Unemployment and Liquidity Constraints*

by

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Abstract

We present a dynamic framework for the interaction between borrowing (liquidity) constraints and deviations of actual hours from desired hours, both measured by discrete-valued indicators, and estimate it as a system of dynamic binary and ordered probit models with panel data from the Panel Study of Income Dynamics. We analyze a household's propensity to be liquidity constrained by means of a dynamic binary probit model. We analyze qualitative aspects of the conditions of employment, namely whether the household head is involuntarily overemployed, voluntarily employed, or involuntarily underemployed or unemployed, by means of a dynamic ordered probit model. We focus on the possible interaction between the two types of constraints. We estimate these models jointly using maximum simulated likelihood, where we allow for individual random effects along with an autoregressive process for the general error term in each equation. A novel feature of our method is that it allows for the random effects to be correlated with regressors in a time-invariant fashion. Our results provide strong support for the basic theory of constrained behavior and the interaction between liquidity constraints and exogenous constraints on labor supply.

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UNEMPLOYMENT AND LIQUIDITY CONSTRAINTS

1 Introduction

The present paper uses panel data on households to address empirically the interaction between liquidity constraints and exogenous restrictions on labor supply decisions. Our techniques allow us to estimate with panel data general dynamic limited dependent variable models with a flexible dynamic structure. The presence of constraints is taken as an institutional datum. Whether and when they bind for particular individuals in a given population are the endogenous variables of interest.

We take as a starting point that capital market imperfections may prevent individuals from borrowing against their future income without collateral.[1] Intuitively, households are most likely to be liquidity constrained at times of events that are closely related to labor market conditions (e.g., unemployment) or other events, such as ill health, that have direct consequences for labor supply behavior. When labor supply is jointly considered with food consumption,[2] some serious analytical difficulties emerge. These stem from the fact that observed hours of work (or employment) are not necessarily the outcome of free choice in the same way as food consumption is. Specifically, individuals may be involuntarily unemployed, underemployed, or overemployed. For such individuals, the unconstrained model of fluctuations in employment and hours worked may not be appropriate. We address here such qualitative aspects of employment jointly with liquidity constraints.

Our treatment of the endogeneity of regime switching and of the possible dependence between liquidity constraints and restrictions on labor supply behavior goes further than previous work. Typically, the past literature has only considered agents who were thought to be either liquidity-constrained or not constrained, but remained so throughout the period of observation. For example, Ball (1990) restricts his sample to those who have never been constrained in the labor market. Casual empiricism suggests, and the data confirm, that switches in the state of households do occur. Households are most likely to be constrained early in their lifetimes, or at times of major purchases, changes in employment conditions, or other unforeseen events (death, catastrophic illnesses, etc.),

[1] See Hall and Mishkin (1982); Flavin (1985); Altonji and Siow (1987); Zeldes (1989a); Ball (1990).

[2] Food and housing are the only major components of the consumption bundle for which data are consistently available in the Panel Study of Income Dynamics (PSID).

while business cycle conditions regularly force them to update their decisions. The evolution over time of a household's socioeconomic circumstances makes it all the more important to allow for endogenous constraints with a dynamic structure.

Allowing for the coexistence of exogenous restrictions on labor supply and liquidity constraints is a novel feature of the present work. It is firmly rooted in the modern life cycle theory of labor supply, while at the same time it encompasses a dynamic generalization of the approach, pioneered by Ashenfelter (1980), that studies unemployment as a "constraint on choice rather than a result of it," the latter being the hallmark of neoclassical theory of freely chosen labor supply. Our results provide strong support for the basic theory of constrained behavior and the interaction between liquidity constraints and constraints on labor supply that we propose in this paper. Our work thus complements important previous research on hours constraints by Ham (1982; 1986), Ham and Reilly (2002), and Kahn and Lang (1992).

Our econometric models may be estimated in their full generality only by simulation estimation methods. In this paper we apply the method of maximum smoothly simulated likelihood (MSSL) developed in Börsch-Supan and Hajivassiliou (1993), Hajivassiliou *et al.* (1996), and Hajivassiliou and McFadden (1998). See also Hajivassiliou (2004) for a detailed development of MSSL for general panel limited dependent variable models with simultaneity.

The paper is organized as follows. Section 2 discusses some important aspects of the data which help motivate our model. Section 3 presents a rudimentary life cycle optimization model and derives a dynamic discrete choice model for liquidity constraints and quantity constraints on labor supply. Section 4 discusses the econometric specification of the model and Section 5 presents the empirical results, reviews diagnostic tests performed on the estimated models, and contrasts with the previous literature. These results pertain to dynamic models for the discrete events of whether or not a household is liquidity constrained and whether or not household heads are subject to quantity restrictions in their labor supply behavior. Section 6 concludes. Appendix A provides technical details on the method of Maximum Smoothly Simulated Likelihood. Appendix B discusses additional details on the recoding of the data.

2 Qualitative Aspects of Employment and Liquidity Constraints: Evidence from the Panel Study of Income Dynamics

Our primary data source is the Panel Study of Income Dynamics [Hill (1992)], PSID for short. The full details of our recoding of the data are given in Appendix B. We originally worked with two different samples, all heads and male heads. The sample of all heads contains 46,031 observations on 3,206 separate household spells. The sample of male heads contains 32,408 observations on 2,410 separate household spells. We have chosen to focus on the sample of male heads because it is substantially more homogeneous than that of all heads. We report summary statistics for key variables in Table 1 below. Tables 2–5 report additional aspects of the data, which we discuss in further detail below. Even within such a homogeneous sample, all key dynamic aspects of the data that pertain to regime switching display a fair amount of hitherto unexplored richness. The regression results, reported in Tables 6–7 and discussed in Section 5 below, were obtained with the sample of male heads.[3]

An overview of the pattern of transitions and the underlying dynamics of regime switching observed in the data may be obtained by looking at cross-tabulations for the transitions from being constrained to unconstrained and vice versa, given in Tables 2–5. A household is classified as liquidity-constrained in a particular time period if its total wealth (the sum of reported housing wealth and calculated nonhousing wealth) is low relative to its reported typical disposable income. See Appendix B, section 8.1, for precise definitions and details. Section 8.2 discusses the construction of the labour constraint indicators with the aid of flowcharts appearing on pp.48-49.

Under the adopted definitions, in the sample of male heads approximately 72% of the observations are associated with unconstrained households and the remainder are constrained. As reported in Table 2, of the households with male heads approximately 53% remain unconstrained in two successive periods, 21% move from constrained to unconstrained, and 17% move from unconstrained to constrained.

Table 3 shows that about 85% of household observations in the sample of male heads exhibit a switch to a different liquidity constraint regime at least once during the period of observation,

[3]The above number of 32,408 observations on 2,410 household spells with male heads used in the estimations, includes observations with missing values filled-in; continuous variables were filled in by individual time-means and discrete ones by most likely individual values.

and nearly 14% switch 10 times or more. Furthermore, more than 98% of the sample changes employment state at least once, and about 35% exhibit 10 or more such transitions. These numbers justify our argument that the dynamics of regime switching need to be investigated properly when working with long panel data sets.

We also have found a rich pattern in dynamics that characterizes transitions over different states of qualitative aspects of employment. Table 4 reports one-period transitions in terms of four categories (cells) of qualitative aspects of employment. About 63% of households with male heads are voluntarily employed in a given period and more than half of this fraction (38% overall) remain voluntarily employed in the subsequent period. An additional 5% percent are classified as overemployed, and the remainder are underemployed (17%), unemployed (2%) and out of the labor force (13%).

Cross-tabulations between labor supply status and liquidity constraint regime, reported in Table 5, strongly suggest substantial contemporaneous correlation between the respective indicators. According to Table 5, only less than a quarter of voluntarily employed households face a binding liquidity constraint, and only slightly more than a fifth of overemployed ones are constrained on the liquidity side. In sharp constrast, 42% of underemployed and 58% of unemployed individuals are so constrained.

We conclude that the data do support a potential joint dependence of being liquidity constrained upon the qualitative state of employment and of the qualitative state of employment upon being liquidity constrained. The presence of unemployment, contemporaneously or in earlier years, may accentuate, in and of its own, the propensity of a worker to be liquidity constrained, as suggested by the cross-tabulations of Table 5. Hence, we turn to a model that addresses these aspects of individual behavior.

3 Life Cycle Optimization with Liquidity and Other Quantity Constraints

We develop a behavioral model where time is discrete, lifetime horizon is of finite length T, and lifetime utility is additively separable across periods. Utility per period depends on consumption and leisure. Let h_t denote hours worked per year, the endowment of leisure be normalized to 1, $\bar{L}_t = 1$, W_t denote the hourly wage rate, G_t consumption (other than leisure), P_{G_t} its price, and P_t the full price vector, $P_t = (W_t, P_{G_t})$. Direct utility per period is written as $u(h, G)$. Extension to the case of a vector of consumption goods is obvious. We assume both consumption good and leisure to be normal. We simplify further by setting $P_{G_t} = 1$, and by letting the real wage, W_t, be the sole source of uncertainty. The real wage is assumed to be independently and identically distributed over time. There exists a single riskless asset with a constant rate of return r, satisfying $r \geq -1$.

To the direct utility per period function $u(h, G)$ there corresponds an indirect utility function $v(b; W)$, where b denotes asset decumulation, $b = G - Wh$. Let $\{\mathcal{N}_t \;\; t = 0, 1, ...\}$ denotes uncertainty, in the form of a stochastic process with well-defined transition probabilities; $\mathcal{N}_t$ denotes new information the household receives at time t. Define $\mathcal{N}^t = \{\mathcal{N}_0, \mathcal{N}_1, ..., \mathcal{N}_t\}$; to be the information state as of time t, which comprises the set of past realizations of all of exogenous state variables, in this case just W_t, and of the endogenous (but predetermined) state variables, in this case just beginning of period t assets, A_t. A standard statement of the consumer lifetime optimization problem[4] is from period t on is:

$$\max_{\{h_t, \mathbf{G}_t; ...\}} u[h_t, \mathbf{G}_t | \mathcal{N}_t] + E_t \left\{ \sum_{k=t+1}^{T} \frac{1}{(1+\rho)^{k-t}} u_k[h_k, \mathbf{G}_k \mid \mathcal{N}_k] \mid \mathcal{N}^t \right\} \tag{1}$$

subject to the constraint

$$b_t = G_t - W_t h_t, \tag{2}$$

and $A_{t+1} = (1 + r)(A_t - b_t)$. Period t decisions are made after W_t has been observed.

3.1 Liquidity Constraints

Unlike the classic treatment [Deaton (1991)] of the liquidity–constrained problem with beginning of period t assets A_t, as the single decision variable, we may fix ideas for our model by using at least two state variables $(A_t, W_t) : W_t$ is an exogenous state variable; A_t is an endogenous one.

[4]This statement of the problem follows MaCurdy (1983) and constitutes a multidimensional version of the problem addressed by Altonji (1986), Browning, Deaton and Irish (1985), and MaCurdy (1983). Our estimation approach adopts elements of Blundell and Walker (1982).

We introduce a liquidity constraint, that is individuals may not hold negative financial wealth at the end of period t, in a "canonical" form[5]

$$A_t - b_t \geq 0, \qquad\qquad t = 1, ..., T. \tag{3}$$

It follows that relative to Deaton, *op. cit.,* the presence of leisure in the utility function implies *ceteris paribus* that the optimal decision is a function of assets and the real wage. This is a special case of the problem handled by Hajivassiliou and Ioannides (1996), who show that the optimal solution of problem (1) subject to the liquidity constraint (3) satisfies

$$\frac{\partial v(b_t; W_t)}{\partial b_t} = \max \left\{ \frac{\partial v(A_t; W_t)}{\partial b_t}, \frac{1}{1+\rho} E_t \left\{ (1+r) \frac{\partial v(b_{t+1}; W_t)}{\partial b_{t+1}} \right\} \right\}. \tag{4}$$

That is, marginal utility is a supermartingale (with a drift). In the infinite horizon case, the solution is of the form $b = b(A; W)$, which is associated with a threshold value of A_t, $\tilde{A}(W_t)$, such that the optimal net asset decumulation has the form:

$$b_t = A_t, \qquad\qquad A_t < \tilde{A}(W_t); \tag{5}$$

$$b_t = B(A_t; W_t), qquad A_t \geq \tilde{A}(W_t). \tag{6}$$

Equ. (5)–(6) define a threshold value of assets as the value of A, $\tilde{A}(W)$, for which the two terms in the RHS of (4) are equal to one another. Assets above this value imply that the individual is unconstrained; otherwise, the individual is constrained. See Hajivassiliou and Ioannides (1996) for more details.

It is straightforward to extend this model so as to define G_t as expenditure on a vector of consumption goods other than leisure with a price vector $\mathbf{P}_{G_t}$. In that case, indirect utility per period reflects the additional parameters, $v[b_t; W_t, \mathbf{P}_{G_t} | \mathcal{N}_t]$. With additive time separability, the problem admits a two-stage budgeting structure [*c.f.*, Blundell and Walker (1986)]. Once b_t is known, labor supply and commodity demands in period t are obtained from Roy's identity.

Our econometric analysis handles liquidity constraints by means of a *liquidity constraint indicator*, a single endogenous variable representing the discrete event of whether or not an individual is liquidity constrained:

$$S_t \equiv S(A_t; W_t, \mathbf{P}_{G_t}; \mathcal{N}^t) = \mathbf{1}[\tilde{A}(W_t, \mathbf{P}_{G_t}; \mathcal{N}^t) - A_t \geq 0], \tag{7}$$

[5] See Clarida (1987) and Zeldes (1989a). Deaton (1991) includes in the definition the value of the endowment of leisure in period t.

where the *indicator function* $\mathbf{1}[\mathcal{C}]$ is equal to 1, if condition $\mathcal{C}$ is true, and to 0, otherwise.

3.2 Quantity Constraints on Labor Supply

We extend formally the life cycle optimization problem (1) subject to (2) and (3), so as to allow for exogenous restrictions on labor supply. Such an extension may be interpreted as a dynamic generalization of Ashenfelter (1980). It is motivated by the availability, within the PSID data, of answers to a number of questions that we interpret as pertaining to voluntary versus involuntary aspects of employment. Appendix B provides details on how we recoded the PSID information in order to measure unemployment, underemployment, or overemployment.

Let us consider, in particular, that the consumer believes his labor supply must satisfy a sequence of constraints

$$h_t \leq h_{RU_t}, \qquad t = 0, 1, \ldots, T; \tag{8}$$

$$h_{RO_t} \leq h_t, \qquad t = 0, 1, \ldots, T; \tag{9}$$

with probability one. Quantity constraint (8) may be used to represent *involuntary* unemployment or underemployment. Quantity constraint (9) may be used to represent, symmetrically, *involuntary* overemployment. We abstract from the labor force participation decision, which of course would introduce an additional qualitative employment state.

When compared to liquidity constraints (3), quantity constraints (8)–(9) may have an even better claim to possessing a strong "Keynesian" flavor. We think of h_{RU_t} and h_{RO_t} as representing demand for an individual's labor in his local labor market. Likely determinants are various cyclical factors and, in addition, such factors as the local unemployment rate, the difference between the number of applicants and vacancies in an individual's labor market, the unemployment rate in an individual's (one-digit) occupation, and regional dummies, all variables that are available in the PSID. However, Ham (1986) notes that the effect on a worker of demand shocks to an industry or a region may depend on his characteristics and various human capital variables, which, following others, we include in the model as determinants of labor supply behavior.[6]

[6] Card (1994), however, argues that Keynesian-style labor market constraints are not indispensable for rationalizing Ham's findings on the importance of demand factors. He suggests instead that individuals may decide on their labor supply at a higher frequency time unit than the year (for which data are available) and that there may be significant fixed costs on either the worker's side or the employer's side of the labor market. We do not test for such effects.

We denote the solution for the unconstrained (*notional*) labor supply from problem (1), subject to all constraints, conditionally upon S_t, by $h_t = H(A_t; W_t, \mathbf{P}_{G_t}; \mathcal{N}^t | S_t)$. As this is a function of assets, following MaCurdy (1983) we may refer to it as the *pseudo* labor supply function. An *employment state indicator* may now be defined in terms of the pseudo labor supply function as follows:

$$E(\mathbf{P}_t; \mathcal{N}^t | S_t) = -1, \qquad \text{if } h_t = h_{RO_t} \geq H(A_t; W_t, \mathbf{P}_{G_t}; \mathcal{N}^t | S_t); \tag{10}$$

$$E(\mathbf{P}_t; \mathcal{N}^t | S_t) = 0, \qquad \text{if } h_{RO_t} < H(A_t; W_t, \mathbf{P}_{G_t}; \mathcal{N}^t | S_t) < h_{RU_t}; \tag{11}$$

$$E(\mathbf{P}_t; \mathcal{N}^t | S_t) = 1, \qquad \text{if } h_t = h_{RU_t} \leq H(A_t; W_t, \mathbf{P}_{G_t}; \mathcal{N}^t | S_t); \tag{12}$$

Appendix B links this definition with all categories available in the data, so as to take advantage of their full detail. It is an important feature of our model, which readily follows from the definition of E_t, that lends itself to an *ordered* discrete-choice formulation.

It is helpful to try and visualize the determination of the employment state indicator in a static-equivalent setting. We note that once the period t net asset decumulation b_t has been determined, we may refer to a standard consumption-leisure choice diagram, such as in Figure 1. Given prices and net asset decumulation, the position of the "budget line" is determined. Furthermore, given parameters and values for the observables and unobservables, a particular individual who is in the labor force, may be in one of three categories. An individual may be of type V, in which case employment is determined according to point V_T, and the individual is voluntarily employed. We note that in this case $h_{RO} \leq h \leq h_{RU}$. Alternatively, an individual may be of type U, i.e., one who wishes to work according to point U_T. He may not, however, work as much as he wishes because of the underemployment constraint h_{RU}. In such a case, employment is determined according to point U_R, and the individual is involuntarily underemployed (or unemployed) working h_{RU} hours. Finally, an individual may be of type O, i.e., one who wishes to work according to point O_T. Such an individual may not, however, be able to work as little as he wishes because of the overemployment constraint h_{RO}. In such a case employment is determined according to point O_R, and the individual is involuntarily overemployed, working h_{RO} hours.[7]

[7] If it may be assumed that the notional labor supply function is locally monotonic with no backward bending portion, the definition of E_t may be alternatively stated in terms of wage comparisons. In fact, such a definition may be more appropriate, given that h_{RU}, and h_{RO} are actually not observed.

An appropriate analytical representation of this choice problem requires that it always be the case that $h_{RU_t} \geq h_{RO_t}$, which we impose econometrically. The economic intuition of this assumption is straightforward. The maximum amount an individual is allowed to work must not be less than the minimum.

In view of the discussion of the determinants of h_{RU_t} and h_{RO_t} above, we would expect that an upturn in the business cycle would increase the magnitudes of both of the constraining quantities. This would cause the overemployment constraint to become tighter and the underemployment one to be relaxed. Both those outcomes accord with economic intuition.

The general problem of dynamic consumption decisions subject to quantity constraints belongs to a class of decision problems with mixed discrete-continuous decisions whose estimation has been discussed by Pakes (1994) and Rust (1994). However, it is important to note that even though in the present paper we are interested only in the estimation of a discrete dynamic decision problem, the original problem is not reducible in terms of discrete decisions only, and a statement of the full dynamic programming problem is called for. We eschew, for reasons of brevity, additional details of the problem, and refer to our earlier working paper Hajivassiliou and Ioannides (1994). We instead propose an estimation model for the vector of endogenous variables (S_t, E_t), defined in (7) and (10)–(12). Our approach admits as special cases some of the problems examined by several previous researchers, including in particular Ball (1990) and Zeldes (1989a), whose contributions we discuss in detail in Section 5.5 below.

In lieu of a complete treatment, a number of remarks are in order. First, if an individual in a particular period is unconstrained with respect to either liquidity or employment, anticipation of constraints' possibly binding some time in the future are reflected in current decisions through the *conditional value functions* $V_t^{s,e}$, defined as the optimal value of remaining lifetime utility, conditional on $\{s, e\}$.[8] Intuitively, to the extent that constraints (3), (8) and (9) ever bind, they would affect total lifetime resources.

Second, in spite of considerable research efforts during the last few years, structural estimation of a general mixed discrete continuous model like ours has run up against insurmountable, at

[8] For the usefulness of the conditional valuation function, see Hotz and Miller (1993) and Rust (1987; 1988). They allow the dynamic discrete choice problem to be transformed to an equivalent but static one; the conditional valuation functions play the role of values of a static utility associated with discrete alternative courses of action.

present, computational difficulties.[9] It is for this reason that we pursue estimation of approximate reduced form aspects of the problem.

Third, the functional form of the optimal solution for b_t as a function of state variables does depend upon whether or not the individual is constrained with respect to either liquidity or employment or both. This dependence is, in turn, transmitted to commodity demands and to labor supply, a fact that we exploit in specifying our estimation models in Section 4 below.

4 Econometric Models

4.1 Simultaneous Determination of Liquidity and Employment Constraint Indicators

We shall aim in this paper at estimating the parameters of the two discrete endogenous variables, defined by (7) and (10)–(12), as functions of observable characteristics of the decision maker and his environment, while allowing for dynamics. We do so by introducing state dependence, via the dependent variable's own lagged values as regressors. In addition, we allow contemporaneous spillover and lagged spillover effects from one to the other endogenous variable. All of our models are jointly estimated as systems of discrete decisions that allow for unobservable persistent heterogeneity in the stochastic structures, while imposing so-called "coherency conditions" required for logical and statistical validity of our models. Even though the individual decisions may be estimated as reduced-forms, the model of Section 3 allows them to be construed in quasi-structural forms also, by means of the conditional value functions as we shall see shortly. That is, the employment indicator E_t may be defined conditionally on S_t, which makes the model consistent with the two-stage budgeting setting of Blundell and Walker (1986), and vice versa for the liquidity constraint indicator, conditional on the employment indicator. To the extent that the discrete indicators may not be perfectly observed in our data, the stochastic shocks in the respective models may be interpreted as consisting partly of an observation error. The implications of this are discussed below.

[9] There are no breakthroughs in the mixed discrete-continuous decision problems comparable to Rust (1988) and to Hotz and Miller (1993) for purely discrete decisions. See Pakes (1994) and Rust (1994).

4.2 General Unordered Reduced Forms

We assume for simplicity linear functional forms for the conditional valuation functions for individual i at time t :

$$V_{it}^{s,e} = \Psi_{it}^{s,e}\beta_{s,e} + \epsilon_{it}^{s,e},\ s \in \{0,1\}, e \in \{-1,0,1\}, \tag{13}$$

where $\Psi_{it}^{s,e}$ are vectors of polynomial functions of explanatory variables, which might include lagged values of endogenous variables, β_{se} is a corresponding vector of parameters, and $\epsilon_{it}^{s,e}$ are random variables that correspond to the unobserved components of utility at time t.

Once we have assumed a particular stochastic structure for the $\epsilon_{it}^{s,e}$s, we may use (13) to estimate the model. This specification yields a six-nomial model, as becomes evident immediately below. As an example, the probability that an individual is observed voluntarily employed and liquidity unconstrained in period t, defined as the probability of $[V_{it}^{0,0} \geq V_{it}^{0,1}, V_{it}^{0,0} \geq V_{it}^{0,-1}]$ is given by:

$$\begin{aligned} Prob[S=0,E=0|\Psi_{it}^{s,e}] = Prob\Big[&\varepsilon_{it}^{0,0} - \varepsilon_{it}^{0,-1} \geq \Psi_{it}^{0,-1}\beta_{0,-1} - \Psi_{it}^{0,0}\beta_{0,0}, \\ &\varepsilon_{it}^{0,0} - \varepsilon_{it}^{0,1} \geq \Psi_{it}^{0,1}\beta_{0,1} - \Psi_{it}^{0,0}\beta_{0,0}, \varepsilon_{it}^{0,0} - \varepsilon_{it}^{1,0} \geq \Psi_{it}^{1,0}\beta_{1,0} - \Psi_{it}^{0,0}\beta_{0,0}, \\ &\varepsilon_{it}^{0,0} - \varepsilon_{it}^{1,1} \geq \Psi_{it}^{1,1}\beta_{1,1} - \Psi_{it}^{0,0}\beta_{0,0}, \varepsilon_{it}^{0,0} - \varepsilon_{it}^{1,-1} \geq \Psi_{it}^{1,-1}\beta_{1,-1} - \Psi_{it}^{0,0}\beta_{0,0}\Big]. \end{aligned} \tag{14}$$

The likelihood of this event may be written in terms of the probability distribution functions of the ε_{it}^{se}s, while allowing for the presence of lagged endogenous variables among the Ψs. Since the ϵ_{it}^{se}s are unobserved components of the state vector [Rust (1988)], it is appropriate to treat them as unobservable random shocks, which may reflect individual heterogeneity. Given the state of the art in estimating dynamic discrete choice models, a fairly general assumption we can make is to treat them as random effects with a time-invariant component and an $AR(1)$ component to the general error term.

Specifically, we assume the $\varepsilon_{it}^{s,e}$s are of the form

$$\varepsilon_{it}^{s,e} = \eta_i^{s,e} + \zeta_{it}^{s,e}, \tag{15}$$

where the $\eta_i^{s,e}$s are time-invariant random individual effects and the $\zeta_{it}^{s,e}$s obey the AR(1) structure:

$$\zeta_{it}^{s,e} = \rho_{AR}^{s,e}\zeta_{it-1}^{s,e} + \xi_{it}^{s,e}, \tag{16}$$

where the $\xi_{it}^{s,e}$s are random variables independently and identically distributed over time with means equal to zero, and a 6×6 variance-covariance matrix. This implies a $T_i \times 6$-dimensional correlated vector for observation i. In general, because the limited dependent variables in this model are purely discrete, to achieve identification one needs to normalize the conditional valuation functions of one of the six outcomes to zero. Hence, the parameters that can be estimated are as follows: five of the six parameter vectors β_{se} in (13), fourteen ($= 5 \times 6/2 - 1$) elements of the contemporaneous variance-covariance matrix of the $\xi_{it}^{s,e}$s in (16), fifteen ($= 5 \times 6/2$) elements of the contemporaneous variance-covariance matrix of the $\eta_i^{s,e}$ random effects in (15), and five of the autoregressive coefficients $\rho_{AR}^{s,e}$ in (16).

Thus, consideration of all possible liquidity and labor supply constraints leads to switching regressions, with switching occurring in two dimensions: one, on account of liquidity constraints; two, on account of quantity constraints on labor supply. The introduction of exogenous constraints on labor supply augments the number of the possible regimes in a given period from two, in the case of liquidity constraints alone, to six. Thus, the number of possible outcomes corresponds to the six possibilities defined by $\{\{0,1\} \times \{1,0,-1\}\}$.[10] This may be handled as a system of simultaneous discrete response models, corresponding to the discrete events (S_t, E_t). In practice, of course, not all regimes will be equally important, an issue that is settled by the data.

4.3 Quasi-Structural Form Models with Ordering

The model we developed above does suggest a more specific (and thus testable) stochastic structure, namely one involving two discrete endogenous variables that jointly generate six regimes with a set of implied restrictions, namely that the employment state indicator is naturally *ordered.* Of those endogenous variables, the liquidity constraint indicator, S_t, introduced in (7), may be handled by means of dynamic probit model. On the other hand, the employment state indicator E_t, defined by (10)–(12), suggests that it be modelled as an ordered probit model. Section 5.1 below describes the binary probit part of our model, which assumes that a binary regime indicator for S_t is perfectly observable for every household in every period. The second part of our model, which assumes a perfectly observed employment state indicator E_t is available, is a dynamic ordered

[10] If the status of being out of the labor force (voluntarily unemployed) is included and underemployment is distinguished from unemployment we would have ten states.

probit model and is discussed in section 5.2. Joint estimation of these two models, discussed in section 5.3, allows for interactions between liquidity-constrained behavior and qualitative aspects of employment behavior and combines the above dynamic probit and ordered probit sides. Specifically, the likelihood of unemployment is allowed to be affected by an individual's being constrained in the labor market.

We highlight the fact that the ordered probit model may be nested in the classical sense into the general unrestricted hexa-nomial model introduced in subsection 4.2 above. It is simpler to show this if we concentrate on the labor employment indicator E_t and drop the time subscript. We then have that:

$$Prob[E = 0] = Prob[\varepsilon_0 - \varepsilon_{-1} \geq \Psi_{-1}\beta_{-1} - \Psi_0\beta_0, \;\; \varepsilon_0 - \varepsilon_1 \geq \Psi_1\beta_1 - \Psi_0\beta_0].$$

By defining $\varepsilon'_1 \equiv \varepsilon_1 - \varepsilon_0$ and $\varepsilon'_{-1} \equiv \varepsilon_{-1} - \varepsilon_0$, the above probability may be written in terms of the bivariate distribution function: $Prob[E = 0] = Prob[\varepsilon'_{-1} \leq \Psi_{-1,1}\beta_{-1,1}, \;\; \varepsilon'_1 \leq \Psi_{1,1}\beta_{1,1}]$. It follows that this setup is equivalent to an ordered probit model in terms of a single underlying random variable, ε'_{-1}, if and only if $\varepsilon'_{-1} \equiv -\varepsilon'_1$ (which implies $\varepsilon_1 \equiv \varepsilon_{-1}$), and provided that, in addition, the following conditions are satisfied: first, the variable components of $\Psi_{-1,1}\beta_{-1,1}$ and $\Psi_{1,1}\beta_{1,1}$ have coefficients which are opposite to one another (i.e., their variable components sum up to 0); and second, their intercepts differ. These testable restrictions are discussed in subsection 5.4 below.

There is a simple way to view the hexa-nomial model in relation to the simultaneous system composed of the binary probit and the ordered probit model. Referring to Figure 2, a constellation of six cells is defined by the outcomes $\{\{0, 1\} \times \{1, 0, -1\}\}$. The hexa-nomial model determines which of the six regimes prevails comparing functions of regressors and parameters against draws of *six* random variables, without reference to any ordering. In contrast, the simultaneous system composed of the binary probit and the ordered probit model orders the outcomes on the employment margin and describes them by *two* underlying random variables.

4.4 The Problem of Imperfections in the Liquidity and Employment Constraint Indicators

Our assumption that the binary regime indicator for liquidity constraints S_t and the ordered employment indicator E_t are perfectly observable, while serving well to illustrate our basic approach, is problematic in its most general setting, especially with respect to S_t. A particular threshold amount of financial assets $\tilde{A}_{i_t}$, which depends on individual characteristics as well as market variables but is not observed directly, was identified by our approach as determining switching of regimes for S_{it}, as exemplified by Figure 2. It is holding assets A_{it} exceeding the threshold level that signifies that the household is not subject to a borrowing constraint in a particular period t.[11]

One could consider generalizing our econometric model to allow for an imperfect indicator, J_{it}, specifying whether or not liquidity constraints are binding, based on $I_{ai_{t+1}}$, the observed value of asset income for household i at the beginning of period $t+1$. Since typically assets vary in their liquidity characteristics, which are unobservable, the procedure we (and many others before us) have used to impute asset stocks is at best imperfect. It is, therefore, important to account for implied imperfections in the regime indicators and thus allow for misclassification [*c.f.*, Lee and Porter (1984)]. One approach would be to allow for random *coding errors* in the equations defining the regime indicators. This model, in contrast to the Lee and Porter (1984) formulation, allows the probability of misclassification to vary endogenously and to be determined by economic fundamentals. Such coding errors, however, would not affect the consistency up to scale of the discrete estimation procedures we adopt here that assumes perfect regime indicators, provided they are IID.

An alternative approach would be to model directly the stochastic relation between the imperfect (J_t) and perfect (S_t) indicators, through a distribution function $F(S_t|J_t)$. In this paper we proceed to assume that the regime classification information is either perfect (i.e., $S_t = J_t$) or that possible imperfections in it do not affect the consistency up to scale of the estimators for the discrete models we consider here. We take up a detailed analysis of the possible misclassification issue elsewhere in a paper in progress.

5 Main Estimation Models and Empirical Results

The discrete response system (7) and (10)–(12) is modelled by a generalized limited dependent variables model consisting of simultaneous binary probit and ordered probit parts. Since households

[11] Of course, this would not be an issue if respondents were asked specifically about whether they felt they had been constrained, which is in fact the case with the 1983 wave of the Survey of Consumer Finances. This event is not observed, however, in our data.

must adapt their behavior to the presence of constraints on asset holdings and on labor supply, the path of the regime indicators $[S_t, E_t]$ is endogenous. Zeldes (1989a), who works with food consumption only, does not deal with switching. Neither do Altonji (1986) and Ball (1990), who work with food consumption and labor supply data, nor Ham (1986), who uses only labor supply data.[12] Given specific assumptions about the distribution of the unobservables, this endogeneity can be analyzed by maximum simulated likelihood estimation methods. In this paper we make a descriptive first cut and proceed with estimating joint models for S_t and E_t. We note, nonetheless, that our conditional quasi-structural reduced form approach is firmly rooted in the theory of Markovian decision problems.

It is instructive to highlight the interaction between the liquidity and labor supply constraint indicators, S_t and E_t, by considering structural forms for the pair of two endogenous variables $[S_t, E_t]$ as a system. Consider first models for $[S_t, E_t]$ symmetrically defined with dummy endogenous variables and general state dependence as follows:

$$S_{it} = \mathrm{BP}(S^*_{it}) \equiv \mathrm{BP}(\gamma_{11}S_{i,t-1} + \gamma_{12}S_{i,t-2} + \delta_0 E_{it} + \delta_1 E_{i,t-1} + \delta_2 E_{i,t-2} + X_{it}\beta^{bp} + \varepsilon^{bp}_{it}); \qquad (17)$$

$$E_{it} = \mathrm{BP}(E^*_{it}) \equiv \mathrm{OP}(\gamma_{21}E_{i,t-1} + \gamma_{22}E_{i,t-2} + \kappa_0 S_{it} + \kappa_1 S_{i,t-1} + \kappa_2 S_{i,t-2} + X_{it}\beta^{op} + \varepsilon^{op}_{it}); \qquad (18)$$

where BP and OP denote *binary probit* and *ordered probit* functions, respectively. In a static version of our setting, coherency conditions [Schmidt (1981)] reduce to conditions that the model be recursive, that is the coefficients δ_0 and κ_0 in (17–18) satisfy $\delta_0 \cdot \kappa_0 = 0$. See Appendix A, subsection 7.4 for details. Note that the correlation between the errors ε^{bp}_{it} and ε^{op}_{it} in (17)–(18) is of particular interest, because the presence of unemployment may accentuate the propensity of an individual to be liquidity constrained even after conditioning on all observable information.

In the remainder of the paper we report and discuss estimation results for the system of quasi-structural forms (17)–(18). We specify their stochastic structure as follows:

$$\varepsilon^{bp}_{it} = \eta^{bp}_i + \zeta^{bp}_{it}, \;\; \zeta^{bp}_{it} = \rho^{bp}_{AR}\zeta^{bp}_{it-1} + \xi^{bp}_{it} \qquad |\rho^{bp}| < 1 \qquad (19)$$

[12] Zeldes (1989a) assumes that regimes are perfectly observable and uses only data for the unconstrained group in the estimations. If, as expected, regimes are endogenously determined, his procedure will give unreliable inferences. Altonji (1986) excludes constrained individuals. Ball's approach differs from Zeldes' only in his using jointly food consumption and labor supply data. Ham (1986)'s use of dummy endogenous variables to account for the impact of constraints is less general than ours, but his separation of underemployment from unemployment is noteworthy, especially in view of his finding that business cycle variables are good instruments for unemployment but not for underemployment.

$$\varepsilon_{it}^{op} = \eta_i^{op} + \zeta_{it}^{op}, \quad \zeta_{it}^{op} = \rho_{AR}^{op}\zeta_{it-1}^{op} + \xi_{it}^{op} \qquad\qquad |\rho^{op}| < 1; \tag{20}$$

where η_i^{bp}, η_i^{op} are time-invariant unobservable characteristics of household i assumed to be Gaussian i.i.d. over the sample with zero means, standard deviations $\sigma_{\eta_i}^{bp}, \sigma_{\eta_i}^{op}$, respectively; and $\zeta_{it}^{bp}, \zeta_{it}^{op}$, are stationary AR(1) random processes with autocorrelation coefficients $\rho_{AR}^{bp}, \rho_{AR}^{op}$, and i.i.d. innovations $\xi_{it}^{bp}, \xi_{it}^{op}$, respectively. The latter are assumed to be contemporaneously correlated, conditional on all explanatory variables, including lagged dependent variables, with correlation coefficient $corr(\xi_i^{bp}, \xi_i^{op})$. The variances of the i.i.d. shocks are normalized to 1. We also assume that the innovations $\xi_{it}^{bp}, \xi_{it}^{op}$ are mean-independent of the explanatory variables X_{it}, while the time-invariant effects η_i^{bp} and η_i^{op} are allowed to be correlated with the regressors X_{it} in a time-invariant fashion. See Hajivassiliou (2003) on this point, which follows Chamberlain (1984) and models the dependence of η_i^{bp} and η_i^{op} on regressors as $E(\eta_i^{bp}|X_{1t}, \cdots, X_{iT_i}) = \bar{X}_{i.}\theta^{bp}$ and $E(\eta_i^{op}|X_{1t}, \cdots, X_{iT_i}) = \bar{X}_{i.}\theta^{op}$. This device introduces $\bar{X}_{i.}$ as additional regressors in S_{it}^* and E_{it}^* in (17)–(18). Assuming that the errors have a non-scalar variance-covariance structure conditional on all explanatory variables including lagged dependent variables is often done to express coexistence of state dependence and heterogeneity, as in Heckman (1981), or to express impact of habits, as in Hotz *et al.* (1988). The full stochastic structure we assume here implies that we do not need to instrument for the lagged dependent variables, but do need to specify the distribution of the initial conditions. Our MSSL/GHK estimation procedure incorporates fully these features. See Appendix A for more details.[13]

Next, we summarize the models that we estimate. It is pretty clear that univariate probit models for $[S_{it}, E_{it}]$ are fully dominated by the bivariate ones. We do not report the univariate results for reasons of brevity, but present diagnostics to that effect. Columns (a) of Tables 6i and 7i report joint estimation of quasi-structural forms respectively for the liquidity constraint and employment indicators, according to (17)–(18), under the restrictions $\delta_0 = \delta_1 = \delta_2 = 0$ and $\kappa_0 = \kappa_1 = \kappa_2 = 0$ respectively, namely that neither contemporaneous, nor lagged spillover effects are included from the other constraint side of the model. Columns (b) of Tables 6i and 7i report a similar joint

[13] In such a setting, the presence of a lagged dependent variable among the regressors does not necessarily imply a contemporaneous correlation in every period. For example, as Heckman (1981) explains, it is still possible to assume that conditional on the RHS variables the only residual correlation is through the random effect plus its $AR(1)$ structure, as we have assumed. Our approach is considerably more general than Heckman's in that it explicitly allows for the unobservable heterogeneity effects to be correlated with regressors in a time-invariant fashion.

estimation after we further augment the dynamic structure by allowing for lagged spillover effects but not contemporaneous ones, that is, in terms of the system (17)–(18), under the restrictions $\delta_0 = 0$, and $\kappa_0 = 0$, respectively. Finally, Columns (c) of Tables 6i and 7i report joint estimations of the full set of quasi-structural forms that include both contemporaneous and lagged spillover effects, but always making sure to guarantee the coherency conditions. That is, column (c) of Table 6i reports the results for quasi-structural form (17) for the liquidity constraint equation, estimated jointly with a model for the employment constraints equation like the one reported in column (b) of Table 7i, that is with the quasi-structural form (18) under the coherency condition $\kappa_0 = 0$. And, column (c) of Table 7i reports the results for quasi-structural form (18) for the employment constraints equation, estimated jointly with a model for the liquidity constraint equation like the one reported in column (b) of Table 6i, or alternatively put, with the quasi-structural form (17) under the coherency condition $\delta_0 = 0$.

Three remarks are in order. First, we underscore that in our simulated maximum likelihood estimation of models (17)–(18) with endogenous variables among the regressors, we make proper allowance for the endogeneity of RHS variables whenever appropriate. A detailed explanation of how we achieve this may be found in Appendix A, subsection 7.3. Second, our modelling of random individual effects allows that they be correlated with the explanatory variables in a time-invariant fashion. See Hajivassiliou (2003) for details. Third, Appendix A focusses on the details of the econometric methodology that we employ, while Appendix B gives details of data construction and recodings.

5.1 Empirical Results: The Liquidity Constraint Side of the Model

Consider the results reported in Table 6i. These report estimations for the liquidity constraint indicator S_{it} model, according to (17), jointly estimated with different versions of the employment constraint indicator E_{it} model, according to (18). The dependent variable S_{it} is measured by a dummy variable identical to Zeldes' "total wealth split" of the data into constrained ($S = 1$) and unconstrained ($S = 0$) households — see Appendix B. The estimations of the employment constraints models are discussed in subsection 5.2 below.

A time-invariant individual effect is allowed in the form of a random effect, and in addition, an

AR(1) shock, in accordance with (19). The variance of the i.i.d. component in the AR(1) shock is normalized to 1. The presence of the random effect structure is statistically very significant. The coefficients of most explanatory variables are also very significant and generally have the expected sign. The importance of the panel structure is confirmed by comparing with estimations of a homogeneous probit model with an identical set of explanatory variables restricted to have an i.i.d. error structure (i.e., $\sigma_{\eta}^{bp} = 0$ and $\rho_{AR}^{bp} = 0$). This is the starting point for our estimations, but do not report them here for reasons of brevity, except to note that a number of key coefficients, e.g., that of the real rate of interest, have the wrong sign when the panel structure is ignored.

The results highlight the importance of the dynamic structure. The lagged values of all endogenous variables are always very significant and imply substantial state dependence. The autoregressive correlation coefficient ρ_{AR}^{bp} is estimated to be 0.68 with an asymptotic t-statistic of 11.8. The standard deviation of the random effect η_i^{bp}, $\sigma_{\eta_i}^{bp}$, is also statistically significant, with a t-statistic of 31.2, and so is $corr(\xi_{it}^{bp}, \xi_{it}^{op})$, whose estimate is 0.43 and its t-statistic is 18.2. The estimated coefficients for the two lags of the endogenous variable $S_{i,t-1}$ and $S_{i,t-2}$, which are included in the regression, are 1.12 and .15, and their t-statistics are 38.9 and 5.04, respectively. Both those effects and the sign of the autocorrelation coefficient suggest a high degree of persistence in the likelihood of being liquidity constrained.

The lagged endogenous variables for overemployment and for under- or unemployment in the previous two periods, respectively, are not included in the regression we report in column (a) but are included in the ones reported in columns (b) and (c). They do not appear significant and their estimated coefficients are numerically small, suggesting no substantial role for lagged spillovers from the employment side.

The other regressors, denoted by X_{it}, include roughly speaking preferences, labor supply variables, and labor demand variables. Specifically, education, food needs (a PSID variable measuring household composition, a weighted sum of the current ages of family members adjusted for total family size), age, race, religion, marital status and the real rate of interest are included in the X_{it} group. Several of these variables have also been used by Zeldes (1989a). Adding to the list, we include such labor demand and supply variables as county unemployment, local labor market conditions, unemployment rate in the household head's occupation and of labor supply variables as job tenure, number of children below the age of five (in order to account for additional effects from the presence of young children, over and above what is accounted for in food needs), union membership and being being disabled. Several of these variables were used by Ham (1982). Also included are geographical dummies and three grouped wave dummies (summarizing the years 1976-9, 1980-3, and 1984-7). A cubic structure for age is very significant, implying a highly nonlinear negative effect of age upon the probability of being liquidity constrained. A higher real rate of interest is associated with a higher probability of being constrained, exactly as expected. A household head's being black has a positive and very significant effect on that probability, and being married and highly educated have very significant negative effects. All these results accord with intuition. Also included in these regressions are 16 time-averages of all time-varying regressors. Their inclusion is very significant according to the χ^2 statistics reported at the top of Table 6i.[14] We discuss the consequences of this finding in section 5.4 below.

Table 6ii reports the estimation results in the form of the estimated marginal effects for the estimated probability of being liquidity constrained with respect to the corresponding independent variable, corresponding to the columns of Table 6i. The line marked $\hat{P}_{lc}$ reports the marginal effects for implied probabilities for a hypothetical individual with independent variables taking values equal to their sample means. There are seven columns of results. The first column reports the respective sample average value for each of the independent variables. The next two columns pertain to the estimation reported in column (a), Table 6i, and give the marginal effects of the respective independent variable when the probability of being liquidity constraint is evaluated at the sample means. For a continuous variable, this is the respective derivative. For a discrete variable, this is the difference between the probability evaluated when the respective variable is equal to 1 minus the probability evaluated when the respective variable is equal to 0. The columns marked $\Delta^*\hat{P}_{lc}$ report, respectively, the marginal effect of each variable alone, $\frac{\partial \hat{P}_{lc}}{\partial X_j}$, and the ones marked $\Delta^{**}\hat{P}_{lc}$, the marginal effect of each variable *paired with its time mean* whenever appropriate, $\frac{\partial \hat{P}_{lc}}{\partial X_j} + \frac{\partial \hat{P}_{lc}}{\partial \bar{X}_j}$. The respective elasticities may be computed readily. Obviously, Δ^* and Δ^{**} are equal for variables entered above without their time average, which include all variables with zero or low time variation. While several of the explanatory variables have substantial marginal

[14] The time invariant regressors are not included for the obvious reasons, nor are the wave dummies, which do not exhibit much variability.

effects, the elasticities associated with the three age variables and the own lagged variables are particularly noteworthy. Especially for the dummy variables, the marginal effects have a very intuitive interpretation. For example, reading from the first two columns, an individual who was liquidity constrained in the previous period has a probability higher by 0.30 of being constrained now.[15]

5.2 The Labor Constraints Side of the Model

Table 7i reports estimation results for the ordered probit side of the model for an employment indicator E_{it} as the dependent variable according to equations (17) and (18) for the sample of male heads. This variable corresponds to the definition (10)–(12) for members of the labor force only and its construction is discussed in subsection 8.2. We present in column (a) estimation results for the quasi-structural form of the ordered probit side while ignoring all spillovers from the liquidity constraint side, that is $\kappa_0 = \kappa_1 = \kappa_2$. The next two columns, (b) and (c), include lagged liquidity constraint spillovers; while column (b) excludes and column (c) includes contemporaneous spillovers. The employment constraints equation is estimated jointly with the liquidity constraints equation: column (b), table 7i, is estimated jointly with column (b), table 6i, and column (c), table 7i, is estimated jointly with table 6i(b) version so as to ensure the coherence condition holds.

We use data for members of the labor force only and do not distinguish econometrically the cases of underemployment and unemployment. These closely reflect the ordering of outcomes according to our theoretical model. The ordered probit side of the model with panel data is given by:

$$\begin{array}{lll} E_{it} = -1, & \text{if } E^*_{it} < \theta^-, & \text{overemployment} \\ E_{it} = 0 & \theta^- \leq \text{if } E^*_{it} \leq \theta^+, & \text{voluntary employment} \\ E_{it} = 1 & \theta^+ < \text{if } E^*_{it}, & \text{under/unemployment,} \end{array} \tag{21}$$

where E^*_{it} is defined in (18). This part of the model estimates an intercept, a vector of unknown coefficients, and a stochastic structure defined by (20), that includes the lower threshold θ^-, standard deviation of the time invariant component, $\sigma^{op}_{\eta_i}$, the autocorrelation coefficient ρ^{op}_{AR}, and $corr(\xi^{bp}_{it}, \xi^{op}_{it})$, the correlation coefficient between ξ^{bp}_{it} and ξ^{op}_{it}, the i.i.d. components of the stochastic

[15]We have also computed but do not report here the marginal effects for implied probabilities for a hypothetical individual with independent variables taking values equal to their sample means, alternatively the sample mean plus the sample standard deviation, and alternatively the sample mean minus the sample standard deviation, respectively. Not surprisingly, those probabilities vary nonlinearly with the standard deviation.

structure of the binary probit and the ordered probit equations (19)-(20). The upper threshold, θ^+, is normalized at 0. We note that, analogously to η_i^{bp}, we allow for the individual effect η_i^{op} to be correlated with the explanatory variables in a time-invariant fashion.

Column (a) of Table 7i reports results for the counterpart for the employment constraints equation of the liquidity constraint equation that is reported in column (a), Table 6i, when those two equations are jointly considered. The panel structure is very significant, as we have already discussed in subsection 5.1 above: the models reported in the respective columns of Tables 6i and 7i, respectively, share the same panel structures.

Two lagged values of the indicator that a household head is involuntarily unemployed are both very significant, with estimated coefficients of .70 and .37, and $t-$statistics of 36.3 and 19.3, respectively. Thus, being involuntarily unemployed makes one more likely to be so again in the future. Dummies for being overemployed in the past have the opposite effect and are also very significant. Also very significant in Table 7i is the threshold θ^- associated with involuntary under- or unemployment relative to voluntary employment. This is negative, as it should be, given that the upper threshold is normalized at 0. These findings strengthen an earlier but somewhat tentative result by Clark and Summers (1982) on the importance of persistence elements in explaining cyclical behavior in labor supply. These results imply a rich dynamic structure for the labor constraints indicator. The model reported in Table 7i, column (b), differs from that of column (a) only on account of the inclusion of the two lags for the liquidity constraint indicator, one of which is marginally significant, although their inclusion is jointly significant according to the χ^2 test.

The remaining explanatory variables included in the regression coincide with those used by Ham (1982). Of the regional dummies the one indicating residence in Western U.S. is highly significant. A cubic effect for age is significant and implies that age reduces the probability of being underemployed. Similar and even more significant is the effect of job tenure on the likelihood of being underemployed. Race and religion are significant. Having a disabling health condition, being male, a union member, and having many children all have very strong and statistically important positive effects. Collecting unemployment insurance and the imputed wage both have numerically very small but statistically significant effects. Being married and being educated both have very significant and negative effects. A set of variables representing demand effects all have very significant coefficients. Higher values of the unemployment rate in the county of residence and in the occupation of the household head imply higher values for the likelihood of underemployment or unemployment. With a few exceptions, these results accord with intuition. They do imply a persistent and possibly "trapping" effect caused by past unemployment and underemployment. Similarly to the liquidity constraint model, also included in these regressions are 16 time-averages of all time-varying regressors. Their inclusion is significant according to the χ^2 statistics reported at the top of Table 7i and we discuss the consequences of this finding in section 5.4 below. Finally, Table 7ii presents estimates of marginal effects of the counterpart for the employment constraints equation. Their interpretation is exactly analogous to that of Table 6i, discussed in section 5.1.

5.3 Quasi-Structural Form Models for Liquidity Constraints and Labor Supply Constraints

Let us now focus on columns (c) of Tables 6i and 7i, which report joint estimation results for quasi-structural forms for S_{it} and E_{it} as a system taking into account the full possibility of the lagged and contemporaneous spillover effects across the two sides of the models, while always imposing the coherency conditions discussed above. Column (c), Table 6i, reports results for equation (17) estimated jointly with (18) with the restriction $\kappa_0 = 0$ imposed. Intuitively speaking, column (b), Table 7i, reports the results for an equation determining the marginal probability for E_{it}; column (c), Table 6i, reports results for an equation determining the probability for S_{it}, conditional on E_{it}. Using analogous intuition, column (c), Table 7i, reports results for equation (18) estimated jointly with (17), with the coherency condition $\delta_0 = 0$, and whose results are reported on column (b), Table 6i. In like manner, column (b), Table 6i, reports the results for an equation determining the marginal probability for $S_{it}; and$column (c), Table 7i, reports results for an equation determining the probability for E_{it}, conditional on S_{it}.

Inclusion of contemporaneous spillover effects, that is inclusion of E_{it} in the liquidity constraint equation for S_{it}, and alternatively of S_{it} in the employment constraints equation for E_{it}, is statistically significant according to the likelihood ratio test.[16] It is crucial to remember that the contemporaneous spillovers are included *in turn* and *not simultaneously*, since that would have

[16]The E_{it} spillover effect was decomposed into its two constrained parts, overemployment ($E_{it} = -1$) and under/unemployment ($E_{it} = 1$).

violated the coherency of the model. The models reported in columns (c), Table 6i, and (b), Table 7i, have a joint loglikelihood function of $-29,401.4$ versus $-29,422.7$ for columns (b), Table 7i, and (b), Table 6i. Similarly, the models reported in columns (c), Table 7i, and (b), Table 6i, have a joint loglikelihood function of $-29,406.3$ versus $-29,422.7$ for columns (b), Table 7i, and (b), Table 6i, jointly. So, the simultaneous equations system passes the likelihood ratio tests.

This approach accounts for the joint determination of S_{it} and E_{it} while imposing the coherency condition, $\kappa_0 = 0$ and $\delta_0 = 0$, respectively for the two models. In Appendix A, subsection 7.3 we explain how we handle the presence of endogenous variables on the right hand side in these specifications through the use of Maximum Simulated Likelihood in conjunction with the GHK simulator.[17] Particularly noteworthy is our estimation of the autoregressive structure and contemporaneous correlations in $(\varepsilon_{it}^{bp}, \varepsilon_{it}^{op})$, the error structure of equ. (17) and (18), detailed in (19) and (20), as well as allowance for individual effects and regressors being possibly correlated in a time-invariant fashion.

All of the components of the stochastic panel structure are estimated to be very significant for both models. Interestingly, the standard deviation for the random effect $\sigma_{\eta_i}^{bp}$ in the liquidity constraint equation varies imperceptibly across the various models but $\sigma_{\eta_i}^{op}$ does vary in the case of the structural form. The respective correlation coefficient is significantly smaller in the case of the structural form. Similar is the case with the autocorrelation coefficients ρ_{AR}^{bp} and ρ_{AR}^{op}, and the estimate of the former is much larger than the latter. The estimated correlation coefficient declines as we move to the right on both tables. In moving from columns (a), Tables 6i and 7i, to columns (b) of Tables 6i and 7i, the lagged dependent variables of the employment constraints indicator are added to the liquidity constraint equation and those of the liquidity constraint indicator to the employment equation. This reduces the contemporaneous correlation as expected. And similarly moving from columns (b), Tables 6i and 7i, to columns (c) of the same tables, contemporaneous spillover effects are added *in turn* as required to guarantee the conherency conditions.

We see from column (c), Table 6i, that being unemployed has a strong positive and significant effect on the likelihood of being liquidity constrained. Being overemployed is not significant. The

[17] The exclusion restrictions for the liquidity constraint model follow Zeldes (1989a), except that we include in addition quadratic and cubic effects for the age variable, marital status, geographical dummies, race and religion. This list follows quite closely results that Zeldes discusses but does not report in his paper.

lagged values of both those variables are actually not statistically significant. Most of the determinants of being liquidity constrained remain significant in the structural form too, as do the own lagged dependent variables. Being black is associated with higher likelihood of being constrained, while being other nonwhite, e.g., Asian, a lower one.

The two right most columns of Table 6ii report elasticities of estimated marginal effects for the liquidity constraint equation of the joint model. Reading across we see that the implied probabilities generally differ little between the restricted and the full quasi-structural form models.

Turning now to the likelihood of being underemployed or unemployed,[18] we see that being liquidity constrained has a very significant positive effect, and so do the own lagged values of the variables expressing being overemployed, which have negative effects, and unemployed, which have positive effects. Most of the determinants of the likelihood of being underemployed retain their significance. Unemployment rate in the county of residence and in the occupation of the head of household, and tightness of local labor market conditions[19] are all very significant and with signs in accord with intuition. Being nonwhite is associated with higher likelihood of being underemployed or unemployed.

Finally, we note that the inclusion of the endogenous variable expressing the employment constraints indicator as an explanatory variable for the liquidity constraint indicator and of the endogenous variable expressing the liquidity constraint indicator as an explanatory variable for the employment constraints indicator are each significant in terms of the likelihood ratio test. This follows from comparing the loglikelihoods from columns (b) and (c) in both Tables 6i and 7i. The respective differences are statistically significant according to the standard χ^2 test.

5.4 Diagnostics

We report at the top of each column of Tables 6ii and 7ii various probability predictions and data proportions of selected regimes. In Table 6ii, the binary probit side estimates are used to construct the predicted probability of being liquidity constrained at the sample means, $\hat{P}_{lc}(\bar{X})$, the average predicted probability $\overline{\hat{P}_{lc}}$, and the percentage of observations that have positive predicted

[18] The exclusion restrictions for this model follow Ham, *op. cit.*.

[19] This categorical variable measures tightness of the local labor market for unskilled workers, with values ranging from 1, for good conditions, to 5, for bad conditions.

latent values for the liquidity constraint indicator $\overline{\mathbf{1}}(x_{it}\hat{\beta}^{bp} > 0)$. Finally, we give the percentage of observations correctly predicted by our models (in terms of the predicted indicator $\overline{\mathbf{1}}(\cdot)$) matching the observed liquidity constraint indicator.

In Table 7ii we present the analogous results obtained from the ordered probit employment side, by focussing on the two regimes with binding constraints, namely $[E_{it} = -1 \equiv$ involuntary overemployment$]$ and $[E_{it} = 1 \equiv$ involuntary underemployment or unemployment$]$. Probability predictions are denoted by $\hat{P}_{ov}$ and $\hat{P}_{un}$ respectively, and regime predictions by $\mathbf{1}(\hat{\theta}^{-} < \mathbf{x_{it}}\hat{\beta}^{\mathbf{op}})$ and $\mathbf{1}(\hat{\theta}^{+} > \mathbf{x_{it}}\hat{\beta}^{\mathbf{op}})$ respectively.

Our estimation results suggest remarkably good fits. Specifically, the percentages of correctly predicted values are 88% for the $S_{it} = 1$ event, 81% for $E_{it} = -1$, and 94% for $E_{it} = 1$, while the mean predicted values match almost exactly their respective observed sample means.

Additional information on how well our models fit the data is provided by Figures 3 and 4, where we have plotted predicted probabilities over time using our model estimates. Calculations based on columns (a) and (c) of Tables 6i and 7i are contrasted to those based columns (c). We note that the year-by-year predictions vary cyclically and conform rather well to the historical economic facts business cycle timing of the US economy for the period under study.

More specifically, Figure 3 compares the time variation in the predicted probabilities of being liquidity constrained based on version (a) of the model (neither lagged nor contemporaneous spillover effects from the employment side), to those obtained from version (c) (with full employment spillovers). The version (c) estimates allow us to obtain predictions for the hypothetical case that all individuals were ivoluntarily under- or unemployed, suggesting that in such a case the probability of a binding liquidity constraint would rise by an additional 10%. Figure 4 presents the results of performing an analogous exercise for the employment constraints side of the model. In that case, the impact of a binding liquidity constraint spilling over to the employment constraints side is slightly more modest: the predicted probabilities of being voluntarily constrained drop by about 7-8%, while those of being under- or unemployed rise by a similar amount.

As should be evident from equations (17)–(18), the joint 6-regime discrete response model we estimate has the specific binary/ordered structure we described above. A test of this specification, which readily follows from the theoretical model, is to estimate the model as an unrestricted, i.e., *unordered* hexa-nomial probit, and test the over-identifying restrictions. Such an estimation is feasible using the simulated maximum likelihood method we employ in this paper.[20]

We discussed in Section 3.1 above that the unordered hexa-nomial probit model involves a staggering increase in the number of parameters to be estimated relative to the ordered bivariate model. E.g., the slope parameters of the valuation functions amount to 180, since 5β vectors are estimated for each explanatory variable. In order to conduct such a test by means of state-of-the-art technology we have to restrict ourselves to a subset of the data. We estimated an unrestricted trinomial probit model for the labor constraint indicator and an unrestricted hexa-nomial probit model for the full model and compared them with the respective restricted ones. We refrain from reporting all of our estimation results because of the number of parameters involved. We are happy to note that key aspects of the overidentifying restrictions are not rejected. In particular, referring to the discussion on p.18 above, we note that the estimated correlation coefficient between the i.i.d. terms of the AR(1) components of the errors for the unrestricted trinomial model is nearly -1, exactly as predicted by the ordered model. Similarly, the most highly significant of the components of the parameter vectors of the indicator functions are quite near the theoretical prediction that they sum up to zero. We take these results as powerful evidence in favor of our theoretical structure.

Finally, we discuss a test of the validity of the assumption made typically that the random effects are uncorrelated with the independent variables of the model. We noted above that we have estimated both models by introducing the time means of those of the independent variables which are time-varying as separate regressors [Chamberlain (1984)] . These are the results that are reported in Tables 6i and 7i, as we indicate on both tables. Exclusion of the time means is statistically rejected according to the likelihood ratio test (χ^2 values in excess of 220 with 16 degrees of freedom, rising to over 240 in the more restrictive column (a) versions). The models that we report lend themselves to a more intuitive interpretation in that the estimated coefficients relate to the effect of a variable's deviation from its time average. The fact that exclusion of the time-means is drastically rejected and that the estimates do not differ very much from those obtained without the time averages implies that the assumption that the random effects are uncorrelated with the

[20] The model we derive from our theory is clearly nested in the classical sense in such a standard hexa-nomial probit model, which makes this testing approach have good asymptotic power properties. The correct distribution theory required for these tests is complicated by the fact that the null hypothesis involves restrictions on the boundary of the parameter space.

regressors in our model is rejected. The model without the time averages would be inconsistent and hence including the time-means is important in soaking such correlations.

5.5 Comparisons with Past Work with Quantity Constraints

We now discuss how our work compares with the previous literature that utilizes qualitative information. Zeldes (1989a) makes no use of employment constraints information and restricts his attention to whether a household is liquidity constrained. Ball (1990) uses data from the PSID for 1968-1981 and classifies a worker as constrained in a given year if he either experiences a spell of unemployment or cannot work as many hours as he wants. A respondent is constrained if he answers "no" to "Was there more work available on your job [or "any of your jobs" if more than one] so that you could have worked more if you had wanted to?" and "yes" to "Would you have liked to work more if you could have found more work?" However, a person is considered constrained in all years if he was classified as constrained *in any year.* Thus, the sample split employed by Ball is time-invariant and results in 9290, or 70%, of his 13,265 annual observations being classified as constrained. We, on the other hand, exploit the substantial time variation associated with these qualitative employment status categories. This is one of the reasons for which this paper may be considered as a generalization of Ball's. The other is that we allow for the possibility of overemployment constraints, which he does not.

Biddle (1988) uses PSID data for 1976-1980 and a scheme similar to Ball's to classify workers as constrained. Workers are constrained, if they are against either an upper bound on hours of work, (i.e., if they answer no to the question of whether more work was available and yes to the question of whether they would like to work more), or if they are against a lower bound, (i.e., if they answer no to the question of whether they could work less). Biddle works with a full sample of 1249 observations on first-differences, of which 1044, or 84%, are classified as constrained.

Ham (1982) explores the qualitative aspects of labor supply in detail while using a single cross-section of 835 workers from the PSID for 1971. A worker is unconstrained if he/she is neither underemployed nor unemployed, and distinguishes three categories of constrained workers: unemployed but not underemployed, underemployed but not unemployed, and underemployed and unemployed. Ham ignores the possibly constraining effect of overemployment, by arguing that it is relatively unimportant. He defines a worker as underemployed if a worker is constrained in terms of hours of work per week, that is, if the worker answers no to the question of whether more work was available and yes to the question of whether he wanted to work more then such a worker is classified as underemployed. A worker is classified as unemployed if the worker is constrained in terms of weeks per year. It is thus possible for a worker to be both underemployed and unemployed. We do not draw such a distinction, especially in view of the fact that hours of work are reported on an annual basis. Ham (1982) uses univariate and bivariate probit models for underemployment and unemployment as distinct selection rules to correct for sample selection bias affecting labor supply behavior. He finds that unemployment and underemployment reflect constraints on behavior. He notes that different factors may determine those states, e.g., business cycle variables are important for unemployment but not for underemployment.

In examining the data, we have also replicated Ham's criteria and confirmed the consistency of our selection with his. The difference of his selection from our labor constraint indicator E_t is that his is not *ordered* and does not distinguish overemployment (which, however, is not numerically very important).

Kahn and Lang (1992) argue hours constraints may be motivated by contract theory. They employ a static ordered probit model of discrete events which are roughly comparable to ours. Their tests of specific features of labor-contract theory with data from the 1981 wave of the PSID largely reject such explanations of hours constraints.

The present paper with its emphasis on possibly time-varying discrete events in panel data is more closely related to Ham (1986), who uses PSID data for 473 individuals from 1971-1979. His experiments with dummy variables for underemployment and unemployment, defining them identically to his earlier work [Ham (1982)] as time-varying right hand side endogenous variables, is an improvement over Ball's notion of time-invariant constraints. In view of the endogeneity of these dummy variables, Ham (1986) instruments them by means of a set of exogenous variables chosen to proxy the labor market conditions facing a worker. However, those events are inherently discrete, and Ham's econometric procedures do not handle them as such.

Hyslop (1999) studies the intertemporal labor force participation behaviour of married women within a dynamic search framework using panel data. He estimates multiperiod linear probability and probit models, allowing for a rich dynamic structure. He finds very significant state dependence, unobserved heterogeneity, and serial correlation. In line with our findings here, he reports a crucial role for lagged state dependence and temporal correlation in the unobservables in such dynamic discrete models of employment behaviour. In contrast to our study here, he places emphasis on the linear probability models whereas we focus solely on probit ones. More importantly, his approach does not allow for the random persistent heterogeneity effects to be correlated with the regressors, whereas our results are more robust in this dimension.

Ham and Reilly (2002) extend the Lucas–Rapping model of equilibrium labor supply by means of the implicit contracts model as an equilibrium model and of the hours restrictions as a disequilibrium model, and and test their models using PSID for 1972–1992, and Current Expenditure Survey data for 1984–1992. They reject the Lucas–Rapping predictions of intertemporal substitution in labor supply. Hours restrictions are introduced by means of an endogenous switching model, where an upper bound on hours worked indicates that unemployment is present when it is binding. The resulting model is a two-sided Tobit, whose discrete part is similar to our ordered probit model. While their model is clearly more closely grounded in economic theory than ours, the dynamics in the stochastic structure of our model are much richer than theirs, which are restricted to time dummies only and appeal to instruments to account for dynamic elements in the stochastic structure. This poses questions about the power of their tests when the stochastic structure is so simple in an explicitly dynamic economic model.

6 Conclusion

We explore in this paper empirical implications of a theory of labor supply and consumption decisions that goes further than previous research in allowing for a role of such institutional constraints as limited access to borrowing and involuntary unemployment and overemployment. We report estimations for discrete dependent variables with two simultaneous dynamic probit models. The first describes a household's propensity to be constrained in borrowing, while the second, a dynamic ordered probit model for a labor constraint indicator, describes qualitative aspects of the conditions of employment, that is whether the household head is involuntarily overemployed, voluntarily employed, or involuntarily underemployed or unemployed. These models are estimated, separately and jointly, as well as in ordered and in unordered quasi-structural form versions. We believe that the dynamic labor constraint model has not been considered before in the literature nor has a panel model with as general a structure for the unobservables. The quasi-structural forms we estimated capture state dependence and spillovers among the underlying decisions, while the panel structure of the unobservables allows for correlation between the time-invariant components of the random effects in the two equations and for an autoregressive component. Our diagnostics suggest that our estimation models exhibit remarkably good fits.

In terms of its structure and empirical objectives, the paper may be considered as an integration of two separate strands of the empirical literature, both with respect to the equilibrium/disequilibrium dichotomy on one hand (Ashenfelter (1980) and Ham (1986)), and with respect to the interaction between labor supply and consumption decisions on the other (Altonji (1986), Ball (1990), and Zeldes (1989a)).

Individuals may face restrictions on the amount of work they can supply to their employers as well as restrictions on borrowing against their future incomes. Though they may resent such restrictions, they still adapt their lifetime plans to them and in the light of the best information they have about the presence of such constraints in the future. The assumption that is made sometimes, namely that all fluctuations in employment status and hours worked over time is voluntary, is an undue restriction that may therefore lead to inconsistent estimation and misinterpretation of the data. These problems can be overcome when information is utilized, as in this paper, about the voluntary/involuntary nature of changes in employment over time.

From among the numerous unexplored areas of research that our approach has opened up, we note the possibility of estimating and testing the extent of the dependence of the structural form for each of the endogenous variables conditionally on the regime characterizing the other. In view of the difficulty of estimating life cycle consistent dynamic models, we note that the simulation methods that we employ here may be combined fruitfully in the future with non parametric methods [Magnac and Thesmar (2002)]. These issues deserve attention in future research.

Table 1: Descriptive Statistics
Number of Household Spells: 2410

Variable	Nobs	Mean	StdDev	Med	Mode	Min	Max	InterQuart
county unempl. rate	32870	6.5878	2.8626	6	5	1	34	3
hd disabled?	35860	0.1271	0.3331	0	0	0	1	0
out of lab. force?	36963	0.1232	0.3287	0	0	0	1	0
overemployed?	36963	0.0484	0.2146	0	0	0	1	0
underemployed?	36963	0.1723	0.3776	0	0	0	1	0
unemployed?	36963	0.0218	0.146	0	0	0	1	0
vol. employed?	36963	0.6341	0.4816	1	1	0	1	1
education hd	34631	4.9438	1.8144	5	4	0	8	2
food needs	36963	1054.895	417.5646	1016	669	337	9999	555
family size	35917	3.1169	1.4472	3	2	1	14	2
growth food needs	35913	-0.0134	0.2296	0	0	-2.7044	2.7044	0.0249
hd age	34828	41.5437	15.0652	38	29	17	92	23
tenure hd (months)	32654	82.1139	96.3621	39	0	0	960	156
live in north-centr?	36961	0.3159	0.4649	0	0	0	1	1
live in north-east?	36961	0.1985	0.3989	0	0	0	1	0
live in south?	36961	0.3055	0.4606	0	0	0	1	1
hd married?	34828	0.8773	0.3279	1	1	0	1	0
num.child. 0-17 yrs	34828	1.0314	1.2217	1	0	0	8	2
num.child. 0-5 yrs	27951	0.3731	0.6815	0	0	0	4	1
occup. unempl. rate	28737	5.8824	3.6405	4.6999	3	1.4	17.0999	4.8000
race of hd: black?	36954	0.0523	0.2226	0	0	0	1	0
race of hd: white?	36954	0.8972	0.3036	1	1	0	1	0
real disposable inc	35793	10588.7	8535.672	9535.164	0	-223144	530110.5	6680.785
hd cath./eastorthdx?	32846	0.1354	0.3422	0	0	0	1	0
hd no religion/DK?	36963	0.4800	0.4996	0	0	0	1	1
hd 'protestant'?	32846	0.4234	0.4941	0	0	0	1	1
real int rate aft.tx	33088	0.0242	0.0241	0.0231	0.0024	-0.0357	0.0946	0.0368
real total asset inc	34767	861.1424	4227.124	7.0049	0	-4085.33	466999.5	404.4456
spouse age	34820	34.6510	18.5908	33	0	0	87	23
unempld in (t-1)?	35917	0.1146	0.3186	0	0	0	1	0
liquidity constrained? *	34563	0.2724	0.4452	1	1	0	1	1

* `zdumc2` = 1 if total asset income relative to average income over last to periods is less the 1/6. See subsection 8.1 for details.

Table 2: One-Period Transitions in Liquidity Indicator S_t – Male Heads

	$S_t = 1$ liq. constrained	$S_t = 0$ not liq. constrained	Row Per Cent
$S(t-1) = 1$ liq. constrained	8.7	21.1	29.8
$S(t-1) = 0$ not liq. constrained	16.9	53.3	70.2
Column Per Cent	25.6	74.4	100.00

Table 3: Dynamic Transition Counts — Male Heads

Number of Transitions	ΔS_t		ΔE_t			
	Frequency	Cumulative	Frequency		Cumulative	
			4 cells	5 cells	4 cells	5 cells
0	15.4	15.4	2.1	2.0	2.1	2.0
1	9.7	25.1	5.0	4.6	7.2	6.7
2	9.4	34.5	6.5	6.2	13.6	12.9
3	8.2	42.7	7.2	7.1	20.9	20.0
4	9.3	52.0	8.3	8.1	29.1	28.1
5	7.9	59.1	8.7	8.8	37.9	37.0
6	7.1	67.0	7.5	7.2	45.4	44.1
7	6.9	74.0	7.4	7.7	52.8	51.8
8	5.1	79.1	7.2	7.4	60.1	59.1
9	4.1	83.2	6.2	6.0	66.3	65.1
10	3.3	86.5	5.4	5.6	71.7	70.7
11	3.2	89.6	4.8	4.8	76.5	75.6
12-19	10.3	100.0	23.5	24.4	100.0	100.0

Table 4: One-Period Transitions in Employment Indicator E_t – Male Heads

	-1 over/ed	0	1 under/- or un/ed	99 out-of-the-labor-force	Row Per Cent
-1 overemployed	0.23	3.08	0.81	0.66	4.78
0	3.01	38.06	10.60	7.30	58.96
1 under/unemployed	0.87	11.03	4.36	2.21	18.48
99 out-of-the-labor-force	0.84	11.00	3.42	2.53	17.78
Column Per Cent	4.94	63.16	19.19	12.71	100.00

Table 5: Cross-Tabulation of S_t vs. E_t – Male Heads

	$E_t = -1$ over/ed	$E_t = 0$	$E_t = 1$ under/- or un/ed	$E_t = 99$ out-of-the-labor-force	Row Per Cent
$S_t = 1$ not liq. constrained	1.15	15.17	8.69	2.22	27.24
$S_t = 0$ liq. constrained	3.73	47.34	11.15	10.54	72.76
Column Per Cent	4.88	62.51	19.85	12.76	100.00

Table 6i: Liquidity Constraint Equation: Parameter Estimates Male Heads, In-the-Labor-Force, Dependent Variable: `zdumc2 (S)`

Liquidity Constraint Equation	Version	6(a)	Version	6(b)	Version	6(c)
Jointly With Empl. Eq.:	Version	7(a)	Version	7(b)	Version	7(b)*
LogLikelihood	-29428.97		-29422.74		-29401.40	
16 $\bar{X}i\cdot$ LR:	192.16		189.77		181.69	
Parameter	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
$corr(\xi_{it}^{bp}, \xi_{it}^{op})$	0.43	18.2	0.38	15.3	0.34	7.89
$\sigma_{\eta_i}^{bp}$	0.85	31.2	0.85	31.2	0.85	31.1
ρ_{AR}^{bp}	0.68	11.8	0.68	14.3	0.68	13.8
Regressor	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
`intercept`	94.4	2.55	95.7	2.59	94.5	2.55
liq.cons. binding at t-1?	1.12	38.9	1.12	38.8	1.12	38.9
liq.cons. binding at t-2?	0.15	5.04	0.15	4.95	0.15	4.98
overemployed?	-.-	-.-	-.-	-.-	0.006	0.11
overemployed at t-1?	-.-	-.-	0.01	0.27	0.02	0.35
overemployed at t-2?	-.-	-.-	-0.04	-0.67	-0.03	-0.65
unemployed?	-.-	-.-	-.-	-.-	0.12	3.85
unemployed at t-1?	-.-	-.-	0.03	1.04	0.02	0.56
unemployed at t-2?	-.-	-.-	0.04	1.34	0.04	1.20
county unmpl rate	-0.0003	-0.06	-0.0006	-0.10	-0.001	-0.21
head disabled?	-0.04	-0.78	-0.04	-0.79	-0.05	-0.86
education head	-0.06	-5.03	-0.06	-4.83	-0.06	-4.61
year=1976–1979	0.89	2.78	0.89	2.76	0.88	2.73
year=1980-1983	0.86	3.02	0.86	3.02	0.85	3.00
year=1984-1987	0.59	2.61	0.58	2.58	0.58	2.57
food needs	-0.0002	-3.70	-0.0002	-3.72	-0.0002	-3.76
growth food needs	-0.25	-5.47	-0.25	-5.51	-0.25	-5.51
head age	-0.41	-10.26	-0.41	-10.23	-0.40	-10.06
head age cubed	-0.00005	-6.73	-0.00005	-6.71	-0.00005	-6.57
head age squared	0.008	7.80	0.008	7.78	0.008	7.63
tenure head (months)	-0.001	-2.77	-0.001	-2.69	-0.001	-2.47
tenure head squared	1.06e-06	0.88	1.04e-06	0.86	8.9e-07	0.73
unempl. insur. head	9.16e-06	0.45	6.66e-06	0.33	-2.02e-06	-0.10
labr market state	0.01	0.70	0.01	0.70	0.01	0.66
live in north-centr?	-0.12	-1.97	-0.12	-1.94	-0.12	-1.93
live in other regions?	0.43	2.80	0.43	2.79	0.43	2.73
live in south?	0.12	1.97	0.12	1.99	0.12	2.00
live in west?	0.08	1.18	0.08	1.22	0.09	1.26
head single?	0.70	14.02	0.70	13.97	0.69	13.92
num chldrn age 0-5	-0.05	-2.35	-0.05	-2.39	-0.05	-2.37
occupational unempl	0.02	3.36	0.02	3.26	0.02	3.16
head black?	0.61	6.27	0.60	6.22	0.59	6.19
head other race?	0.18	1.60	0.17	1.55	0.17	1.50
head relig chr./eorth?	0.09	1.58	0.09	1.61	0.09	1.57
head relig jewish?	0.16	1.45	0.17	1.45	0.16	1.42
head relig protestant?	0.16	3.75	0.16	3.76	0.16	3.77
real interest rate	14.25	7.64	14.1	7.57	13.6	7.31
head union member?	-0.03	-0.73	-0.03	-0.77	-0.03	-0.86
plus 16 time-averages	see text,	p.16	see text,	p.16	see text,	p.16

* Joint estimation with Employment Version 7(c) would have violated the Coherency condition discussed above.

Table 6ii: Liquidity Constraint Equation: Estimated Marginal Effects Male Heads, In-the-Labor-Force, Dependent Variable: `zdumc2 (S)`

Liquidity Constraint Eq.		Version	6(a)	Version	6(b)	Version	6(c)
Jointly With Empl. Eq.:		Version	7(a)	Version	7(b)	Version	7(b)*
$\widehat{P}_{lc}(\bar{X})$		0.18		0.18		0.18	
$\overline{\widehat{P}_{lc}}$		0.27		0.27		0.27	
$\overline{\mathbf{1}(X_{it}\hat{\beta} > 0)}$		0.26		0.26		0.26	
Correct Predictions		0.88		0.88		0.88	
Regressor	$\bar{X}$	$\Delta^{*}\widehat{P}_{lc}$	$\Delta^{**}\widehat{P}_{lc}$	$\Delta^{*}\widehat{P}_{lc}$	$\Delta^{**}\widehat{P}_{lc}$	$\Delta^{*}\widehat{P}_{lc}$	$\Delta^{**}\widehat{P}_{lc}$
liq.cons. at t-1? **	0.27	0.30	0.30	0.30	0.30	0.30	0.30
liq.cons. at t-2? **	0.27	0.032	0.032	0.032	0.032	0.032	0.032
overemployed? **	0.055	-.-	-.-	-.-	-.-	0.001	0.001
overemployed at t-1? **	0.06	-.-	-.-	0.003	0.003	0.004	0.004
overemployed at t-2? **	0.06	-.-	-.-	-0.008	-0.008	-0.007	-0.007
unemployed? **	0.22	-.-	-.-	-.-	-.-	0.03	0.03
unemployed at t-1? **	0.22	-.-	-.-	0.007	0.007	0.004	0.004
unemployed at t-2? **	0.22	-.-	-.-	0.008	0.008	0.008	0.008
county unmpl rate	6.51	-7.2e-5	-0.02	-0.0001	-0.02	-0.0003	-0.02
head disabled? **	0.08	-0.009	-0.009	-0.009	0.009	-0.009	-0.009
education head	4.80	-0.01	0.12	-0.013	0.12	-0.01	0.12
year=1976–1979	0.21	0.24	0.24	0.24	0.24	0.24	0.24
year=1980-1983	0.24	0.22	0.22	0.22	0.22	0.22	0.22
year=1984-1987	0.25	0.14	0.14	0.14	0.14	0.14	0.14
food needs	1094	-3.9e-5	-4.32e-5	-3.95e-5	0.0001	-4.01e-5	-8.8e-5
growth food needs	-0.01	-0.05	-0.43	-0.05	-0.44	-0.05	-0.45
head age	39.07	-0.09	-2.47	-0.08	-2.47	-0.08	-2.46
head age cubed	78546	-1.12e-5	0.0007	-1.11e-5	0.0007	-1.09e-5	0.0007
head age squared	1679.4	0.002	0.08	0.002	0.08	0.002	0.08
tenure head (months)	93.1	-0.0002	0.01	-0.0002	0.01	-0.0002	0.01
tenure head squared	18142	2.2e-7	1.55e-5	2.2e-7	1.48e-5	1.86e-7	1.46e-5
unempl. insur. head	108.4	1.92e-6	1.01e-5	1.39e-6	1.53e-5	-4.23e-7	-1.42e-5
labr market state	3.83	0.002	0.05	0.002	0.05	0.002	0.05
live in north-centr? **	0.32	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
live in other regions? **	0.007	0.11	0.11	0.11	0.11	0.11	0.11
live in south? **	0.30	0.03	0.03	0.03	0.03	0.03	0.03
live in west? **	0.17	0.02	0.02	0.02	0.02	0.02	0.02
head single? **	0.11	0.19	0.19	0.19	0.19	0.19	0.19
num chldrn age 0-5	0.37	-0.01	2.89	-0.01	2.83	-0.01	2.82
occupational unempl	5.89	0.004	0.02	0.004	0.02	0.003	0.02
head black? **	0.05	0.17	0.17	0.16	0.16	0.16	0.16
head other race? **	0.05	0.04	0.04	0.04	0.04	0.04	0.04
head relig chr./eorth? **	0.14	0.02	0.02	0.02	0.02	0.02	0.02
head relig jewish? **	0.03	0.04	0.04	0.04	0.04	0.04	0.04
head relig protestant? **	0.44	0.03	0.03	0.03	0.03	0.03	0.03
real interest rate	0.02	2.98	0.22	2.95	0.22	2.86	0.23
head union member? **	0.21	-0.006	-0.006	-0.006	-0.006	-0.007	-0.007
plus 16 time-averages		see text,	p.16	see text,	p.16	see text,	p.16

* Joint estimation with Employment Version 7(c) would have violated the Coherency condition.

**: denotes a dummy variable regressor.

$$\text{Marginal effects: } \Delta^{*}\hat{P}_{lc} \equiv \begin{cases} \frac{\partial \hat{P}_{lc}}{\partial X_j} & \text{for a continuous regressor } X_j, \\ \hat{P}_{lc}(X_j = 1) - \hat{P}_{lc}(X_j = 0) & \text{for a dummy variable regressor } X_j. \end{cases}$$

$$\Delta^{**}\hat{P}_{lc} \equiv \begin{cases} \frac{\partial \hat{P}_{lc}}{\partial X_j} + \frac{\partial \hat{P}_{lc}}{\partial \bar{X}_j} & \text{for a continuous regressor } X_j \text{ paired with its time-mean,} \\ \hat{P}_{lc}(X_j = 1, \bar{X}_j = \text{time-mean}) - \hat{P}_{lc}(X_j = 0, \bar{X}_j = 0) & \text{for a dummy variable regressor } X_j \text{ paired with its time-mean.} \end{cases}$$

Table 7i: Employment Constraints Equation: Parameter Estimates
Male Heads, In-the-Labor-Force, Dependent Variable: `LabCon3 (E)`

Employment Constraints Equation	Version	7(a)	Version	7(b)	Version	7(c)
Estimated Jointly With Liquid. Eq.:	Version	6(a)	Version	6(b)	Version	6(b)*
LogLikelihood	-29428.97		-29422.74		-29406.32	
16 $\bar{X}i\cdot$ LR	241.72		236.85		222.69	
Parameter	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
$corr(\xi_{it}^{bp},\xi_{it}^{op})$	0.43	18.26	0.38	15.3	0.34	7.89
$\sigma_{\eta_i}^{op}$	0.52 22.4	0.52	21.8	0.49	20.4	
ρ_{AR}^{op}	0.45	7.47	0.43	8.23	0.40	7.40
θ^-	-2.72	-4.25	-2.72	-4.26	-2.72	-4.26
θ^+	normalized	at 0	normalized	at 0	normalized	at 0
Regressor	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
`intercept`	33.7	24.3	31.6	24.3	31.9	24.3
overemployed at t-1?	-0.68	-21.3	-0.68	-21.3	-0.68	-21.3
overemployed at t-2?	-0.32	-10.1	-0.32	-10.1	-0.32	-10.1
unemployed at t-1?	0.70	36.3	0.69	36.1	0.69	36.1
unemployed at t-2?	0.37	19.3	0.36	19.1	0.36	19.1
liq.const. binds	-.-	-.-	-.-	-.-	0.12	5.07
liq.cons. at t-1	-.-	-.-	0.05	1.99	-0.01	-0.49
liq.cons. at t-2	-.-	-.-	0.01	0.51	-0.002	-0.10
county unmpl rate	0.007	2.11	0.007	2.13	0.007	2.15
head disabled?	0.04	1.62	0.04	1.59	0.04	1.61
education head	-0.03	-5.78	-0.03	-5.62	-0.03	-5.52
year=1976–1979	0.11	0.54	0.12	0.57	0.10	0.49
year=1980-1983	0.26	1.41	0.26	1.44	0.25	1.34
year=1984-1987	0.19	1.31	0.20	1.34	0.18	1.23
food needs	0.0001	4.40	0.0001	4.44	0.00001	4.39
growth food needs	-0.09	-2.68	-0.10	-3.00	-0.08	-2.54
head age	-0.09	-5.16	-0.08	-4.90	-0.07	-4.37
head age cubed	-0.00001	-4.19	-0.00001	-4.05	-0.00001	-3.67
head age squared	0.002	4.47	0.002	4.29	0.002	3.85
tenure head (months)	-0.002	-8.19	-0.002	-8.07	-0.002	-7.96
tenure head squared	3.2e-06	5.29	3.2e-06	5.22	3.2e-06	5.16
unempl. insur. head	0.0003	16.63	0.0003	16.63	0.0003	16.62
imputed wage	0.002	2.45	0.002	2.52	0.003	2.63
labr market state	0.02	1.93	0.02	1.90	0.02	1.88
in north-centr?	-0.05	-2.32	-0.05	-2.25	-0.05	-2.16
in other regions?	0.05	0.60	0.05	0.54	0.04	0.46
in south?	-0.02	-0.92	-0.02	-0.95	-0.02	-0.98
in west?	-0.15	-6.08	-0.15	-6.08	-0.15	-6.08
head single?	0.05	1.92	0.04	1.51	0.03	0.96
num chldrn age 0-5	0.01	0.99	0.01	1.00	0.01	1.03
occupational unempl	0.01	5.06	0.01	4.96	0.01	4.88
head black?	0.15	4.34	0.14	4.04	0.13	3.79
head other race?	0.25	5.24	0.25	5.24	0.25	5.20
head relig chr./eorth?	0.03	1.19	0.03	1.24	0.03	1.20
head relig jewish?	0.05	1.06	0.05	1.05	0.05	0.98
head relig protestant?	-0.01	-0.57	-0.01	-0.54	-0.01	-0.63
real interest rate	13.2	12.83	12.9	12.54	12.6	12.22
head union member?	0.08	4.35	0.08	4.43	0.08	4.45
plus 16 time-averages	see text,	p.16	see text,	p.16	see text,	p.16

* Joint estimation with Liquidity Constraint Version 6(c) would have violated the Coherency condition.

Table 7ii: Employment Constraints Equation: Estimated Marginal Effects Male Heads, In-the-Labor-Force, Dependent Variable: `LabCon3 (E)`

Employment Constraints Eq.		Version	7(a)	Version	7(b)	Version	7(c)
Jointly With Liquid. Eq.:		Version	6(a)	Version	6(b)	Version	6(b)*
$\widehat{P}.(\bar{X})$		overE:0.03	unE:0.19	overE:0.03	unE:0.19	overE:0.03	unE:0.19
$\overline{\widehat{P}}.$		overE:0.06	unE:0.22	overE:0.06	unE:0.22	overE:0.06	unE:0.22
Correct Predictions		overE:0.94	unE:0.81	overE:0.94	unE:0.81	overE:0.94	unE:0.81
Regressor	$\bar{X}$	$\Delta^*\widehat{P}_{vol}$	$\Delta^{**}\widehat{P}_{vol}$	$\Delta^*\widehat{P}_{vol}$	$\Delta^{**}\widehat{P}_{vol}$	$\Delta^*\widehat{P}_{vol}$	$\Delta^{**}\widehat{P}_{vol}$
head overemployed in t-1?**	.06	.05	.05	.05	.05	.05	.05
head overemployed in t-2?**	.06	.04	.04	.04	.04	.04	.04
head unemployed in t-1?**	.22	-.18	-.18	-.18	-.18	-.18	-.18
head unemployed in t-2?**	.22	-.08	-.08	-.08	-.08	-.08	-.08
liquidity constraint binds?**	.27	-.-	-.-	-.-	-.-	-.02	-.02
liquidity constraint binds at t-1?**	.27	-.-	-.-	-.009	-.009	.002	.002
liquidity constraint binds at t-2?**	.27	-.-	-.-	-.002	-.002	.0004	.0004
county unemployment rate	6.51	-.001	-0.005	-.001	-0.005	-.001	-0.005
head disabled?**	.08	-.009	0.08	-.008	0.09	-.008	0.08
education of head	4.80	.006	-0.09	.006	-0.09	.006	-0.09
year=1976–1979	.21	-.02	-.02	-.02	-.02	-.02	-.02
year=1980-1983	.24	-.06	-.06	-.06	-.06	-.05	-.05
year=1984-1987	.25	-.04	-.04	-.04	-.04	-.04	-.04
household food needs	1094.	-.00002	0.0002	-.00002	0.0002	-.00002	0.0002
growth of household food needs	-.01	.02	0.58	.02	0.61	.02	0.59
head age	39.1	.02	0.58	.02	0.58	.01	0.54
head age cubed	78546.	2.4e-06	9.9e-05	2.3e-06	0.0001	2.1e-06	9.1e-05
head age squared	1679.	-.0003	-0.01	-.0003	-0.01	-.0003	-0.01
tenure of head (months)	93.1	.0003	0.0009	.0003	0.0008	.0003	0.001
tenure of head squared	18142.	-6.2e-07	-3.7e-06	-6.1e-07	-3.55e-06	-6.18e-07	-4.0e-06
unemployment insurance of head	108.4	-.00005	-0.0002	-.00005	-0.0002	-.00005	-0.0002
imputed wage of head	8.49	-.0005	-0.001	-.0005	-0.001	-.0005	-0.001
labour market state	3.83	-.003	0.004	-.003	0.002	-.003	0.003
live in north-centr?**	.32	.01	.009	.01	.009	.009	.009
live in other regions?**	.007	-.01	-.01	-.01	-.009	-.008	-.008
live in south?**	.30	.004	.004	.004	.004	.004	.004
live in west?**	.17	.03	.03	.03	.03	.03	.03
head single?**	.11	-.01	-.01	-.008	-.008	-.005	-.005
number of chlidren aged 0-5	.37 -	-.002	0.24	-.002	0.22	-.003	0.25
occupational unemployment	5.89	-.003	-0.004	-.003	-0.004	-.003	-0.004
head black?**	.05 -	-.03	-.03	-.03	-.03	-.03	-.03
head other race?**	.05 -	-.06	-.06	-.06	-.06	-.06	-.06
head religion chr./eorth?**	.14	-.007	-.007	-.007	-.007	-.007	-.007
head religion jewish?**	.03	-.01	-.01	-.01	-.01	-.01	-.01
head religion protestant?**	.44	.002	.002	.002	.002	.003	.003
real interest rate (after tax)	.02	-2.53	0.14	-2.48	0.13	-2.42	0.13
head union member?**	.21	-.02	-0.29	-.02	-0.30	-.02	-0.29
plus 16 time-averages		see text,	p.16	see text,	p.16	see text,	p.16

* Joint estimation with Liquidity Constraint Version 6(c) would have violated the Coherency condition.
**: denotes a dummy variable regressor.
Marginal effects (all evaluated at $\bar{X}$):

$$\Delta^*\hat{P}_{vol} \equiv \begin{cases} \frac{\partial \hat{P}(E=0)}{\partial X_j} & \text{for a continuous regressor } X_j, \\ \hat{P}(E=0)(X_j=1) - \hat{P}(E=0)(X_j=0) & \text{for a dummy variable regressor } X_j. \end{cases}$$

$$\Delta^{**}\hat{P}_{vol} \equiv \begin{cases} \frac{\partial \hat{P}(E=0)}{\partial X_j} + \frac{\partial \hat{P}(E=0)}{\partial \bar{X}_j} & \text{for a continuous } X_j \text{ paired with its time-mean,} \\ \hat{P}(E=0)(X_j=1, \bar{X}_j=\text{timavg}) - \hat{P}(E=0)(X_j=0, \bar{X}_j=0) & \text{for a dummy variable } X_j \text{ paired with its time-mean.} \end{cases}$$

Analogously for $[oe \equiv (E=-1)]$ and $[ue \equiv (E=1)]$.

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7 Appendix A: Econometric Methodology

7.1 The Method of Maximum Smoothly Simulated Likelihood (MSSL)

In this paper we employ the method of maximum smoothly simulated likelihood (MSSL) in conjunction with the Geweke-Hajivassiliou-Keane (GHK) simulator in order to overcome the well-known computation intractabilities of the multiperiod (panel) limited-dependent-variable models presented in section 4. The MSSL approach was developed in Börsch-Supan and Hajivassiliou (1993), while its theoretical properties were derived rigorously in Hajivassiliou and McFadden (1998).

7.2 The GHK Simulator

The leading simulator for multivariate normal rectangle probabilities of the form encountered in ML estimation of LDV models under Gaussian distributional assumptions is the Geweke-Hajivassiliou-Keane approach. See Hajivassiliou *et al.* (1996) for extensive Monte-Carlo evidence that this simulator is to be preferred over all other known simulators for this problem. To outline this method, define $q(u, a, b) \equiv \Phi^{-1}(\Phi(a) \cdot (1-u) + \Phi(b) \cdot u)$, where $0 < u < 1$ and $-\infty \leq a < b \leq \infty$. Then q is a mapping that takes a uniform $(0, 1)$ random variate into a truncated standard normal random variate on the interval $[a, b]$.

Proposition 1 Consider the multivariate normal $M \times 1$ random vector $Y \sim N(X\beta, \Omega)$ with Ω positive definite, the linear transformation $Z = FY \sim N(FX\beta, \Sigma)$, with F non-singular and $\Sigma = F\Omega F'$, and the event $\mathbf{B} \equiv \{a^* \leq Z = FY \leq b^*\}$, with $-\infty \leq a^* < b^* \leq +\infty$. Define $P \equiv \int_B n(z; FX\beta, \Sigma)dz$, $a \equiv a^* - FX\beta$, $b \equiv b^* - FX\beta$, and let L denote the lower-triangular Cholesky factor of Σ. Let $(u_1, \cdots, u_M)$ be a vector of independent uniform $(0, 1)$ random variates. Define recursively for $j = 1, \cdots, M$:

$$e_j = q\left(u_j, (a_j - L_{j1}e_1 - \cdots - L_{j,j-1}e_{j-1})/L_{jj}, (b_j - L_{j1}e_1 - \cdots - L_{j,j-1}e_{j-1})/L_{jj}\right), \qquad (22)$$

$$Q_j \equiv \Phi\left((b_j - L_{j1}e_1 - \cdots - L_{j,j-1}e_{j-1})/L_{jj}\right) - \Phi\left((a_i - L_{j1}e_1 - \cdots - L_{j,j-1}e_{j-1})/L_{jj}\right). \qquad (23)$$

Define $e \equiv (e_1, \cdots, e_M)'$, $\tilde{Y} \equiv X\beta + F^{-1}Le$, and $Q(e) \equiv Q_1 \cdot \cdots \cdot Q_M$. Then $\tilde{Y}$ is a random vector on $\mathbf{B}$, and the ratio of the densities of $\tilde{Y}$ and Y at $y = X\beta + F^{-1}Le$, where e is any vector satisfying $a \leq Le \leq b$, is $P/Q(e)$.
Proof: Börsch-Supan and Hajivassiliou (1993) and Hajivassiliou and McFadden (1997).

These studies also explain that combining Proposition 1 about the GHK simulator together with importance-sampling arguments, one can show that GHK is a smooth, unbiased, and consistent simulator for the likelihood contributions P_i and their derivatives $P_{\theta i}$, and a smooth, asymptotically unbiased, and consistent simulator for the logarithmic derivatives of the $P(\cdot)$ expressions.

A complete implementation of the GHK simulator requires a computational procedure that returns the simulated probability, $\tilde{P}$, as a function of the following arguments:
m=dimension of multivariate normal vector Z;
mu=EZ;
w=V(Z);
wi=w^{-1};
c=Cholesky factor of w;
vectors a and b, defining the restriction region $a < Z < b$;
r=number of replications;
u=a $m \times r$ matrix of i.i.d. uniform [0,1] variates.
Such computational procedures in GAUSS, FORTRAN, and C versions are publicly available

through the World-Wide-Web at the URL:
`http://econ.lse.ac.uk/staff/vassilis/pub/simulation`.

7.3 Simultaneous Determination of the Liquidity and Employment Constraint Indicators

For a typical household spell i (assumed to be independently distributed from other household spells) and dropping the i index for simplicity, the MSSL method allows us to take fully into account the simultaneity in the determination of the liquidity (S_t) and the employment constraint (E_t) indicators. Let us define two latent dependent variables $y_{1t}^* \equiv S_t^*$ and $y_{2t}^* \equiv E_t^*$ that are the underpinnings of S_t and E_t according to the LDV models given by equations (19)-(20), namely:

$$S_t = \begin{cases} 1 & \text{if } S_t^* > 0, \\ 0 & S_t^* \leq 0. \end{cases}$$

$$E_t = \begin{cases} -1 & \text{if } E_t^* < \theta^- \\ 0 & \text{if } \theta^- \leq E_t^* < \theta^+ \\ 1 & \text{if } \theta^+ \leq E_t^*. \end{cases}$$

Also dropping the t subscript for ease of notation, we consider the model with spillover effects on both sides, i.e., the one exhibiting full simultaneity:

$$y_1^* \equiv S^* = \mathbf{1}(y_2^* < \theta^-)\delta_{01} + \mathbf{1}(y_2^* > \theta^+)\delta_{02} + x_1\beta_1 + \epsilon_1$$
$$y_2^* \equiv E^* = \mathbf{1}(y_1^* > 0)\kappa_0 + x_2\beta_2 + \epsilon_2$$

Note that we have decomposed the contemporaneous spillover effect $\delta_0 E$ on the RHS of S^* into $\delta_{01}\mathbf{1}(\mathbf{E} = -\mathbf{1}) + \delta_{\mathbf{02}}\mathbf{1}(\mathbf{E} = \mathbf{1})$, i.e., into separate terms for the overemployment and the under/unemployment indicators.

Since (S, E) lie in $\{0,1\}\times\{-1,0,1\}$, the 6 possible configurations may be enumerated as follows:

S	E	$y_1^* \equiv S^*$			$y_2^* \equiv E^*$				
0	-1	$\delta_{01} + x_1\beta_1 + \epsilon_1$	$<$	0,			$x_2\beta_2 + \epsilon_2$	$<$	θ^-
0	0	$x_1\beta_1 + \epsilon_1$	$<$	0,	θ^-	$<$	$x_2\beta_2 + \epsilon_2$	$<$	θ^+
0	1	$\delta_{02} + x_1\beta_1 + \epsilon_1$	$<$	0,	θ^+	$<$	$x_2\beta_2 + \epsilon_2$		
1	-1	$\delta_{01} + x_1\beta_1 + \epsilon_1$	$>$	0,			$\kappa_0 + x_2\beta_2 + \epsilon_2$	$<$	θ^-
1	0	$x_1\beta_1 + \epsilon_1$	$>$	0,	θ^-	$<$	$\kappa_0 + x_2\beta_2 + \epsilon_2$	$<$	θ^+
1	1	$\delta_{02} + x_1\beta_1 + \epsilon_1$	$>$	0,	θ^+	$<$	$\kappa_0 + x_2\beta_2 + \epsilon_2$		

In terms of the GHK simulator described in subsection 7.2 above, the probability of a pair (S, E) is equivalent to the probability:

$$\begin{pmatrix} a_1 \\ a_2 \end{pmatrix} < \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix} < \begin{pmatrix} b_1 \\ b_2 \end{pmatrix}$$

where $(\epsilon_1, \epsilon_2)' \sim N((\mu_1, \mu_2)', \Sigma_\epsilon)$, and a and b are given by:

S	E	a_1	a_2	b_1	b_2
0	-1	$-\infty$	$-\infty$	$-(\delta_{01} + x_1\beta_1)$	$\theta^- - x_2\beta_2$
0	0	$-\infty$	$\theta^- - x_2\beta_2$	$-x_1\beta_1$	$\theta^+ - x_2\beta_2$
0	1	$-\infty$	$\theta^+ - x_2\beta_2$	$-(\delta_{02} + x_1\beta_1)$	$+\infty$
1	-1	$-(\delta_{01} + x_1\beta_1)$	$-\infty$	$+\infty$	$\theta^- - \kappa_0 - x_2\beta_2$
1	0	$-x_1\beta_1$	$\theta^- - \kappa_0 - x_2\beta_2$	$+\infty$	$\theta^+ - \kappa_0 - x_2\beta_2$
1	1	$-(\delta_{02} + x_1\beta_1)$	$\theta^+ - \kappa_0 - x_2\beta_2$	$+\infty$	$+\infty$

The variance-covariance matrix captures the contemporaneous correlation between ϵ_1 and ϵ_2. Given the binary probit nature of S and the ordered probit nature of E, σ_{ϵ_1} and σ_{ϵ_2} need to be normalized. Subsection 7.5 below explains how our estimations take full account of the contemporaneous correlation in the ϵs *as well as* their flexible forms of serial correlation.

7.4 Coherency Conditions

To maintain the logical consistency of the model (known in the literature as "statistical coherency"), S_t^* should not depend on E_t^*, if E_t^* depends on S_t^* and vice-versa. Formally, the coherency conditions in terms of the above notation are:

$$(\delta_{01} + \delta_{02})\kappa_0 = 0 \text{ and } \delta_{01}\delta_{02}\kappa_0 = 0.$$

In other words, either $\kappa_0 = 0$, in which case δ_{01}, δ_{02} are free to differ from 0, or $\kappa_0 \neq 0$ in which case both δ_{01} and δ_{02} must be zero.

To verify this requirement, suppose $(S, E) = (0, 0)$. This rules out $(S, E) = (0, -1)$ because $x_2\beta_2 + \epsilon_2 > \theta^-$, and rules out $(S, E) = (1, 0)$ because $x_1\beta_1 + \epsilon_1 < 0$. But $(1, -1)$ is not ruled out if the coherency conditions do not hold, since δ_{01} could be sufficiently negative and κ_0 sufficiently positive to imply the $(1, -1)$ conditions. Similarly, the $(1, 1)$ possibility cannot be ruled out in the absence of the coherency conditions, since δ_{02} and κ_0 can be sufficiently positive. Such logical inconsistencies are clearly ruled out if either (a) $\kappa_0 = 0$ or (b) δ_{01} and δ_{02} are simultaneously 0.

In our econometric implementation above, the regression reported in table 6i, column (c), imposes the "$\delta_2 = 0$, δ_{01}, δ_{02} free" version of the coherency condition, while table 7i, column (c), imposes the "κ_0 free, $\delta_{01} = \delta_{02} = 0$" version of the coherency conditions. For novel ways of approaching "coherency" conditions in LDV models with simultaneity, see Hajivassiliou (2003).

7.5 Treatment of Flexible Serial and Contemporaneous Correlations

We have described in subsection 7.3 how the probability of a pair (S_{it}, E_{it}) can be represented in terms of the GHK implementation through the linear inequality:

$$\begin{pmatrix} a_{1it} \\ a_{2it} \end{pmatrix} < \begin{pmatrix} \epsilon_{1it} \\ \epsilon_{2it} \end{pmatrix} < \begin{pmatrix} b_{1it} \\ b_{2it} \end{pmatrix}$$

Define the 2×1 vectors a_{it}, b_{it}, and ϵ_{it}. Stacking all the T_i periods of observation for individual i gives the $2 \cdot T_i \times 1$ vectors a_i, b_i, and ϵ_i, where ϵ_i has the $2 \cdot T_i \times 2 \cdot T_i$ var-covariance matrix with structure characterized by the precise serial correlation assumptions made on the ϵ_{it}s. In particular, one-factor random effect assumptions will imply an equicorrelated block structure on Σ_ϵ, while our most general assumption of one-factor random effects *combined with* an AR(1) process for each error implies that Σ_ϵ combines equicorrelated and Toeplitz-matrix features.

Through this representation, the probability of a complete sequence of the observable (S, E) behaviour for individual household i, conditionally on the initial conditions S_{i0} and E_{i0}, is given by:

$$P(S_1, \cdots, S_{T_i}, E_1, \cdots, E_{T_i}) = Prob(a_i < \epsilon_i < b_i)$$

Consequently, our approach incorporates fully: (a) the contemporaneous correlations in ϵ_{it}; (b) the one-factor plus AR(1) serial correlations in ϵ_i; and (c) the dependency of S_{it} on E_{it}, and vice versa. The possible endogeneity of S_{i0} and E_{i0} is handled by the approximation of allowing them to depend on all exogenous information available to the econometrician, following Heckman (1981(b)). We argue that these approximations should be adequate in our case in view of the relatively large number of time-periods available for each individual household.

8 Appendix B: Data

Our panel data come from the first twenty waves of the Panel Study of Income Dynamics, corresponding to years 1968-1987. In processing the data, we followed Zeldes (1989a) and Ball (1990) as closely as possible and applied selection criteria similar to theirs.[21] Zeldes and Ball stopped with Wave 14, which includes data from the 1981 wave of interviews and was the latest wave available at the time their research was completed. We include data up to Wave 20, which reports on the 1987 wave of interviews. It should be remembered that the data are based on interviews conducted in the early Spring, but pertain to households' circumstances during the preceding calendar year, unless otherwise indicated. We too excluded from our extract the non-random subsample of the PSID, known as the Office of Economic Opportunity sample. Wherever variables are constructed, such as the end-of-period stock of financial assets which we detail below, we followed exactly the calculations performed by Zeldes and Ball.

Our data are organized according to the following principle. From all panel members interviewed in 1987 we selected those who were heads of households at the time of the interview, or had been household heads at least once prior to 1987. We then follow them back up until 1970 and select "household spells" defined to be sequences of at least four consecutive years during which the same individuals remained household heads. This design is in accordance with Zeldes' definition, even though his model did not require that he keep track of the panel structure of the data on households, after first differencing the relevant variables. This is an important difference between our data and the data as used by Zeldes and Ball. Our need for the full panel structure of the data causes us to end up with a smaller data set because of missing values. It is also a reason why their data (and, in particular, Zeldes' data, to which he kindly gave us access) do not suffice for the full set of econometric experiments we are interested in.

The restriction that a household spell be at least four years long was dictated by our desire to study higher than first-order dynamics in our switching regressions models. Finally, because of unavailability of crucial data, we go back only as far as 1970, thus deleting two years of panel data. We end up with 2410 household spells (thus defined) with male heads, and with a mean length of household spell being equal to 13.45 years. The distribution of spell lengths is fairly uniform, with about one-fifth of the sample comprised of spells of length equal to 20. The frequency distribution of available time-periods per household spell is as follows:

4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
30	130	131	93	132	121	116	103	121	138	124	124	118	125	127	103	528

8.1 Construction of the Liquidity Constraint Indicator

As the main indicator variable for a binding liquidity constraint, we adopted Zeldes' (1989a) definition of:

$$zdumc2 = \begin{cases} 1 & \text{if } \dfrac{\text{total calculated asset holdings}}{\text{real disposable annual income averaged over last 2 years}} < \frac{1}{6} \\ 0 & \text{otherwise.} \end{cases}$$

The logic of this construction is that a household is categorized as liquidity constrained if its asset holdings would be insufficient to replace their current levels of disposable income if the latter were to be lost two months in succession.

Because the PSID contains data on housing wealth, but not on non-housing net worth, we follow bold assumptions made by several others [Zeldes (1989a); Ball (1990)] to circumvent the lack of direct data on assets. Specifically, we calculated nonhousing wealth using the flow of asset income

[21] We benefitted from their kind advice, too.

and an assumed rate of return on wealth, assuming that the first $250 of interest and dividend income is held in savings accounts at commercial banks earning the passbook rate, and that all additional such income is saved in 3-month Treasury bills or equivalent. We then used these rates to "scale up" interest and dividend asset income to provide an approximation for the amount of assets held in savings accounts.[22] Real non-housing assets were obtained by deflating the nominal amount by the personal consumption expenditure deflator. Finally, we calculated housing equity as the difference between house value minus outstanding mortgage principal, both reported in the PSID. More details may be found in Zeldes (1989a), p.341.

It should be noted that Zeldes proposes three additional classification schemes or "splits" — see *ibid.*, pp.338-344, for details. Our justification for focussing on the particular scheme defined above is two-fold: first, Zeldes' other three schemes require the use of information that is only available in waves 1–5, 8, and 13 of the PSID. Consequently, such classifications would have hindered critically our ability to study the dynamics of intertemporal behaviour using the full panel structure of our data. Second, we carried out extensive experimentation with the data, which suggested that even though the proportions of constrained and unconstrained households as measured by the various indicators may differ, the pattern of switching in and out of being constrained is quite similar. In addition, we have obtained similar results for the dynamic probit model for liquidity constraints even with Zeldes' most stringent classification scheme.

8.2 Construction of Labor Constraint Indicators

In view of our data, the endogenous variable E_{it} is inherently ordinal. The actual numbers used to code the employment indicator E are not, of course, of any consequence. Further details on the actual questions asked of survey respondents are presented further below in this Appendix in the form of flow charts. In recoding the data here we went further than all other previous researchers. The classifications are:

$E_{it} = -1$: *overemployment.* (6%)

This is the case if, in year $t-1$, individual i was an employed member of the labor force who answered yes to the question (variable V14230 in wave 20 of the PSID): "Now thinking about your job(s) over the past year, was there more work available on your job [or "any of your jobs" if more than one] so that you could have worked more if you wanted to?", and answered no to the question "Could you have worked less if you had wanted to?" This question was asked of those who answered yes to the previous question, and was coded as variable V14232 in wave 20 of the PSID. It was also asked of those who answered no, and was coded as v14235 in that same wave. Unfortunately, the latter variable does not appear to be available for years prior to 1979. Also, as a referee pointed out, these answers are in principle consistent with the respondent's being happy with the hours worked rather than being overemployed.

$E_{it} = 0$: *voluntary employment.* (62%)

This is the case if, in year $t-1$, person i was an employed member of the labor force who was classified as neither overemployed, according to the above definition, nor underemployed, as defined below.

$E_{it} = 1$: *underemployment/unemployment.* (22%)

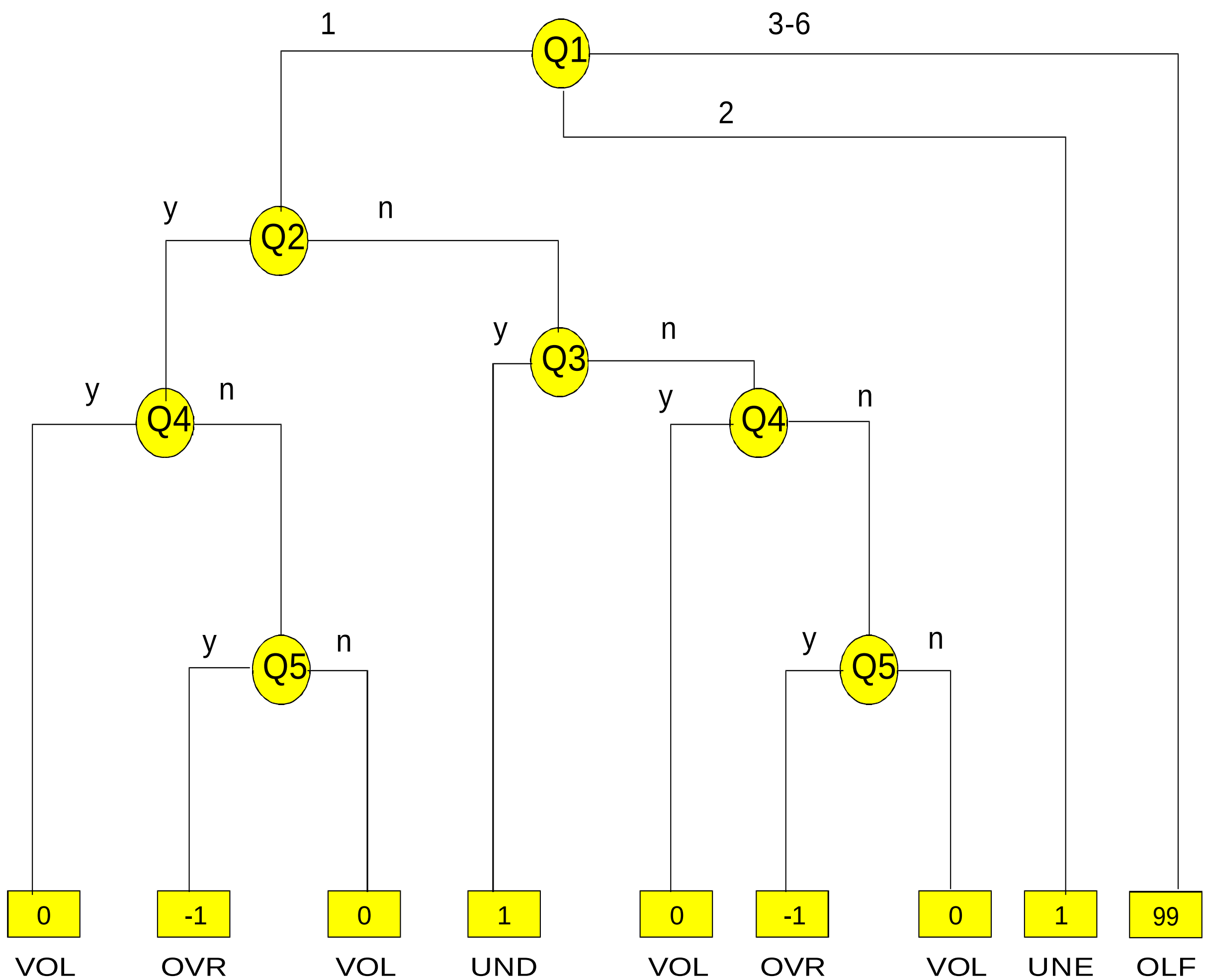
This is the case if in year $t-1$ person i was either underemployed or unemployed. A person is underemployed if he/she is an employed member of the labor force who answered no to the question whether more work was available, and answers yes to the question "Would you have liked to work

[22] Because of the obvious difficulties in adopting this procedure for any asset income other than interest and dividends, observations with substantial "other asset income" were excluded.

more if you could have found more work?" This is variable V14234 in wave 20 of the PSID. The questions which lead to variables V14230, V14232, and V14234 became more precise over the years but retained their basic meaning. Our definition is consistent with previous work [Ham (1982; 1986); Kahn and Lang (1992)]. As previous authors recognized, there is some ambiguity in how individuals may respond to these questions; e.g., there is no indication in the data as to whether or not a worker would require a premium to work overtime. Nevertheless, we think the phenomenon of involuntary overemployment is real enough and makes sufficiently good sense as an element of labor contracts to warrant attention within our framework. A person was unemployed if he/she was temporarily laid off, on a maternity or sick leave, or unemployed and looking for work. The latter possibilities were ascertained on the basis of the question "Are you working now, looking for work, retired, keeping house, a student or what?" For years 1975 and earlier, the coding of the variable used to determine employment status, that is whether a person is employed, unemployed or out of the labor force for a variety of reasons is coarser unfortunately, so that it includes temporarily laid off workers among the employed. An important attribute of this variable is that it pertains to the employment status of the respondent as of the actual time of the interview.

Whenever inconsistent answers to the above questions are reported, we proceed in the following way (rather than delete them as others do). If an individual reports that he/she is neither voluntarily employed, nor underemployed nor unemployed, then we classify the respondent as involuntarily unemployed if the person was out of the labor force last year, and as voluntarily employed, if the respondent was a member of the labor force. If, on the other hand, a person reports belonging to more than one of the above categories, and was out of the labor force in that same year, then such a person is recoded as involuntarily unemployed. Alternatively, if he/she was in the labor force and classified as involuntarily unemployed, then he/she was recoded as not voluntarily employed and not involuntarily overemployed; finally, if he/she was classified as involuntarily overemployed, then he/she was recoded as not voluntarily employed and not involuntarily unemployed. Such a set of variables have never before been used in their full generality to analyze employment status and, in particular, the possibly involuntary nature of reported unemployment or underemployment.

Construction of Labour Constraint Indicator, 1967-1975



Q1. What is your current employment status? (V3967 in 1975)

1. Working now or temporarily laid off
2. Looking for work, unemployed
3. Retired, permanently disabled
4. Housewife
5. Student
6. Other

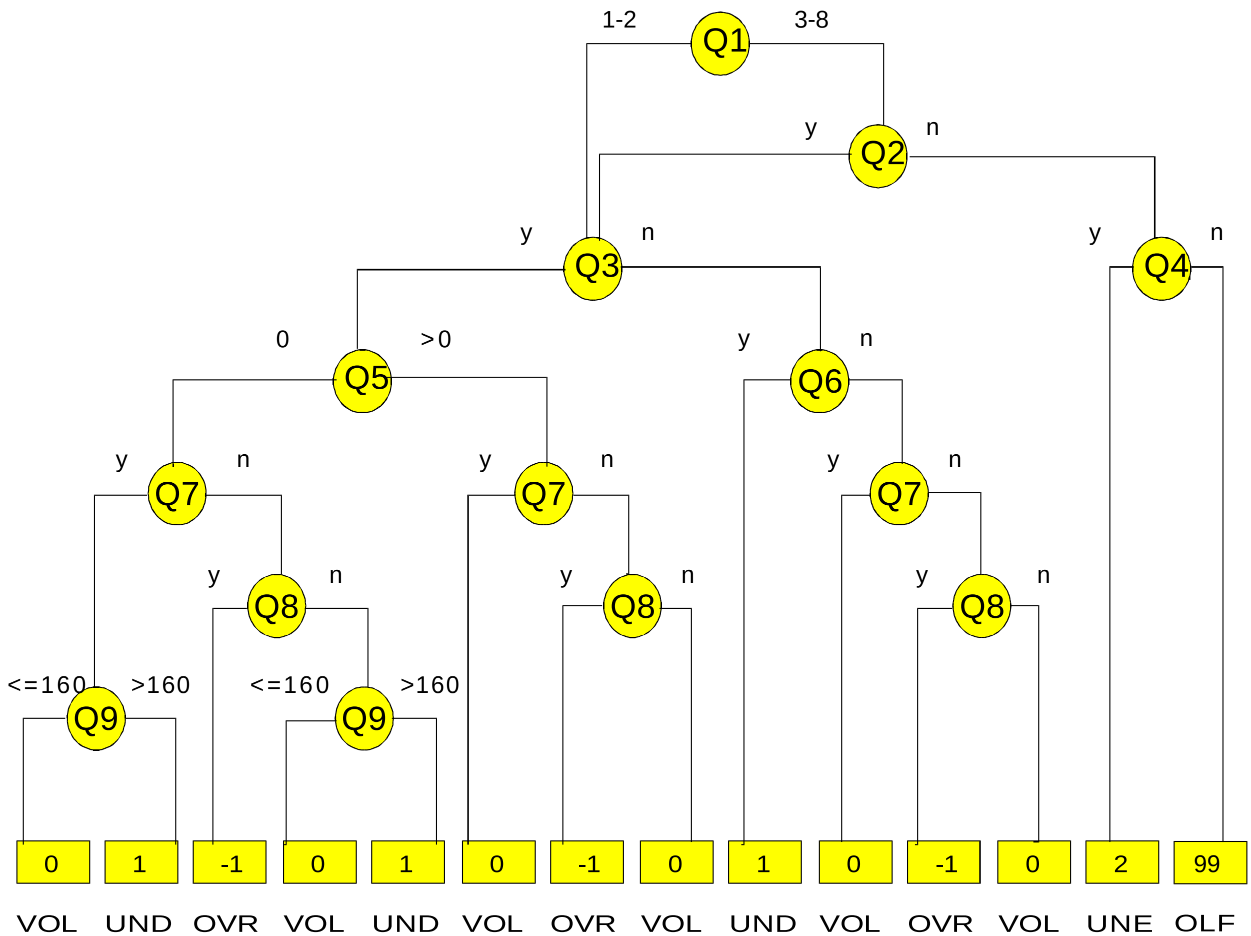
Q2. Could you have worked more hours at (any of) your job(s) this past year? (V4011 in 1975)

Q3. Would you have liked to work more if you could have found more work? (V4012 in 1975)

Q4. Could you have worked less if you had wanted to? (V4013 in 1975)

Q5. Would you have preferred to work less even if you earned less money? (V4014 in 1975)

(continued)



Q1. What is your current employment status? (V14146 in 1987)

1. Working now
2. Temporarily laid off, on sick or maternity leave
3. Looking for work, unemployed
4. Retired
5. Temporarily or permanently disabled
6. Keeping house
7. Student
8. Other

Q2. Are you doing any work for money now at all? (V14148 in 1987)

Q3. Could you have worked more hours at (any of) your job(s) this past year? (V14230 in 1987)

Q4. Have you done anything in the last four weeks to find a job? (V14237 in 1987)

Q5. How much would you have earned per hour? (V14231 in 1987)

Q6. Would you have liked to work more if you could have found more work? (V14234 in 1987)

Q7. Could you have worked less if you had wanted to? (V14232/V14235 in 1987)

Q8. Would you have preferred to work less even if you earned less money? (V14233/V14236 in 1987)

Q9. How many hours of work (if any) did you miss because you were unemployed and looking for work or temporarily laid off? (V13752 in 1987)

Note: Q2 was not included in the 1976 PSID questionnaire. Q4 was included in the 1976 questionnaire and was asked of all individuals responding to Q1 with answers in categories 3-8.

Figure 1: Labor Constraints

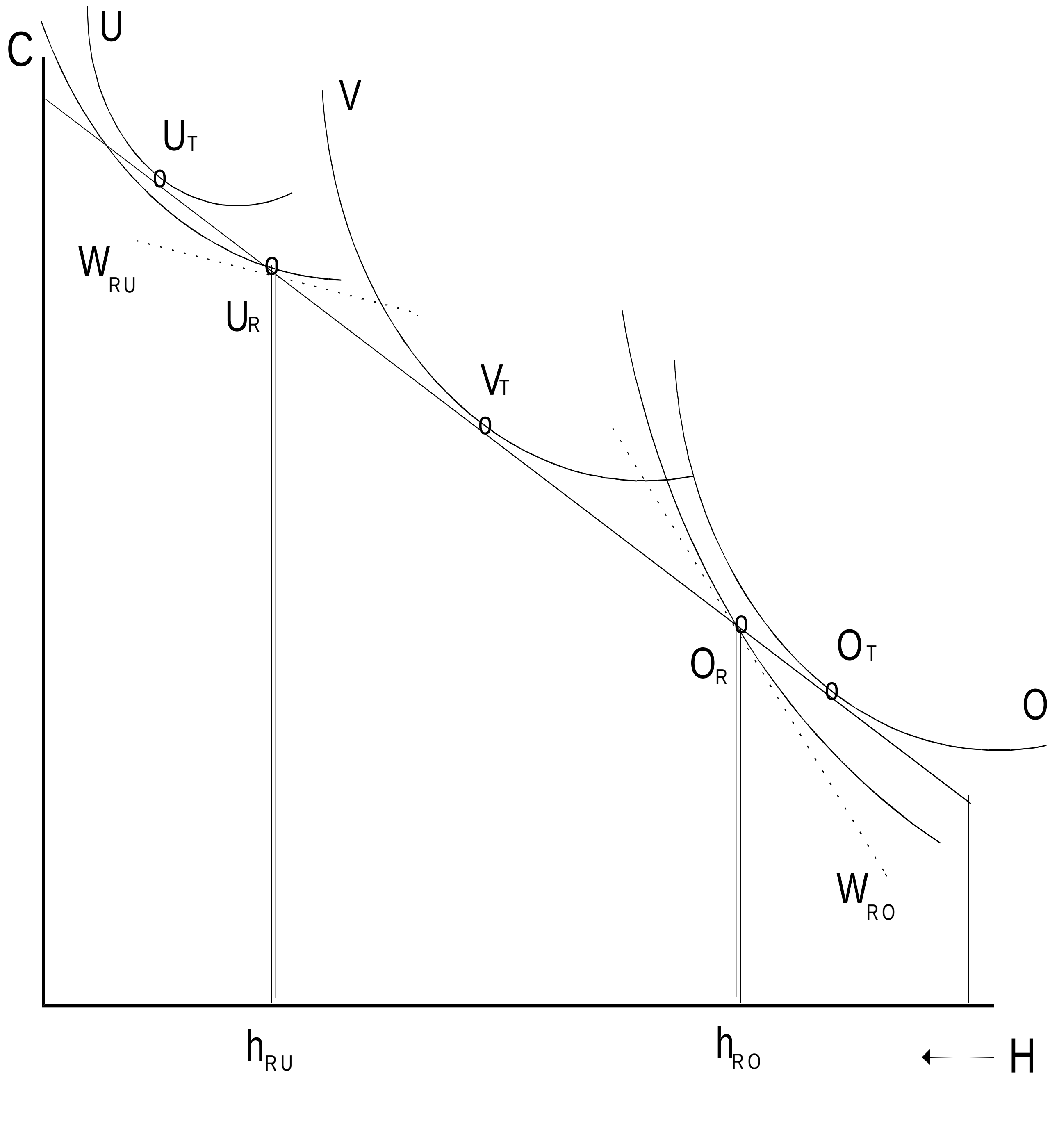


Figure 2: Regimes

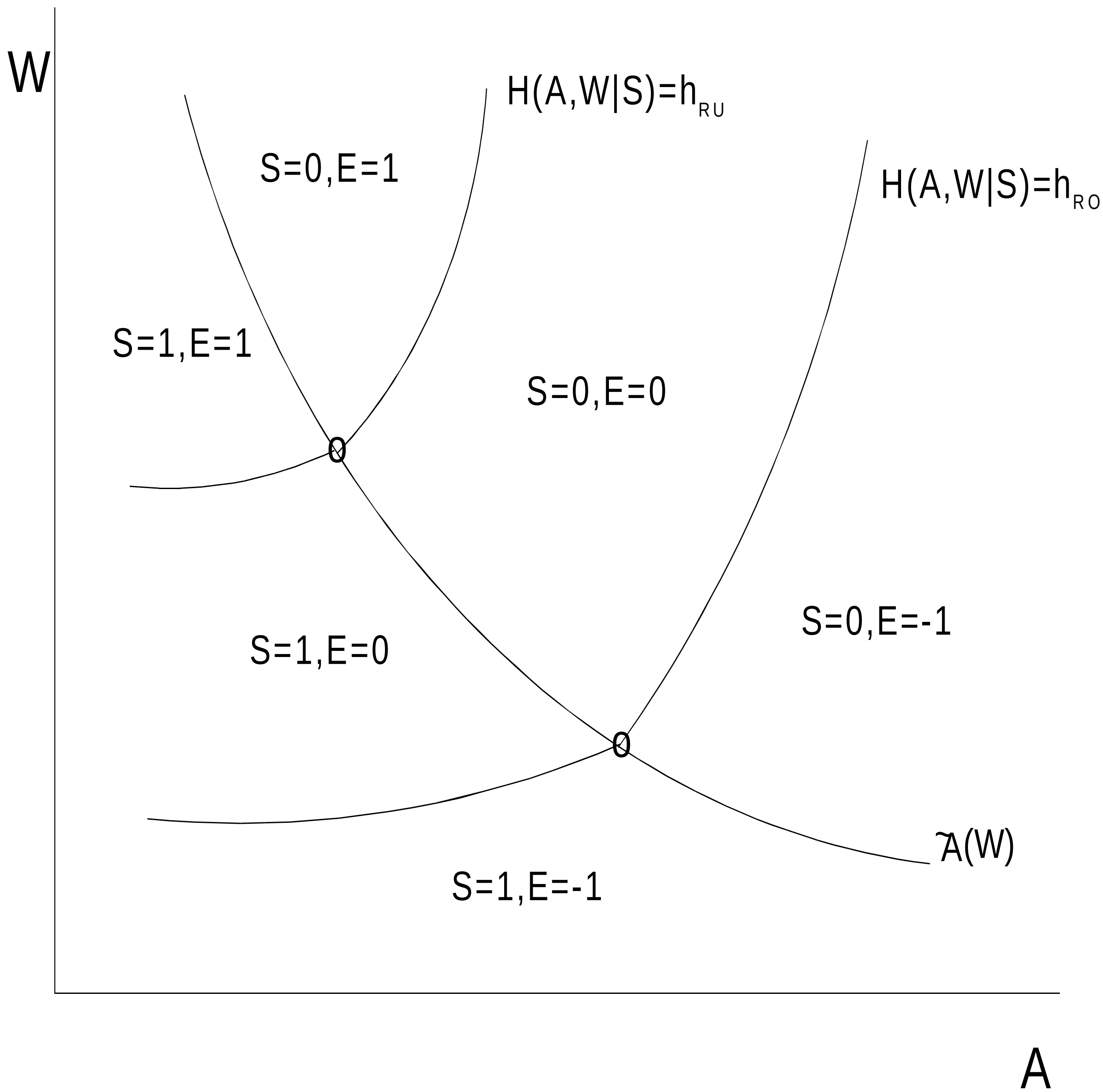
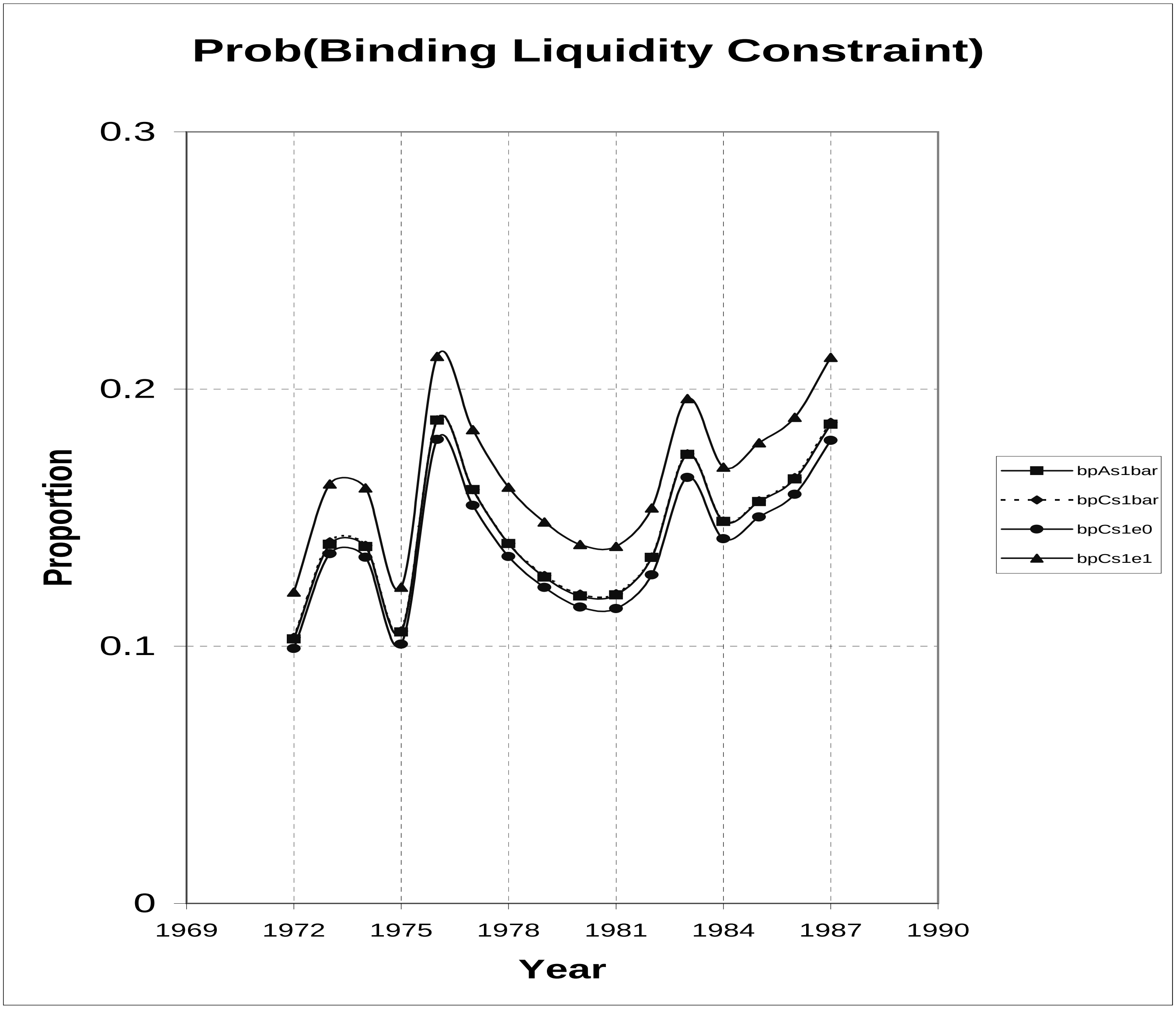


Figure 3: Binary Probit S=1 Predictions



bpAS1bar Version (A) predictions, evaluated at mean values of explanatory variables

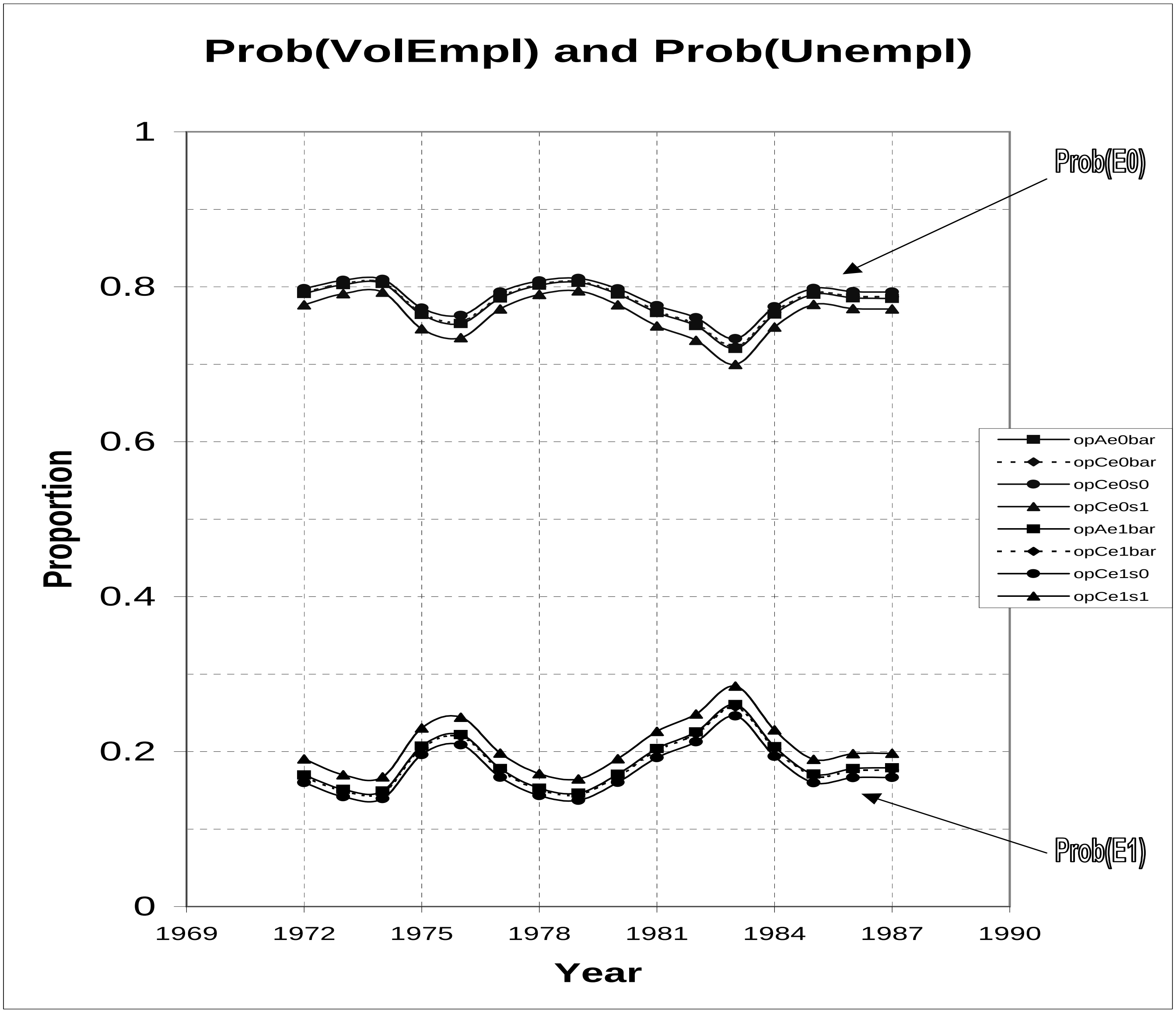
bpCS1bar Version (C) predictions, evaluated at mean values of explanatory variables

bpCS1e0 Version (C) predictions, individuals assumed voluntarily employed

bpCS1e1 Version (C) predictions, individuals assumed involuntarily unemployed or underemployed

NB: Recall that Version (A) estimations ignore all spillover effects between the Liquidity and Employment Constraint sides, while version (C) estimations take full account of such spillovers.

Figure 4: Ordered Probit Predictions



opAE0bar Version (A) E0 predictions, evaluated at mean values of explanatory variables

opCE0bar Version (C) E0 predictions, evaluated at mean values of explanatory variables

opCE0s0 Version (C) E0 predictions, individuals assumed liquidity unconstrained.

opCE0s1 Version (C) E0 predictions, individuals assumed liquidity constrained.

opAE1bar Version (A) E1 predictions, evaluated at mean values of explanatory variables

opCE1bar Version (C) E1 predictions, evaluated at mean values of explanatory variables

opCE1s0 Version (C) E1 predictions, individuals assumed liquidity unconstrained.

opCE1s1 Version (C) E1 predictions, individuals assumed liquidity constrained.

NB: Recall that Version (A) estimations ignore all spillover effects between the Liquidity and Employment Constraint sides, while version (C) estimations take full account of such spillovers.