisely than those for the unconstrained group. Typically, the standard errors are three to four times as large.

The main reason for the relatively large standard errors for the constrained group is that the imputed probability of being constrained tends to be much smaller for our constraint indicator than for the asset split. The imputed probabilities are clustered between 0 and 0.4, with very few observations having a probability above 0.5. As shown in the last line of table 3, this is because few households have been turned down for loans. As a result, there is relatively precise information on which households are very likely to be unconstrained, but there is much uncertainty about which particular households face binding constraints. This is reflected in the larger standard errors for the constrained regime. Using the asset-to-income ratio to split the sample results in a much larger constrained group, and therefore more precise results. As we argue above, many of the consumers classified as constrained by the asset split are likely to be truly unconstrained. We thus regard the asset split as inferior to the alternative measures—it will give estimates that appear precise, but they will also be biased.

In columns (2) and (3) we employ alternative definitions for being constrained. Column (2) classifies households as constrained if they have been turned down for a loan and have no credit card or credit line. The point estimate on lagged income is rather larger in absolute value, while the standard error for the constrained group rises further due to the smaller number of households in this group (only about 6% of households). In order to focus more directly on nondurable consumption loans, in column (3) we use the indicator of whether the household has a credit card or credit line. The point estimate on lagged income for the constrained group is -0.028, again much larger in magnitude than for the unconstrained group, whose coefficient is insignificant. The estimate for the constrained group in column (3) is significant at the 1% level in this case because of the larger group size (about 24% of households). Even though we showed above that the group without credit cards or credit line is rather different in terms of demographics from those turned down for loans, the point estimates are not very different from column (1).

We experimented with changing the instrument set and found that the results are rather robust to the exact set of variables used to predict liquidity constraints. In particular, we included the asset-to-income ratio on which Zeldes' split is based into the first stage. This variable was often insignificant at conventional levels and the second-stage coefficients hardly changed. This indicates that conditional on a large set of demographic characteristics, assets seem to contain little additional information on whether households are likely to face constraints.

In order to check the sensitivity of the results to the particular sample period used, we report in table 4 the excess sensitivity coefficients restricting the sample to 1979–1984 (including the consumption changes from 1982–1979 up to 1987–1984). This sample, which contains about half the data, covers a period that is closer to the timing of the SCF indicators of constraints, which refer either to the early 1980s (the turned-down question) or just to 1983 (credit card ownership). Our comparison of the 1989 and 1983 SCF suggests that this period should be characterized by the stability of the first-stage coefficients (see section II). For convenience the excess sensitivity coefficients for the full sample from table 3 are repeated in the first panel of table 4.

[22] If we restrict the sample to Zeldes' sample period (up to the 1979 to 1982 change), we find stronger evidence of excess sensitivity. For the low-wealth group the coefficient on lagged income is -0.018 with a standard error of 0.006. For the high-asset sample the coefficient is close to zero and insignificant.

[23] For the liquid-asset measure it is not necessary to rely on the SCF for the first-stage regression because this indicator is also available in the PSID. Running the first-stage regression in the PSID yields very similar results to those in column (4) of table 3 (not reported for brevity). This is a further check on the compatibility of the SCF and PSID samples and thus of the validity of the two-sample method.

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TABLE 4.—EULER EQUATION ESTIMATES FOR DIFFERENT TIME PERIODS. COEFFICIENTS ON LAGGED DISPOSABLE INCOME

	Two-Sample Switching Regression Model				Sample Split
Constraint Indicator	Turned Down for Loan (1)	Turned Down, No Credit Card (2)	No Credit Card or Credit Line (3)	Asset-to-Income Ratio (4)	Asset-to-Income Ratio (5)
Full Sample Period					
Unconstrained regime	−0.011 (0.005)	−0.012 (0.006)	−0.011 (0.008)	−0.012 (0.011)	−0.003 (0.008)
Constrained regime	−0.035 (0.023)	−0.060 (0.040)	−0.028 (0.011)	−0.024 (0.008)	−0.012 (0.005)
1979 to 1984 Subsample Only					
Unconstrained regime	−0.006 (0.008)	−0.007 (0.009)	−0.009 (0.012)	−0.020 (0.016)	0.003 (0.013)
Constrained regime	−0.054 (0.031)	−0.108 (0.050)	−0.037 (0.016)	−0.029 (0.012)	−0.010 (0.008)
Percent Constrained in the SCF	14.4	5.8	23.7	62.1	62.1

Notes: Dependent variable is the three-year change in log of food consumption. All regressions include the poverty subsample of the PSID, and second-stage regressions are weighted using the family weight. Number of observations in the second stage is 35,280 for the full sample and 18,028 for the subsample. In column (1) a household is constrained if it reported being denied credit or discouraged from borrowing; in column (2) if it also does not have a credit card or credit line. In column (3) a household is constrained if it does not have a credit card or credit line. In columns (4) and (5) the household is constrained if liquid assets are below two months' income. Columns (1) to (4) use the two-sample estimator described in text; standard errors are adjusted for two-sample estimation and for the overlapping data structure. Column (5) reports OLS estimates based on spliting the PSID sample.

The magnitude of the estimated excess sensitivity coefficients for the constrained group increases in absolute value uniformly across our alternative indicators of constraints. In columns (2) and (3) the excess sensitivity coefficient is now significantly different from zero at the 5% level. For the unconstrained group, by contrast, the coefficients of lagged income are now closer to zero. In column (2) the coefficients for the constrained and unconstrained are significantly different from each other at the 6% level, in column (3) at the 14% level. Access to credit is generally believed to have been easier in the 1980s than in the 1970s, and yet we find stronger evidence in favor of liquidity constraints in the later part of our sample. This result is consistent with the idea that the imputed constraint probabilities using the 1983 SCF are more accurate for the later part of the sample. This is also supported by the fact that the results for the sample split based on assets in column (5) are not very different across sample periods, which makes it less likely that our estimates are picking up some other effects differing over time.[24]

V. Conclusion

The applied consumption literature often relies on sample separation rules based on wealth to classify households as liquidity constrained and unconstrained. Such rules pose some problems, however. If households are misclassified, the excess sensitivity coefficient will be estimated incorrectly for both the constrained and the unconstrained groups. We show that for the sample split used by Zeldes (1989) as many as 80% of the households in the low-wealth group may in fact have access to credit. Nonetheless Zeldes still finds evidence of excess sensitivity for the constrained. On the other hand, using a similar approach to Zeldes', Runkle (1991) does not find significant excess sensitivity. In this paper we check the robustness of the asset-based sample-splitting approach using an alternative method.

The alternative that we propose is to identify liquidity-constrained households using direct indicators of credit status: households that have been denied loans or discouraged from borrowing, or have credit cards or lines of credit. Such information is available in the Survey of Consumer Finances and allows us to relate the probability of being liquidity constrained to a set of demographic variables, income, and employment status. Using a first-stage model estimated on the SCF, we impute the constraint probabilities in a second sample, the Panel Study of Income Dynamics, which contains information on consumption. We then estimate Euler equations for constrained and unconstrained households using a switching regression model with uncertain sample separation. Ultimately the estimation procedure relies on detecting a correlation between consumption growth and the demographic variables used in the first-stage estimation.

The point estimates based on indicators of credit availability suggest that liquidity constraints affect the allocation of food expenditures more strongly than estimates based on splits by assets. This is particularly true in the later part of the period we analyze when the timing of the two samples is closer. Our excess sensitivity coefficients for the constrained group are two to ten times as large as those found by splitting the sample. We also find that only relatively few households may be facing binding liquidity constraints, which makes it hard to pin down the effects of constraints precisely. In order to say something more definite about the behavior of constrained households, those collecting new surveys in this area in the future may want to consider oversampling the groups who are likely to be affected by constraints.

Since many researchers have come to expect no detectable effects of liquidity constraints in Euler equations estimated with microdata,[25] our method seems rather successful in detecting impacts of constraints on the intertemporal allocation of consumption. This seems an important first step in helping to determine the importance of liquidity constraints for expenditure allocations and welfare of households and for the economy as a whole. The magnitude of the excess sensitivity coefficients depends on the income process and other sources of uncertainty so they bear no direct relation to the economic importance of liquidity constraints. Nevertheless, our methodology of combining information from complementary data sources should be helpful in future investigations that try to assess the quantitative

[24] Note that by using a smaller sample period the problem of macroeconomic shocks potentially biasing our estimates becomes more severe.

[25] In particular just using food consumption (see Attanasio (1995) for an example of this argument).

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importance of liquidity constraints more directly. More generally, our methodology could be applied in other settings with switching regimes where the data for the switching model and the sample separation information come from different data sources.

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APPENDIX

Standard Errors

Our second-stage regression can be written as

$$\Delta \ln c_{it} \equiv y_{it} = \theta_1' W_{it} + \theta_2' L_{it} W_{it} + \epsilon_{it}.$$

Define $X = [W \quad \mathrm{diag}\,(L)W]$, where W is an $n \times k$ matrix and $\theta' = [\theta_1' \quad \theta_2']$ to rewrite this as

$$y = X\theta + \epsilon.$$

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Regarding the first stage we make

Assumption 1:

$E(L|Z) = Z\pi$, which says that the conditional expectation of the liquidity constraint is a linear function of Z. This implies that the error term $v = L - E(L|Z)$ is independent of Z.

Let subscripts on variables denote data sets, a 1 referring to the SCF and a 2 referring to the PSID. We make the following assumption of sample independence (note that $W \subset Z$).

Assumption 2:

The data $\{L_1, Z_1\}$ and $\{y_2, Z_2\}$ are jointly independent.

Define $\hat{L}_{21} = Z_2\hat{\pi}_1$ as the imputed constraint probability, where $\hat{\pi}_1 = (Z'_1Z_1)^{-1} Z'_1L_1$ is the coefficient vector from a linear probability model, and $\hat{X}_{21} = [W_2 \quad \text{diag}\,(\hat{L}_{21})W_2]$ as the complete matrix of cross-sample fitted values. Our estimator is then

$$\hat{\theta} = (\hat{X}'_{21}\hat{X}'_{21})^{-1}\hat{X}'_{21}y_2.$$

Standard substitutions yield

$$\hat{\theta} = (\hat{X}_{21}\hat{X}_{21})^{-1}\hat{X}'_{21}X_2\theta + (\hat{X}'_{21}\hat{X}_{21})^{-1}\hat{X}'_{21}\epsilon_2.$$

The following lemma establishes consistency of the estimator.

LEMMA 1: $\text{plim}\, n_2^{-1}\hat{X}'_{21}\hat{X}_{21} = \text{plim}\, n_2^{-1}\hat{X}'_{21}X_2.$

Proof: Using the component blocks of the matrix $X'X$,

$$\begin{aligned}
\text{plim}\, n_2^{-1}W'_2\,\text{diag}\,(\hat{L}_{21})W_2 &= \text{plim}\, n_2^{-1}W'_2\,\text{diag}\,(Z_2\hat{\pi}_1)W_2 \\
&= \text{plim}\, n_2^{-1}W'_2\,\text{diag}\,(Z_2\pi)W_2 \\
&= \text{plim}\, n_2^{-1}W'_2\,\text{diag}\,(Z_2\pi + v_2)W_2 \\
&= \text{plim}\, n_2^{-1}W'_2\,\text{diag}\,(L_2)W_2
\end{aligned}$$

where the second equality follows from consistency of $\hat{\pi}_1$, and the third equality follows from assumption 1. A similar argument establishes

$$\begin{aligned}
&\text{plim}\, n_2^{-1}W'_2\,\text{diag}\,(\hat{L}_{21})\,\text{diag}\,(\hat{L}_{21})W_2 \\
&\quad = \text{plim}\, n_2^{-1}W'_2\,\text{diag}\,(\hat{L}_{21})\,\text{diag}\,(L_2)W_2.
\end{aligned}$$

The asymptotic covariance matrix for the estimator is derived by a straight-forward extension of proposition 2 in Angrist and Kreuger (1995). Define the moment conditon $g_n(\theta) = n_2^{-1}\hat{X}'_{21}y_2 - n_1^{-1}\hat{X}'_{11}X_1\theta$ and let $n_2 = kn_1$ for some fixed constant k. By assumption 2 $\sqrt{n_1}g_n(\theta) \sim N(0, k\phi + \omega)$, where ϕ is the limiting convariance matrix of $n_2^{-1}\hat{X}'_{21}y_2$ and ω is the limiting covariance matrix of $n_1^{-1}\hat{X}'_{11}X_1\theta$. Then

$$\sqrt{n_1}(\hat{\theta} - \theta) \sim N\,(0, \Sigma_{xx}^{-1}\,(k\phi + \omega)\Sigma_{xx}^{-1})\,.$$

An estimated version of $\Sigma_{xx}^{-1}\,(k\phi + \omega)\,\hat{\Sigma}_{xx}^{-1}$ is easily computed from two regressions. Note that premultiplying $\hat{X}'_{21}y_2$ by $(\hat{X}'_{21}\hat{X}_{21})^{-1}$ yields $\hat{\theta}$ as computed in the PSID, and premultiplying $\hat{X}'_{11}X_1\theta$ by $(\hat{X}'_{11}\hat{X}_{11})^{-1}$ yields a regression of the predicted value of y (using the actual L) on $\hat{X}_{11}$ (which uses $\hat{L}$ instead of L) in the SCF. The covariance matrix of $\hat{\theta}$ is simply the sum of the covariance matrices of these two regressions.

There is one more complication to be taken care of. The errors in the PSID will have an MA (2) structure because we use three-year changes in food consumption as the dependent variable but adjacent years of data. Thus the covariance matrix of errors is going to be $\sigma_\epsilon^2 A$, and A is a block diagonal matrix given by

$$A = \begin{bmatrix} B_1 & & & 0 \\ & B_2 & & \\ & & \cdots & \\ 0 & & & B_m \end{bmatrix}$$

where B_i is a $t_i \times t_i$ weighting matrix for household i. Since under the null hypothesis the Euler equation error follows a martingale for each household at the annual level (ignoring within-year time aggregation), that is,

$$\ln c_{it+1} - \ln c_{it} = \epsilon_{ir+1}$$

we will have for the three-year changes

$$\ln c_{it+3} - \ln c_{it} = \epsilon_{it+3} + \epsilon_{it+2} + \epsilon_{it+1}.$$

Assuming constant innovation variances, the weighting matrix is going to be of the form

$$B_i = \begin{bmatrix} 1 & \frac{2}{3} & \frac{1}{3} & 0 & & & \\ \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} & 0 & & \\ \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & & & \\ 0 & \frac{1}{3} & \frac{2}{3} & \cdots & \cdots & \cdots & \\ & 0 & \cdots & \cdots & \cdots & \frac{2}{3} & \\ & & & \cdots & \frac{2}{3} & 1 & \end{bmatrix}$$

if there are complete data for t_i years available for the household. For many households some intervening years are missing, so that some of the elements on the first two off-diagonals will be zero instead. We constructed the household-specific weighting matrices and estimated ϕ as $\hat{\phi} = \hat{\sigma}_\epsilon^2 \times (\hat{X}'_{21}\hat{X}_{21})^{-1}\hat{X}'_{21}A\hat{X}_{21}(\hat{X}'_{21}\hat{X}_{21})^{-1}$. For $\hat{\omega}$ we use the White covariance matrix $(\hat{X}'_{11}\hat{X}_{11})^{-1}\hat{X}'_{11}\hat{C}\hat{X}'_{11}(\hat{X}'_{11}\hat{X}_{11})^{-1}$, where $\hat{C}$ is the matrix with elements $\hat{V}_i^2$ on the diagonal, since this is the appropriate covariance matrix for the linear probability model.

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