

The Decision to Use Alternative Payment Methods, State Dependence or Unobserved Heterogeneity?

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First Draft: June 12, 2003

This Draft: August 25, 2003

Abstract

In recent years interest-bearing checking accounts and ATM cards have become quite ubiquitous. These alternative payment methods offer many benefits, but a majority of households have yet to adopt these technologies as a means of payment. The goal of this paper is to answer why some households have been reluctant to make the switch. This paper uses dynamic discrete choice techniques to model household behaviour in adopting alternative payment technologies. The Bank of Italy's Survey of Household Income and Wealth is used to conduct this study. Preliminary evidence indicates that the household previous financial adoption decisions are a major factor in current period adoption choice.

Key Words: Financial Innovation, Discrete-Choice Dynamic Panel Data,

JEL Classification: E41, C33

*The author is grateful to Giovanni D'Alessio for kindly providing the Bank Italy Survey of Household Income and Wealth dataset. Helpful comments and suggestions from Gregor Smith is greatly appreciated and acknowledged. Many thanks to Katerina Kyriazidou for kindly providing the code for the semiparametric conditional logit estimator and Shannon Seitz for the use of her computer and software. Editorial comments and suggestions from Vien Huynh greatly improved the readability of this paper. Financial support from the Social Sciences and Humanities Research Council of Canada is gratefully acknowledged. The usual disclaimer on liability applies.

1 Introduction

Currency has taken many forms in its history. In 9000 B.C., cattle and crops were used as a form of currency; in 1000 B.C. base metal coins were introduced, then paper money in 800 A.D. In the modern age, money has taken on a more sophisticated form. Through technological progress, the use of paper and coin currency has almost become unnecessary. This decision for households to use alternative methods of payments other than money is commonly referred to as financial innovation. Recent examples of financial innovation are interest-bearing checking accounts, credit cards, and ATM cards. The obvious advantage of these payments tools is that it allows the household to economize on their money holdings while providing liquidity services. A concise and lucid survey of the evolution of payment systems is contained in the book by Evans and Schmalensee (1999).

The introduction of financial innovation has resulted in a significant increase in personal efficiency, reducing the time, and cost, involved with money transactions. A greater benefit has proven to be the opportunity to circumvent the inflation tax. By depositing money into a bank account which pays a nominal interest rate, ensures that money retains its value. Safety is also a factor, reducing the amount of cash that is held. Shoe leather costs associated with money are reduced. In addition, issues of counterfeiting and deterioration of money are also avoided. With the myriad of benefits associated with financial innovation, why is it that some households are hesitant to adopt financial innovation?

Theoretical studies such as Ireland (1995), Lacker and Schreft (1996), and Uribe (1997) have shown that episodes of high inflation have spurred on the rate of financial innovation. However, empirical studies such as Gordon, Leeper, and Zha (1998) are unable to match the trends in the aggregate data. One reason for this inadequacy is the assumption that households can smoothly substitute between alternative payment methods. The relaxation of this assumption requires that the household decisions are made in a sequential order. First the household has to decide whether to adopt financial innovation or the *extensive margin*; then conditional on this adoption decision the household decides how much to allocate to each payment method or the *intensive margin*.

Modelling both the extensive and intensive margins has shed many interesting insights into the study of monetary economics. As Mulligan and Sala-i-Martin (2000) note in their study; 59 percent of U.S. households in 1989 did not have an interest-bearing banking account. What could be the reason for the failure to adopt by a non-trivial segment of the population? An explanation put forth by Mulligan and Sala-i-Martin is that the fixed costs of adopting financial innovation introduce frictions into the participation decision. Using the 1989 cross-section of the Survey of Consumer of Finances they find that the fixed costs of adoption, approximately 111 USD, are quite low. Another important finding is that half of the interest rate elasticity is due to the extensive margin. However, this study is incomplete since it only provides a snapshot on the role of fixed costs.

A study that adds a temporal component is by Attanasio, Guiso, and Jappelli (2002). They study the role of financial innovation and its effect on money demand in Italy for the period 1989 to 1995. Using multiple cross-sections from the Bank of Italy's Survey of Household Income and Wealth (SHIW). Attanasio et al. specify a static specification for the financial innovation decision and money demand function. The household decision to adopt financial innovation is modelled using the following static discrete choice model:

$$(1) \quad \begin{aligned} w_i^* &= x_i\beta + v_i, \\ w_i &= \begin{cases} 1 & \text{if } w_i^* > 0, \\ 0 & \text{if } w_i^* \leq 0. \end{cases} \end{aligned}$$

Where w_i is a binary choice variable which takes value of one if the household i has adopted financial innovation, and zero otherwise. The variable x_i contains a vector of household characteristics such as consumption level, financial wealth, and various demographic factors (education, place of residence, age and sex of head of household). It also contains information on the nominal deposit interest rate and number of bank branches in the region that household resides.

The probit estimates are used to form the inverse Mills ratio which are used as the conditioning variable in their switching regressions of household money demand; refer to Maddala (1983) for a discussion of this technique. The estimates of the household money demand function are used to quantify the welfare costs of inflation (Bailey triangles), a welfare metric first discussed by Bailey (1956). Other than calculating the direct inflation tax, which is trivial, they also calculate the cost of financial innovation borne by households. These costs are included in the welfare comparison since they are incurred by households in order to aid in the avoidance of the inflation tax. They find that adoption costs are quite low, ranging from 14.3 to 28.1 euros. This cost, comparable to direct financial adoption cost, is about 6.2 euros. The direct financial costs are from a sample of representative Italian banks.

Why do such low trivial financial adoption costs result in such low adoption rates of financial innovation? An explanation of this phenomena focuses on the heterogeneity between the households. Up to now the studies involving financial innovation use only cross-sectional methods; there is no attempt to follow households across time. For example, studies on household adoption of alternative payment methods by Stavins (2001) or effect of financial innovation on stock market participation by Reynard (2003) use only multiple cross-sections of the Survey of Consumer Finances. In alternative fields longitudinal or panel data has proven to be quite fruitful approach to investigating household decisions; the field of labour economics has been quite an active research area for panel data. Many sharp and interesting results have been completed with longitudinal data that refutes the findings of cross-sectional studies. Panel data has been used in the study by Humphrey, Pulley, and Vesala (1996) to look at cross-country differences in financial innovation. However, the study of financial innovation using household panel data is still in its infancy.

One of the contributions of this paper is to utilize panel data in the study of financial innovation. The SHIW has a panel component but Attanasio et al. ignored this feature of the data

and treated the data as one large cross-section. A preliminary study by Huynh (2003) exploits the panel component of the SHIW to account for this heterogeneity. This study recalculates some key summary statistics and estimates the models using static panel data techniques. An insight of this study was that major determinants of financial innovation are interest rates, consumption, and wealth after controlling for household characteristics such as education, place of residence, presence of a male head of household. These findings beg the question, why do poorer households in Italy have low adoption rates of financial innovation? What is preventing them from adopting financial innovation so as to avoid the inflation tax? Answering this question has many policy implications. A calibration study by Erosa and Ventura (2002) demonstrates that when households do not participate on the extensive margin then inflation is a regressive tax. The results are particularly interesting since Italian inflation was quite high (six to eight percent) in the beginning of the 1990's.

The static specification is unsatisfying since it ignores the dynamic nature of the decision to adopt financial innovation. Table 1 and 2 summarize the participation sequences of households. The decision to adopt an interest-bearing account and ATM cards are quite persistent processes. Accounting for this persistence involves looking at the issue of state dependence, or how current behaviour affects future behaviour. The notion of state dependence indicates that current participation directly affects the preferences or opportunities of the household which, in turn affects future participation.

Although, technological progress has greatly simplified the knowledge required, the cost of learning still remains a nontrivial cost. The panel, which consists of a sample of Italian households, can be used to explore this heterogeneity across households. Apart from the inflation tax; these varied fixed costs may explain households reluctance to adopt financial innovation. The data also indicates that once households have adopted they will retain their financial innovation barring a shock to their household state.

An alternative explanation to the persistence of these discrete outcomes is that unobservable characteristics may affect households behaviour towards financial innovation. For example, a household that engages in illegal activities and/or is active in the underground economy would not adopt financial innovation so as to avoid detection by the legal authorities. Mistrust of financial institutions could be another reason for the lack of adoption by households.

If the major reason for this persistence is state dependence, then one method for policymakers to ameliorate the effect of the inflation tax is to encourage households to adopt financial innovation. If it is unobserved heterogeneity then policies that are aimed at increasing adoption rates would be ineffective. Therefore, an important task is to disentangle these two effects. Dynamic discrete choice panel data models can be used to disentangle these two effects and model the behaviour households. The use of panel data is particularly appropriate in this case as it contains repeated observations of a given group or individuals over time; therefore, their behaviour and choices can be modelled by looking at the differences between households and time.

The rest of the paper is organized in the following fashion. Since dynamic discrete choice models are quite novel, these techniques are discussed in Section 2. Section 3 looks at a dynamic model of financial innovation. Section 4 empirically implements the model specification of financial innovation; dynamic discrete choice models are used to estimate the conditional probability that a household will choose to adopt financial innovation. The empirical results are presented in Section 5. Section 6 concludes with some remarks and some ideas on future work.

2 Dynamic Discrete Choice Panel Data Models

The following discussion is drawn from the following sources Arellano and Honoré (2001), Hsiao (2002), and Miniaci and Weber (2002). A dynamic discrete choice panel data model has the following structure:

$$(2) \quad w_{it}^* = \underbrace{x_{it}\beta}_{\text{observables}} + \underbrace{\gamma w_{i,t-1}}_{\text{state dependence}} + \underbrace{\alpha_i}_{\text{unobserved heterogeneity}} + \underbrace{u_{it}}_{\text{error term}}, \quad i = 1 \dots N, t = 1 \dots T,$$

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

where $v_{it} = \alpha_i + u_{it}$.

Where w_{it} denotes the adoption decision of household i in period t ; x_{it} is a vector of observable household characteristics; β is the effect of x_{it} on the participation decision; γ is the parameter that represents the extent of *true state dependence* (TSD) on the adoption decision. With panel data, repeated observations of a given group of individuals, the error term v_{it} can be decomposed into two components: α_i is the time-invariant household-specific or *unobserved heterogeneity* and u_{it} is assumed to be independently distributed over i with a distribution $F(\cdot)$.

Identifying the source of persistence is a challenging task. Persistence in this model arises from three sources:

1. true state dependence,
2. unobserved heterogeneity,
3. error term.

How should a statistically significant coefficient $\gamma \neq 0$ be interpreted? Is it really TSD or is it unobserved heterogeneity? The cautious approach is to agree that $\gamma \neq 0$, is a necessary, but not a sufficient condition for TSD. To ensure that the correct inference is made, consistent model estimated are required.

A classic example of this identification problem is the issue of labour supply. Phelps (1972) found that current unemployment spells affected future unemployment spells. This result implies that, due to the the effects of state dependence, short-term policies can have a long term

impact on alleviating unemployment. However, Cripps and Tarling (1974) argued that unobservable characteristics were driving individual unemployment spells, not their past behaviour. Concluding that there is true state dependence when it is really unobserved heterogeneity is called *spurious state dependence* (SSD).

The issue of how to treat the initial conditions of the model exacerbates the identification problem. Incorrect handling of the initial condition will yield inconsistent parameter estimates. This is particularly a problem in large N and short T panels. Also, these dynamic discrete choice models are nonlinear, which complicates the estimation method.

In the literature two type of estimators are employed: the *fixed effects* and *random effects* models. The choice of estimator is unclear, as each has its merits and weaknesses. For this reason, it would be useful to follow the approach of Chay and Hyslop (2000) who consider in detail both types of estimators. Consequently, a brief discussion these estimators will be provided.

2.1 The Parametric Likelihood and the Random Effects Estimator

The *random effects* estimator is often referred to as an parametric estimator since it requires distributional assumptions for both α_i and the initial condition. To assist in the parameterization of the initial condition the following assumptions can be made:

1. The initial conditions are an exogenous process.
2. The process is in an equilibrium.

The first assumption can be taken seriously when the starting point of the sample is observable. An example of this is the study of labour supply decisions; one observes at the beginning of the sample the decisions of individuals who have just graduated from high school who are entering the labour force. The latter assumption is not as attractive, since in many cases the stochastic process is being driven by time-varying exogenous variables.

To see how each of the assumptions are treated in the estimation technique, it would be useful to look at the likelihood functions of each approach.

2.1.1 The Likelihood

Suppose that the dynamic discrete choice model follows a first-order Markov process with no exogenous variables:

$$(3) \quad \begin{aligned} w_{it}^* &= \beta_0 + \gamma w_{i,t-1} + v_{it}, \\ \text{where } v_{it} &= u_{it} + \alpha_i, \\ w_{it} &= \begin{cases} 1 & \text{if } w_{it}^* > 0 \\ 0 & \text{if } w_{it}^* \leq 0 \end{cases} \end{aligned}$$

- *Exogenous initial conditions:*

For this case the joint probability of w_{it} for a given α_i is:

$$(4) \quad \prod_{t=1}^T F(w_{it}|w_{i,t-1}, \alpha_i) = \prod_{t=1}^T \Phi\{(\beta_0 + \gamma w_{i,t-1} + \alpha_i)(2w_{it} - 1)\}.$$

Let Φ denote the standard normal cumulative distribution function. If α_i is random with a distribution $G(\alpha)$ the likelihood function is:

$$(5) \quad L = \prod_{i=1}^N \int \prod_{t=1}^T \Phi\{(\beta_0 + \gamma w_{i,t-1} + \alpha)(2w_{it} - 1)\} dG(\alpha).$$

- *Equilibrium process:*

For this case the the limiting marginal probabilities are:

$$\begin{aligned} w_{i0} = 1 & \quad \text{with } P_i = \frac{\Phi(\beta_0 + \alpha_i)}{1 - \Phi(\beta_0 + \gamma\alpha_i) + \Phi(\beta_0 + \alpha_i)} \\ w_{i0} = 0 & \quad \text{with } 1 - P_i = \frac{1 - \Phi(\beta_0 + \gamma\alpha_i)}{1 - \Phi(\beta_0 + \gamma\alpha_i) + \Phi(\beta_0 + \alpha_i)}. \end{aligned}$$

Therefore the joint probability of w_{it} for a given α_i is:

$$(6) \quad \prod_{t=1}^T \Phi\{(\beta_0 + \gamma w_{i,t-1} + \alpha)(2w_{it} - 1)\} \times P_i^{w_{i0}} (1 - P_i)^{1-w_{i0}}.$$

The likelihood function for the random effects is:

$$(7) \quad L = \prod_{i=1}^N \int \prod_{t=1}^T \Phi\{(\beta_0 + \gamma w_{i,t-1} + \alpha)(2w_{it} - 1)\} \times P_i^{w_{i0}} (1 - P_i)^{1-w_{i0}} dG(\alpha).$$

With the random-effects the maximum likelihood estimates (MLE) of β_0 , γ , and σ_α^2 are consistent if either $N \rightarrow \infty$ or both N or $T \rightarrow \infty$. The weakness of the likelihood approach is that if the parametric assumptions can be rejected, the estimates will be inconsistent. To avoid inconsistent estimators when the above initial conditions assumptions fail, less restrictive likelihoods will have to be specified.

2.1.2 Intractable Likelihoods

In the event that neither of the assumptions hold; the of relationship between w_{i0} and α_i must be considered. The likelihood for the random-effects model is:

$$(8) \quad L = \prod_{i=1}^N \int_{-\infty}^{\infty} \prod_{t=1}^T F(w_{it}|w_{i,t-1}, \alpha) f(w_{i0}|\alpha) dG(\alpha).$$

An even more complicated likelihood would be to introduce a fixed-effects model so that:

$$(9) \quad L = \prod_{i=1}^N \prod_{t=1}^T \Phi\{(\beta_0 + \gamma w_{i,t-1} + \alpha_i)(2w_{it} - 1)\} f(w_{i0}|\alpha_i).$$

Where $f(w_{i0}|\alpha)$ is the marginal probability of w_{i0} given α_i . Finding a closed-form expression for this marginal probability is non-trivial. Maximizing such a likelihood can be computationally expensive. One could overcome the complexity of the likelihood by using simulation techniques, for example see Lee (1997). Alternatively, Bayesian and Markov-Chain Monte-Carlo methods can be used to obtain *exact* estimators, an example of this approach is McCulloch and Rossi (1994).

2.1.3 Heckman's Approximate Method

If the initial conditions assumptions or alternative simulation-based methods are not palatable, an approximation method can be employed. Heckman (1981b) suggests such a method to deal with the initial conditions problem. The method can be broken down into the following three steps

1. Approximate the initial condition, w_{i0} by estimating the following probit model with an general index $Q(x_i)$:

$$\begin{aligned} w_{i0}^* &= Q(x_i) + \epsilon_{i0} \\ w_{i0} &= \begin{cases} 1 & \text{if } w_{i0}^* > 0 \\ 0 & \text{if } w_{i0}^* \leq 0 \end{cases} \end{aligned}$$

2. Allow ϵ_{i0} to be correlated with v_{it} with $t = 1 \dots T$.
3. Maximize the likelihood and obtain an estimate of the model without any restrictions between the structural parameters and approximated initial conditions.

Heckman provides Monte Carlo evidence that this approximate random-effects estimator is superior to the fixed-effects model. However, the estimators are still biased in small samples. Nevertheless, this method is quite easy to implement.

2.2 The Conditional Logit or Fixed-Effects Estimator

The random-effects/parametric likelihood will yield inconsistent estimates if the individual effects are indeed fixed. This assumption can be tested using a Durbin-Wu-Hausman test. If the random effects model is rejected, then, the fixed-effects can be employed.

An alternative to the parametric likelihood/random-effects method is the conditional approach discussed by Chamberlain (1993) and generalized by Honoré and Kyriazidou (2000). The conditional approach is quite technical; interested readers are advised to consult these references directly. The main idea behind this method is to *concentrate* the fixed-effects (α_i) out of the likelihood. The approach involves assuming a logistic distribution for the error terms (u_{it}), therefore completing the term *conditional logit*.

2.2.1 Conditional Logit

Chamberlain (1993) shows that when $T \geq 3$ the parameters β and γ can be estimated independent of α_i . T refers to the number of usable data points excluding the initial condition. Suppose the model of $(y_{i0} \dots y_{iT})$ is of the form:

$$(10) \quad P(w_{i0} = 1 | \alpha_i) = P_0(\alpha_i),$$

$$(11) \quad P(w_{it} = 1 | \alpha_i, w_{i0} \dots w_{i,t-1}) = \frac{\exp(\gamma w_{i,t-1} + \alpha_i)}{1 + \exp(\gamma w_{i,t-1} + \alpha_i)}, \quad t = 0, 1, 2, \dots T.$$

The following discussion looks at the simplest case when $T = 3$. Consider the following sequences:

$$A = \{w_{i0}, w_{i1} = 1, w_{i2} = 0, w_{i3}\},$$

$$B = \{w_{i0}, w_{i1} = 0, w_{i2} = 1, w_{i3}\},$$

where the initial and terminal condition (w_{i0} and w_{i3}) are allowed to vary (either 1 or 0). The sequences $(w_{i0}, 0, 0, w_{i3})$ or $(w_{i0}, 1, 1, w_{i3})$ are not considered because these events do not help identify changes in states. The probabilities of each event are:

$$(12) \quad P(A) = P_0(\alpha_i)^{w_{i0}} [1 - P_0(\alpha_i)]^{1-w_{i0}} \frac{1}{1 + \exp(\gamma w_{i,0} + \alpha_i)} \frac{\exp(\alpha_i)}{1 + \exp(\alpha_i)} \frac{\exp[(\gamma + \alpha_i)w_{i3}]}{1 + \exp(\gamma + \alpha_i)},$$

$$(13) \quad P(B) = P_0(\alpha_i)^{w_{i0}} [1 - P_0(\alpha_i)]^{1-w_{i0}} \frac{\exp(\gamma w_{i,0} + \alpha_i)}{1 + \exp(\gamma w_{i,0} + \alpha_i)} \frac{1}{1 + \exp(\alpha_i)} \frac{\exp(\alpha_i w_{i3})}{1 + \exp(\alpha_i)}.$$

The conditional probabilities are then:

$$(14) \quad \begin{aligned} P(A|A \cup B) &= P(A|w_{i0}, w_{i1} + w_{i2} = 1, w_{i3}) \\ &= \frac{\exp(\gamma w_{i3})}{\exp(\gamma w_{i3}) + \exp(\gamma w_{i0})} \\ &= \frac{1}{1 + \exp[\gamma(w_{i0} - w_{i3})]} \end{aligned}$$

$$(15) \quad \begin{aligned} P(B|A \cup B) &= P(B|w_{i0}, w_{i1} + w_{i2} = 1, w_{i3}) \\ &= 1 - P(A|A \cup B) \\ &= \frac{\exp[\gamma(w_{i0} - w_{i3})]}{1 + \exp[\gamma(w_{i0} - w_{i3})]} \end{aligned}$$

Notice that the conditional probabilities (14) and (15) are no longer depend on the fixed-effect α_i . The log-likelihood is similar in form to the conditional logit discussed by Chamberlain (1993):

$$(16) \quad \log L = \sum_{i=1}^N \mathbf{1}(w_{i1} + w_{i2} = 1) \times \{w_{i1}[\gamma(w_{i0} - w_{i3})] - \log[1 + \exp \gamma(w_{i0} - w_{i3})]\}.$$

2.2.2 Semiparametric Conditional Logit Estimator

The method described by Chamberlain (1993) does not include exogenous variables (x_{it}). Once x_{it} is added, the likelihood is more complicated because the conditional probabilities are no longer independent of α_i . To deal with this problem Honoré and Kyriazidou (2000) make a further restriction that $x_{i2} = x_{i3}$ so that:

$$(17) \quad P(A|A \cup B, x_i, \alpha_i, x_{i2} = x_{i3}) = \frac{1}{1 + \exp[(x_{i2} - x_{i3})'\beta + \gamma(w_{i0} - w_{i3})]}.$$

In most cases, especially with continuous variables, $x_{i2} \neq x_{i3}$ so the log-likelihood is modified into the following form:

$$(18) \quad \sum_{i=1}^N \mathbf{1}(w_{i1} + w_{i2} = 1) K\left(\frac{x_{i2} - x_{i3}}{\sigma_N}\right) \log \left\{ \frac{\exp[(x_{i2} - x_{i3})'b + \gamma(w_{i0} - w_{i3})]^{w_{i1}}}{1 + \exp[(x_{i2} - x_{i3})'b + \gamma(w_{i0} - w_{i3})]} \right\}.$$

The kernel density function, $K(\cdot)$, is introduced in order to give more weight to observations for which x_{i2} is close to x_{i3} . For the formulation of the more generalized case, $T > 3$, please refer to Honoré and Kyriazidou (2000).

One of the major advantages of the conditional approach is that the problem of initial conditions does not have to be modelled explicitly. Also, assumptions are not required for the relationship between the individual effects, explanatory variables, and initial condition. The disadvantage is the requirement that $x_{i2} = x_{i3}$; as a result some explanatory variables such as time dummies cannot be used. When Honoré and Kyriazidou (2000) propose to replace this restriction with a kernel density estimator the rate of convergence is lower $n^{-\frac{1}{3}}$ i.e. more data is required for the asymptotics to hold. Another disadvantage is that the individual effect are not estimated therefore it is not possible to calculate elasticities or make predictions with the model.

2.3 A Simple Test for State Dependence

These estimators discussed have been discussed to quantify the extent of state dependence and unobserved heterogeneity. A simple test has been suggested by Chamberlain (1978) to test for the presence of state dependence. Chamberlain makes the following observation: the difference between TSD versus SSD is whether the dynamics are due to a policy intervention. $\gamma = 0$ implies that changes in x_{it} will affect w_{it} immediately; but if $\gamma \neq 0$ then changes in x_{it} will have a distributed lag affect on w_{it} . A simple test for TSD could be:

$$(19) \quad TSD : P(w_{it} = 1|x_{i,t}, x_{i,t-1}, \dots, \alpha_i) = P(w_{it} = 1|x_{it}, \alpha_i),$$

$$(20) \quad SSD : P(w_{it} = 1|x_{i,t}, x_{i,t-1}, \dots, \alpha_i) \neq P(w_{it} = 1|x_{it}, \alpha_i).$$

This test can be implemented by estimating the following relationship:

$$(21) \quad \begin{aligned} w_{it}^* &= x_{it}\beta + \phi(L)x_{it} + \alpha_i + u_{it}, \\ w_{it} &= \begin{cases} 1 & \text{if } w_{it}^* > 0, \\ 0 & \text{if } w_{it}^* \leq 0, \end{cases} \end{aligned}$$

If the lag structure, $\phi(L)$, is statistically significant then there is some evidence of TSD.

3 A Model of Financial Innovation

Households make consumption/savings decision subject to an intertemporal budget constraint augmented with a transactions cost function. The transactions costs are increasing in consumption and decreasing in money balances. The role of money is to lower transactions cost. The cost of holding money is that it is subject to an inflation tax. To avoid the inflation tax households can choose to pay a fixed cost in order to adopt financial innovation such as an interest-bearing bank account. The total opportunity cost of using money is the foregone real return on interest plus any inflation tax. Therefore, households must make the following discrete/continuous decisions:

1. Extensive margin - this discrete decision determines whether or not to adopt financial innovation,
2. Intensive margin - conditional on the discrete choice this continuous decision involves choosing the optimal portfolio of the household.

A dynamic optimization approach is required to solve such a problem.

3.1 Dynamic Optimization Problem

The household optimization problem is to maximize the following utility function:

$$(22) \quad \max U_t = \sum_{t=0}^{\infty} \delta^t \mathbf{E}_t u(c_t),$$

subject to the following budget constraint:

$$(23) \quad \begin{aligned} a_{t+1} &= \phi_t a_t + h_t(1 - \phi_t)(1 + r_t)a_t + y_t - c_t - s(\phi_t a_t, c_t) \\ &\quad - (\pi_t \phi_{t-1} a_t)(1 - h_{t-1}) - \max[(h_t - h_{t-1})\kappa, 0]. \end{aligned}$$

Where c_t is consumption and δ is the discount rate. h_t is the binary choice variable which takes value one if the household has adopted financial innovation otherwise it is equal to zero. The amount of assets that household brings into time t is a_t ; while ϕ_t is the share of the asset held as money and $(1 - \phi_t)$ is the fraction held in a bank account, r_t is real return of the bank account, y_t is exogenous stream of labour income, π_t is the inflation rate, and κ is the fixed cost of financial adoption. The term $\pi_t \phi_{t-1} a_t$ is the amount of inflation tax that household incurs by not adopting financial technology. The transaction technology or shopping cost function, $s(\phi_t a_t, c_t)$, has the following properties:

$$\begin{aligned} s(\phi_t a_t, c_t) &\geq 0, s(\phi_t a_t, 0) = 0, \\ s_1(\phi_t a_t, c_t) &\leq 0, s_2(\phi_t a_t, c_t) \geq 0, \\ s_{11}(\phi_t a_t, c_t) &\geq 0, s_{22}(\phi_t a_t, c_t) \geq 0, s_{12}(\phi_t a_t, c_t) \leq 0. \end{aligned}$$

3.2 Dynamic Programming Problem

The value function depends on the following state variables: previous choices on whether to adopt financial innovation (h_{t-1}), previous portfolio weights (ϕ_{t-1}), amount of assets brought into the current time period (a_t), and observable household state or characteristics (Z_t). Household control or choice variables are then: consumption (c_t) and savings (a_{t+1}), financial innovation (h_t), and current portfolio weights (ϕ_t).

The Bellman equation at time t is:

$$(24) \quad V(h_{t-1}, \phi_{t-1}, a_t, Z_t) = \max[V^0(h_{t-1}, \phi_{t-1}, a_t, Z_t), V^1(h_{t-1}, \phi_{t-1}, a_t, Z_t)],$$

where superscript 0 and 1 denote the period t no-adopt and adopt states. To gain some insight into the problem lets consider the following cases: First, households who have not adopted financial innovation must decide whether to pay the fixed cost κ in order to adopt financial innovation; Second, households who have adopted financial innovation must make the decision whether to keep on using such financial innovation. To elucidate these problems look at the household dynamic programming in the two possible states.

3.2.1 Households who did not adopt financial innovation

The dynamic program for a household that has not adopted financial innovation in period $t - 1$ is:

$$(25) \quad V(0, 1, a_t, Z_t) = \max[V^0(0, 1, a_t, Z_t), V^1(0, 1, a_t, Z_t)].$$

The household will adopt financial innovation if $V^0(0, 1, a_t, Z_t) < V^1(0, 1, a_t, Z_t)$, or:

$$(26) \quad \underbrace{u[a_t + y_t - a_{t+1} - s(a_t, c_t) - \pi_t a_t, 0, Z_t] + \delta E_t V(0, 1, a_t, Z_{t+1})}_{\text{did not adopt financial innovation}} < \underbrace{u[\phi_t a_t + (1 - \phi_t)(1 + r_t)a_t + y_t - a_{t+1} - s(\phi_t a_t, c_t) - \pi_t a_t - \kappa, 1, Z_t] + \delta E_t V(1, 1, a_t, Z_{t+1})}_{\text{did adopt financial innovation}}.$$

Rearranging so as to compare current utility versus future expected utility yields:

$$\begin{aligned} & u[\phi_t a_t + (1 - \phi_t)(1 + r_t)a_t + y_t - a_{t+1} - s(\phi_t a_t, c_t) - \pi_t a_t - \kappa, 1, Z_t] \\ - & u[a_t + y_t - a_{t+1} - s(a_t, c_t) - \pi_t a_t, 0, Z_t] > \delta [E_t V(0, 1, a_t, Z_{t+1}) - E_t V(1, 1, a_t, Z_{t+1})]. \end{aligned}$$

Inverting these monotonic utility functions then approximating the difference yields:

$$(27) \quad r_t a_t (1 - \phi_t) + s(\phi_t a_t, c_t) - s(a_t, c_t) - k > \varphi \{ (\delta E_t [V(0, 1, a_t, Z_{t+1}) - V(1, 1, a_t, Z_{t+1})]) \}^{-1},$$

or

$$\underbrace{r_t a_t (1 - \phi_t) + s(\phi_t a_t, c_t) - s(a_t, c_t)}_{\text{benefit of having adopted financial innovation}} > \underbrace{k + \varphi \{ \delta E_t [V(0, 1, a_t, Z_{t+1}) - V(1, 1, a_t, Z_{t+1})] \}^{-1}}_{\text{fixed adoption cost + Difference in expected future utility}}.$$

3.2.2 Households who did adopt financial innovation

The dynamic program for household who has adopted financial innovation in period $t - 1$ is:

$$(28) \quad V(1, \phi_{t-1}, a_t, Z_t) = \max[V^0(1, \phi_{t-1}, a_t, Z_t), V^1(1, \phi_{t-1}, a_t, Z_t)].$$

The household will keep using their financial innovation if $V^0(1, \phi_{t-1}, a_t, Z_t) < V^1(1, \phi_{t-1}, a_t, Z_t|\omega^1)$ or:

$$(29) \quad \underbrace{u[a_t + y_t - a_{t+1} - s(a_t, c_t), 0, Z_t] + \delta E_t V(0, \phi_{t-1}, a_t, Z_{t+1})}_{\text{Un-adopt financial innovation}} < \underbrace{u[\phi_t a_t + (1 - \phi_t)(1 + r_t)a_t + y_t - a_{t+1} - s(\phi_t a_t, c_t), 1, Z_t] + \delta E_t V(1, \phi_{t-1}, a_t, Z_{t+1})}_{\text{Retain financial innovation}}.$$

Similar derivation yields the following condition for households to keep their bank account:

$$(30) \quad \underbrace{r_t a_t (1 - \phi_t) + s(\phi_t a_t, c_t) - s(a_t, c_t)}_{\text{Benefit of Retaining financial innovation}} > \underbrace{\varphi \{ \delta E_t [V(0, \phi_{t-1}, a_t, Z_{t+1}) - V(1, \phi_{t-1}, a_t, Z_{t+1})] \}^{-1}}_{\text{Difference in expected utility}}.$$

4 Empirical Specification and Estimation

The previous sections have discussed the econometric issues involved with estimating dynamic discrete choice models and laid the framework for a model of financial innovation. This section casts the model of financial innovation into an econometric framework, using the choices of Italian households in the SHIW. This approach has previously been used by Hyslop (1999) to look at female labour participation rates.

4.1 Theory Taken to the Data

The value functions (25) and (28) describe the behaviour of households. The decision to adopt financial innovation is a function of:

1. Consumption (c_t)
2. Financial Wealth (a_t)
3. Interest rate (r_t)
4. Fixed cost of setting up bank account (κ)
5. Previous state of the household choices (h_{t-1}, ϕ_{t-1})
6. Household characteristics (Z_t)

The decision to adopt financial innovation, checking account or an ATM card, is modelled using a dynamic binary choice model. The empirical specification is of the form described in (2):

$$w_{it} = \mathbf{1}\{x_{it}\beta + \gamma w_{i,t-1} + \alpha_i + \epsilon_{it}\},$$

where w_{it} is a binary variable that takes value 1 if household has adopted that form of financial innovation and zero otherwise. The observable variables, x_{it} , are: consumption (**logc**), financial wealth (**logfinw**), interest rate (**logr**), and household characteristics.

The household characteristics variables are introduced to control for differences in households. These variables consist of:

1. Education level for the head of the household (**educ**); dummy variables with four controls.
2. Where does the household reside (**live**); dummy variable with three controls.
3. Whether the head of household is male (**malehead**); equal to 1 if male 0 otherwise.
4. Age of the head of household (**eta**); continuous variable.

Tables 1, 2, and 3 summarize the characteristics of these variables. The balanced panel consists of 1236 households but for estimation purposes, only 1234 household observations are used. Two households are excluded because their financial wealth is unreported in 1991.

To control for the supply of financial innovation, the number of bank branches in the region the household resides is included (**logQ**). At the present time there is no data on the cost structure of the financial industry, or a technological change; as a result, a quadratic time trend is added to proxy for these processes. The fixed cost, κ , is unobserved so it cannot directly estimated, but it is assumed that α_i captures part of this term. For a detailed explanation of the variables please refer to the Appendix.

4.2 Estimation Techniques

The estimation and inference strategy is similar in spirit to that of Hyslop (1999) and Chintagunta, Kyriazidou, and Perktold (2001). The general test for TSD suggested by Chamberlain (1978) will be implemented. Next the parameters of the discrete choice models are estimated using the following estimators: Heckman (1981b) approximate random-effects (HRE), a probit random-effects (XTRE), a fixed-effects conditional logit (XTFE), and the Honoré and Kyriazidou (2000) semiparametric fixed-effects conditional logit (HK). Since the HK estimator relies on kernel smoothing five different bandwidths are presented. Another feature of the HK estimator is that it has less conditioning variables than the other estimators. The reason for this feature is to avoid the curse-of-dimensionality problem related with kernel smoothing multivariate models and time-variant variables such as time dummies are not allowed.

5 Results

The participation sequences are calculated for household adoption of interest-bearing bank account, bank account conditional on not having an ATM, and ATM card. The results are summarized in Table 1; a striking feature of this table is the segmentation between the two groups. The full participation sequences for households with bank accounts is quite high - 984 out of possible 1234 or about 80% households always had a bank account. For the ATM case there are two large groups the full adopters (322) versus non adopters (407). Another case is the group of households who adopted post-1995 (95).

To attempt to control for the possible stepwise decision, the participation sequences are calculated for households who have always had a bank account in all five periods (984); the results are summarized in Table 2. This table indicates that out of possible 984 households 322 have adopted an ATM card never gave it up. Also, 223 households or about 23% who had an interest-bearing checking account never adopted an ATM card at all. These results indicate that there is some evidence of state-dependence.

To test this empirically the binary choice models are applied to three different classifications:

1. Check: household who have adopted interest-bearing bank accounts,
2. ATM: households who have adopted ATM cards,
3. CATM: households who have adopted ATM cards conditional on having a bank account in all five periods.

The first step is to apply the test for TSD suggested by Chamberlain (1978). Results are summarized in Table 6 and point to evidence that it is TSD since the coefficients of the lagged independent terms are statistically significant.

The next step is to estimate the binary choice models for each of the three different decisions. The results of these estimates are summarized in Table 7, 8, and 9. For the check case both the random-effects estimator, HRE and XTRE, indicate that there is strong evidence of positive state dependence. However, the XTFE indicates that γ is negative and is not statistically different from zero. This result implies that there is no state dependence. However, the HK estimator confirms the results of the random-effects estimator since for all bandwidth parameters γ is statistically significant. Another interesting observation is that the estimated parameters from the fixed-effect have larger standard errors than the random-effects estimators. This implies that household differences do not have much explanatory power in the fixed-effects models.

For the ATM and CATM cases the conclusion is the same as the Check case; the random-effects and HK estimator indicate that state dependence is statistically significant while the XTFE shows that γ is statistically insignificant. Also, the parameter estimates from the random-effects estimator are much sharper than the fixed-effects model. It seems that conditioning on

households who always had a bank account did not really change the results; as the coefficients from both state dependence equations are roughly the same. The only difference seems to be the effect of interest rates and financial wealth on the decision to adopt. For the CATM case, these variables were lesser in magnitude than the ATM case.

6 Conclusions

The result of the dynamic discrete models indicate that there is evidence that the decision to adopt financial innovation displays true state dependence. This implies that past household decisions to adopt financial innovation play a role in current household decision to adopt financial innovation. This result concurs with the data. From the participation sequences, a large number of households who have adopted financial innovation keep it and never switch out. Households who did not adopt financial innovation tend to stay in this state.

However, it is unsettling that the econometric evidence is not overwhelming. The fixed-effects conditional logit clearly indicates that there is no state dependence. This conflict conclusion needs to be reconciled. Monte Carlo studies by Chintagunta, Kyriazidou, and Perktold (2001) have found that the fixed-effect conditional logit models are negatively biased towards zero. A natural extension is to use the actual design matrix of this problem and conduct a Monte-Carlo study. Alternatively, more complicated estimators can be considered. In the case of Chay and Hyslop (2000) the authors use simulation-based estimators with much more complicated error structures. Another complication that one can consider is to model the stepwise decision process; a bank account is a necessary condition for an ATM card. It maybe fruitful to look at dynamic discrete nested logit models. Finally these reduced-forms methods might not be able to distinguish between the state dependence and unobserved heterogeneity. A natural extension is to consider Markov decision process methods advocated by Rust (1987), Hotz and Miller (1993), and Aguirregabiria and Mira (2002).

References

- AGUIRREGABIRIA, V., AND P. MIRA (2002): “Swapping the Nested Fixed Point Algorithm: A Class of Estimators for Discrete Markov Decision Models,” *Econometrica*, 70(4), 1519–1543.
- ARELLANO, M., AND B. HONORÉ (2001): *Handbook of Econometrics* vol. 5, Chapter 53: Panel Data Models: Some Recent Developments, pp. 3229–3296. Elsevier.
- ATTANASIO, O. R., L. GUISO, AND T. JAPPELLI (2002): “The Demand for Money, Financial Innovation, and the Welfare Cost of Inflation: An analysis with Household Data,” *Journal of Political Economy*, 110(2), 317–351.
- BAILEY, M. J. (1956): “The Welfare Costs of Inflationary Finance,” *Journal of Political Economy*, 64, 93–110.
- BRANDOLINI, A., AND L. CANNARI (1994): *Saving and the accumulation of wealth : essays on Italian household and government saving behavior* Chapter Methodological Appendix: The Bank of Italy’s Survey of Household Income and Wealth. Cambridge University Press.
- CHAMBERLAIN, G. (1978): “On the Use of Panel Data,” paper presented at the Social Science Research Council Conference on the Life-Cycle Aspects of Employment and the Labor Market, Mt. Kisco, N.Y.
- (1993): “Feedback in Panel Data Models,” mimeo. Department of Economics, Harvard University.
- CHAY, K., AND D. HYSLOP (2000): “Identification and Estimation of Dynamic Binary Response Panel Data Models: Empirical Evidence Using Alternative Approaches,” unpublished.
- CHINTAGUNTA, P. K., E. KYRIAZIDOU, AND J. PERKTOLD (2001): “Panel Data Analysis of Household Brand Choices,” *Journal of Econometrics*, 103, 111–153.
- CRIPPS, T., AND R. TARLING (1974): “An Analysis of the Duration of Male Unemployment in Great Britain, 1932-1973,” *Economic Journal*, 84, 289–316.
- EROSA, A., AND G. VENTURA (2002): “On Inflation as a Regressive Consumption Tax,” *Journal of Monetary Economics*, 49, 761–795.
- EVANS, D. S., AND R. SCHMALENSEE (1999): *Paying with Plastic: The Digital Revolution in Buying and Borrowing*. MIT Press.
- GORDON, D. B., E. M. LEEPER, AND T. ZHA (1998): “Trends in Velocity and Policy Expectations,” *Carnegie-Rochester Conference Series in Public Policy*, 49, 265–304.
- HECKMAN, J. J. (1981b): *Structural Analysis of Discrete Data with Econometric Applications* Chapter Four: The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process, pp. 179–195. MIT Press.

- HESTER, D. D., G. CALCAGNINI, AND R. DE BONIS (2001): "Competition through Innovation: ATMs in Italian banks," *Rivista Italiana degli Economisti*, (3), 359–381.
- HONORÉ, B. E., AND E. KYRIAZIDOU (2000): "Panel Data Discrete Choice Models with Lagged Dependent Variables," *Econometrica*, 68(4), 839–74.
- HOTZ, V., AND R. MILLER (1993): "Conditional Choice Probabilities and the Estimation of Dynamic Models," *Review of Economic Studies*, 60(3), 497–531.
- HSIAO, C. (2002): *Analysis of Panel Data*. Cambridge University Press.
- HUMPHREY, D. B., L. B. PULLEY, AND J. M. VESALA (1996): "Cash, Paper, and Electronic Payments: A Cross-Country Analysis," *Journal of Money, Credit, and Banking*, 28(4), 914–939.
- HUYNH, K. P. (2003): "Money Demand and Financial Innovation: A Dynamic Microeconomic Approach," mimeo.
- HYSLOP, D. (1999): "State Dependence, Serial Correlation and Heterogeneity in Intertemporal Labor Force Participation of Married Women," *Econometrica*, 67, 1255–1294.
- IRELAND, P. (1995): "Endogenous Financial Innovation and the Demand for money," *Journal of Money Credit and Banking*, 27, 107–123.
- LACKER, J., AND S. L. SCHREFT (1996): "Money and credit as means of payment," *Journal of Monetary Economics*, 38(1), 3–23.
- LEE, L.-F. (1997): "Simulated Maximum Likelihood Estimation of Dynamic Discrete Choice Statistical Models: Some Monte Carlo Results," *Journal of Econometrics*, 82, 1–35.
- MADDALA, G. (1983): *Limited Dependent and Qualitative Variables in Econometrics*. Cambridge University Press.
- MCCULLOCH, R. E., AND P. P. ROSSI (1994): "An exact likelihood analysis of the multinomial probit model," *Journal of Econometrics*, 64, 207–240.
- MINIACI, R., AND G. WEBER (2002): *Household Portfolios* Chapter Four: Econometric Issues in the Estimation of Household Portfolios. MIT Press.
- MULLIGAN, C. B., AND X. SALA-I-MARTIN (2000): "Extensive Margins and the Demand for Money at Low Interest Rates," *Journal of Political Economy*, 108(5), 961–991.
- PHELPS, E. (1972): *Inflation Policy and Unemployment Theory: The Cost Benefit Approach to Monetary Planning*. London: Macmillan.
- REYNARD, S. (2003): "Financial Market Participation, Wealth, and the Extensive Margins of Money Demand," mimeo.

- RUST, J. (1987): “Optimal Replacment of GMC Bus Engines: An Empirical Model of Harold Zurcher,” *Econometrica*, 55(5), 999–1033.
- STAVINS, J. (2001): “Effect of Consumer Characteristics on the Use of Payment Instruments,” *New England Economic Review*, 3, 19–31.
- URIBE, M. (1997): “Hysteresis in a Simple Model of Currency Substitution,” *Journal of Monetary Economics*, 40, 185–202.

A Appendix

A.1 Data

The dataset is the Italian *Survey of Household Income and Wealth* (SHIW) constructed by the Bank of Italy. The data is collected as part of the Bank of Italy Historical Database of the Survey of Italian Household Budgets from 1977-2000. The database contains information on:

- Individual characteristics and occupational status,
- Sources of household income,
- Consumption expenditures,
- Housing information,
- Household financial assets and liabilities.

These surveys were conducted on an annual basis from 1977 to 1984 then 1986. It was then conducted bi-annually from 1987 to 2000 (replacing 1997 with 1998). Since 1987 some of the households were re-interviewed in order to introduce a longitudinal aspect to the survey. The following table summarizes the composition of households in each of the survey:

	1987	1989	1991	1993	1995	1998	2000
1987	8,027	1,206	350	173	126	85	61
1989		7,068	1,837	877	701	459	343
1991			6,001	2,420	1,752	1,169	832
1993				4,619	1,066	583	399
1995					4,490	373	245
1998						4,478	1,993
2000							4,128
N	8,027	8,274	8,188	8,089	8,135	7,147	8,001

For example, of the 8,001 households that made up the sample in 2000 survey, 61 had participated since 1987, 343 since 1989, 832 since 1991, 399 since 1993, 245 since 1995 and 1,993 since 1998. The remaining 4,128 were being interviewed for the first time in 2000.

To accurately represent Italy, the survey employs a two-stage sampling method. In the first stage municipalities are sampled from the area of interest with probability proportional to its size. In the second stage households are drawn with a probability that is commensurate to its size. The survey is conducted with the head of the household and involves a computer assisted personal interview, commonly known as CAPI. Interested readers are directed to Brandolini and Cannari (1994) for more a discussion of sample design. External users are provided sample weights but no information on strata or cluster. Therefore, the following caveat is placed on any

statistics calculated using sample weights; the point estimates will be precise but the sample standard errors will be smaller than the standard errors that condition on the strata or cluster.

The questions regarding assets and liabilities is quite difficult to elicit for two reasons. First, respondents might not want to reveal their wealth. This problem is exacerbated at the extreme left and right tail of the wealth distribution. Second, respondents might not have an accurate measure of their wealth at the time of the interview. To take into account of this problem the interviewer first asks if the household is involved in any of the following categories - savings, bonds, mutual funds, equities, etc. After these questions are elicited the method of unfolding brackets is employed. Households are shown a set of range cards that have numerical values to which they are asked to choose the card that most appropriately fits them. In recent 1998 and 2000 survey the interviewer will attempt to ask for the exact amount. If the household does not respond they are asked if the exact amount closer to the upper or lower bound.

The interest data is drawn from the Bank of Italy public database available at:

<http://bip.bancaditalia.it/4972unix/homebipeng.htm>

The banking concentration data was drawn from a special survey from the Bank of Italy made available by Giorgio Calcagnini. More information on its characteristics is available in Hester, Calcagnini, and de Bonis (2001).

A.2 Definitions

Stock variables such as currency-related, deposits, financial wealth, and consumption are expressed in 2000 lire and then converted to euros. The price deflator (13699BVRZF) and lire/euro exchange rate (136..EA.ZF...) is taken from the IMF/IFS database.

- *Bank account*: The questionnaire asks the household “In the survey year did you or any other member of your household have a bank account?” This binary variable takes the value one if the respondent has an account. An account is defined as either a checking, savings, or post office account.
- *ATM card*: The questionnaire asks the household “Did you or any other member of your household have an ATM card?”
- *Currency*: The questionnaire asks the household “What sum of money do you usually have in the house to meet household needs?”
- *Minimum amount of currency*: The questionnaire asks the household “How much money do you usually have in the household when you decide to withdraw more?”
- *Number of withdrawals and average withdrawal at an ATM*: The questionnaire asks the household “On average, how many withdrawals were made per month during the survey year using an ATM card?” and “What was the average amount?”

- *Number of withdrawals and average withdrawal at the Bank/Post Office:* The questionnaire asks the household “On average, how many withdrawals were made per month at the bank or post office, exclude trips to the at the ATM?” and “What was the average amount?”
- *Consumption:* consists of non-durable consumption which is the total sum of expenditure on food, entertainment, education, clothes, medical expenses, renovations, and imputed rents.
- *Deposits:* Total deposits in checking accounts, savings accounts, and postal deposits.
- *Financial wealth:* Deposits + equities + bonds + mutual funds. Both deposits and and financial wealth are approximated since the questionnaire answer ask households to put themselves into 15 bands. The level is taken as the average of the upper and lower band.
- *Fraction of income received in currency or direct deposit:* The questionnaire asks the household “Putting the total value of amounts received during the year equal to 100, what percentage was received in the form of...?”
- *Education:* Households were asked what was the highest education they attained. They placed themselves into six categories:
 1. None,
 2. Elementary school,
 3. Junior high school,
 4. High school,
 5. Bachelor’s degree,
 6. Post-graduate experience.

In the survey the number of individuals with post-graduate experience is quite low and therefore is amalgamated with bachelor’s degree.

- *Place of Residence:* Households were asked where their dwelling is located. Households were given four categories to choose from:
 1. Rural Area,
 2. Suburbs,
 3. Semi-Center,
 4. Center.
- *Interest rates:* Since, there is no contiguous source that spans the time period 1991 to 2000; the interest data was constructed from two sources.

TABLE TDC20012
 NOMINAL DEPOSIT RATES - DISTRIBUTION BY BRANCH LOCATION (REGION) AND
 TYPE OF DEPOSIT

Sample: 1995Q1 to 2002Q3

VOCESOTVOC	PHENOMENA OBSERVED
035001039	SAVINGS CERTIFICATES AND CDS
035001037	SIGHT CURRENT ACCOUNT DEPOSITS
035001036	SIGHT SAVINGS DEPOSITS
035001040	TIME CURRENT ACCOUNTS
035001038	TIME DEPOSITS
035001041	TOTAL DEPOSITS

TABLE TDB20620
 NOMINAL DEPOSIT RATES ON SAVINGS DEPOSITS - DISTRIBUTION BY BRANCH
 LOCATION (REGION) AND SIZE OF DEPOSIT - SAMPLE OF BANKS RAISING
 SHORT-TERM FUNDS

Sample: 1989Q4 to 1997Q4

CLASSE_PARZ	SIZE OF PARTIAL DEPOSITS
25	1 BILLION LIRE AND MORE (516457 EUROS AND MORE)
23	FROM \geq 51646 TO $<$ 129114 EUROS
04	FROM \geq 129114 TO $<$ 258228 EUROS
22	FROM \geq 25823 TO $<$ 51646 EUROS
24	FROM \geq 258228 TO $<$ 516457 EUROS
21	LESS THAN 25823 EUROS
16	TOTAL

A series was constructed from these two samples in the following fashion:

$$R_{jt} = \begin{cases} OLD_{jt} & \text{if } t \in [1990Q1, 1994Q4], \\ \frac{1}{2}(OLD_{jt} + NEW_{jt}) & \text{if } t \in [1995Q1, 1997Q4], \\ NEW_{jt} & \text{if } t \in [1998Q4, 2002Q3], \end{cases}$$

where

$$OLD_{jt} \equiv TDB20620 : CLASSE_PARZ = 16,$$

$$NEW_{jt} \equiv TDC20012 : VOCESOTVOC = 035001038.$$

The series were chosen by minimizing a loss function based on the mean and variance of the spread. Subscript j refers to the region that the interest rate was drawn from. The following table summarizes the 20 regions in Italy; IREG and PVDIP are the SHIW and Bank of Italy region identifier and AREA5 is the identifier for the five major areas.

REGION	IREG	PVDIP	AREA5	PVDIP
PIEDMONT	1	10010	NW	20001
VALLE D' AOSTA	2	10012	NW	20001
LOMBARDY	3	10016	NW	20001
TRENTINO-ALTO ADIGE	4	10018	NE	20002
VENETO	5	10020	NE	20002
FRIULI-VENEZIA GIULIA	6	10022	NE	20002
LIGURIA	7	10014	NW	20001
EMILIA-ROMAGNA	8	10024	NE	20002
TOSCANA	9	10028	CENTRE	20003
UMBRIA	10	10030	CENTRE	20003
MARCHE	11	10026	CENTRE	20003
LAZIO	12	10032	CENTRE	20003
ABRUZZI	13	10036	SOUTH	20004
MOLISE	14	10038	SOUTH	20004
CAMPANIA	15	10034	SOUTH	20004
PUGLIA	16	10040	SOUTH	20004
BASILICATA	17	10042	SOUTH	20004
CALABRIA	18	10044	SOUTH	20004
SICILY	19	10046	ISLANDS	20005
SARDINIA	20	10048	ISLANDS	20005

- *Banking concentration:* The file contains the number of bank branches that a bank has in the province in a certain year. Two measures of banking concentration is calculated. First, Q is calculated by summing the total number of banks that are in a region (b):

$$Q_j = \sum_{i=1}^b Bank_{ij}, \quad j = 1 \dots 20.$$

Second, a Herfindahl-type index is created using the following formula:

$$\alpha_j = \sum_{i=1}^b \left(\frac{Bank_{ij}}{Q_j} \right)^2, \quad j = 1 \dots 20.$$

The intuition is straightforward for α_j the bigger the magnitude implies that the concentration of banks is dominated by a few firms.

Table 1: Participation Sequences

1991	1993	1995	1998	2000	check	checknoatm	atm
0	0	0	0	0	25	361	407
1	0	0	0	0	17	111	16
0	1	0	0	0	3	16	13
0	0	1	0	0	0	9	12
0	0	0	1	0	4	19	23
0	0	0	0	1	15	26	64
1	1	0	0	0	7	73	6
1	0	1	0	0	1	11	3
1	0	0	1	0	2	9	5
1	0	0	0	1	5	9	4
0	1	1	0	0	4	12	6
0	1	0	1	0	4	5	2
0	1	0	0	1	0	3	2
0	0	1	1	0	3	3	8
0	0	1	0	1	4	6	7
0	0	0	1	1	11	16	95
1	1	1	0	0	16	97	12
1	1	0	1	0	2	11	1
1	1	0	0	1	4	12	1
1	0	1	1	0	3	4	4
1	0	1	0	1	1	4	0
1	0	0	1	1	8	6	7
0	1	1	1	0	1	10	4
0	1	1	0	1	7	12	6
0	1	0	1	1	3	4	9
0	0	1	1	1	6	7	67
1	1	1	1	0	31	70	14
1	1	1	0	1	14	26	10
1	1	0	1	1	16	18	6
1	0	1	1	1	10	14	12
0	1	1	1	1	23	27	86
1	1	1	1	1	984	223	322

Note: Check - households who have an interest-bearing bank account, Checknoatm - households who have an interest-bearing bank account but no ATM card, ATM - households who have interest-bearing bank account and an ATM card.

Table 2: Conditional ATM Participation Sequences

1991	1993	1995	1998	2000	atm
0	0	0	0	0	223
1	0	0	0	0	14
0	1	0	0	0	10
0	0	1	0	0	11
0	0	0	1	0	16
0	0	0	0	1	53
1	1	0	0	0	4
1	0	1	0	0	3
1	0	0	1	0	3
1	0	0	0	1	4
0	1	1	0	0	3
0	1	0	1	0	2
0	1	0	0	1	2
0	0	1	1	0	8
0	0	1	0	1	6
0	0	0	1	1	81
1	1	1	0	0	9
1	1	0	1	0	1
1	1	0	0	1	0
1	0	1	1	0	3
1	0	1	0	1	0
1	0	0	1	1	7
0	1	1	1	0	3
0	1	1	0	1	6
0	1	0	1	1	8
0	0	1	1	1	61
1	1	1	1	0	10
1	1	1	0	1	10
1	1	0	1	1	6
1	0	1	1	1	12
0	1	1	1	1	83
1	1	1	1	1	322

Note: Households who have an ATM card conditional on having a checking account in 1991, 1993, 1995, 1998, and 2000.

Table 3: Currency, Wealth, and Financial Innovation - Balanced Panel

Variable	1991	1993	1995	1998	2000
Currency	581	407	425	394	383
<i>No ATM</i>	623	450	457	436	437
<i>ATM</i>	499	344	388	358	341
<i>No Bank Account</i>	716	417	415	383	427
<i>Bank Account</i>	567	406	426	395	378
<i>Bank Account and No ATM</i>	609	455	467	450	440
Deposits	9,030	9,183	9,294	7,692	7,824
<i>No ATM</i>	7,708	7,335	7,354	6,392	6,614
<i>ATM</i>	11,551	11,894	11,531	8,804	8,753
<i>No Bank Account</i>	712	425	278	234	1,438
<i>Bank Account</i>	9,867	10,082	10,318	8,516	8,655
<i>Bank Account and No ATM</i>	8,841	8,617	9,018	8,087	8,488
Financial Wealth	18,668	22,546	22,287	19,137	19,145
<i>No ATM</i>	13,987	15,560	15,849	12,596	11,227
<i>ATM</i>	27,600	32,795	29,712	24,743	25,217
<i>No Bank Account</i>	958	425	458	474	367
<i>Bank Account</i>	20,450	24,816	24,765	21,201	21,222
<i>Bank Account and No ATM</i>	16,096	18,368	19,467	15,931	14,461
Nondurable consumption	20,801	18,774	17,256	18,703	18,989
<i>No ATM</i>	18,482	16,065	14,100	14,224	14,170
<i>ATM</i>	25,226	22,747	20,895	22,536	22,691
<i>No Bank Account</i>	13,338	11,894	10,277	10,682	11,561
<i>Bank Account</i>	21,552	19,480	18,048	19,589	19,810
<i>Bank Account and No ATM</i>	19,315	16,839	14,999	15,199	14,945
Currency/consumption ratio	0.033	0.026	0.028	0.026	0.024
<i>No ATM</i>	0.039	0.032	0.035	0.034	0.033
<i>ATM</i>	0.023	0.017	0.021	0.018	0.017
<i>No Bank Account</i>	0.058	0.039	0.042	0.039	0.037
<i>Bank Account</i>	0.031	0.024	0.027	0.024	0.022
<i>Bank Account and No ATM</i>	0.036	0.030	0.033	0.033	0.032
Observations	1236	1236	1236	1236	1236

Table 4: Cash Management - Balanced Panel

Variable	1991	1993	1995	1998	2000
Fraction with a bank account	0.909	0.907	0.898	0.900	0.900
<i>No Education</i>	0.730	0.712	0.580	0.645	0.691
<i>Elementary</i>	0.848	0.843	0.820	0.824	0.824
<i>Junior High School</i>	0.930	0.934	0.932	0.930	0.913
<i>High School</i>	0.973	0.974	0.997	0.977	0.969
<i>College</i>	0.989	0.990	0.978	0.990	0.990
Fraction using ATMs	0.344	0.405	0.464	0.539	0.566
<i>No Education</i>	0.063	0.068	0.087	0.066	0.055
<i>Elementary</i>	0.175	0.194	0.258	0.303	0.297
<i>Junior High School</i>	0.335	0.447	0.500	0.591	0.611
<i>High School</i>	0.554	0.624	0.679	0.746	0.775
<i>College</i>	0.611	0.635	0.717	0.817	0.867
Average withdrawal at Bank	499	583	505	569	450
<i>Bank Account</i>	499	583	505	569	450
<i>Bank Account and No ATM</i>	503	623	503	559	479
Average withdrawal at ATM	262	226	203	236	220
Minimum Currency	135	142	108	147	158
<i>No ATM</i>	141	157	120	192	192
<i>ATM</i>	125	125	96	117	138
Total Number trips to bank (yearly basis)	16	16	12	16	16
Total Number of trips to ATM	37	40	41	48	57
Fraction of income received in currency	0.39	0.40	0.392	0.326	0.309
<i>No ATM</i>	0.53	0.55	0.588	0.535	0.519
<i>ATM</i>	0.19	0.20	0.166	0.147	0.148
<i>No Bank Account</i>	0.86	0.82	0.852	0.863	0.833
<i>Bank Account</i>	0.36	0.36	0.340	0.267	0.251
<i>Bank Account and No ATM</i>	0.47	0.49	0.526	0.445	0.426
Fraction of income received via direct deposit	0.39	0.42	0.46	0.54	0.60
<i>No ATM</i>	0.25	0.26	0.26	0.33	0.38
<i>ATM</i>	0.64	0.65	0.68	0.72	0.76
<i>Bank Account</i>	0.43	0.46	0.51	0.59	0.66
<i>Bank Account and No ATM</i>	0.30	0.31	0.33	0.41	0.49
Observations	1236	1236	1236	1236	1236

Table 5: Demographic Characteristics of Households

Variable	1991	1993	1995	1998	2000
No Education	0.05	0.06	0.06	0.06	0.04
Elementary	0.32	0.31	0.31	0.29	0.29
Middle School	0.31	0.31	0.30	0.29	0.30
High School	0.24	0.25	0.26	0.28	0.29
Bachelor	0.08	0.08	0.07	0.08	0.09
Rural Area	0.07	0.10	0.10	0.12	0.14
Suburbs	0.43	0.32	0.30	0.30	0.27
Semicenter	0.27	0.32	0.32	0.30	0.32
Center	0.24	0.27	0.28	0.28	0.27
Male Head	0.86	0.80	0.79	0.77	0.70
Age of Head of the Household	51	52	54	56	58
Income Earners per Household	1.75	1.81	1.87	1.89	1.85
Observations	1236	1236	1236	1236	1236

Table 6: Chamberlain's Test for TSD

$$P(w_{it} = 1) = \mathbf{1}\{x_{it}\beta + \phi(L)x_{it} + \alpha_i\}.$$

	Check	ATM
	(1)	(2)
llogc	.152 (.162)	.434 (.102)
llogr	-28.719 (7.265)	-17.275 (3.832)
llogfinw	.12 (.014)	.03 (.011)
leduc0	.139 (.719)	-.838 (.407)
leduc1	.182 (.673)	-.307 (.328)
leduc2	.324 (.649)	-.164 (.304)
leduc3	.564 (.606)	.294 (.275)
llive1	-.182 (.245)	-.043 (.159)
llive2	.079 (.173)	.121 (.112)
llive3	.226 (.161)	.115 (.1)
lmalehead	.068 (.234)	-.064 (.153)
llogQ	.769 (.452)	1.416 (.29)
leta	-.004 (.014)	.008 (.009)
cons	-11.098 (1.909)	-16.585 (1.477)
N*T	4936	4936
LogL	-580.124	-1983.731

Note: Standard errors in parentheses;

Check - households who have an interest-bearing bank account and ATM - households who have interest-bearing bank account and an ATM card. Only the lag of the exogenous variables are reported.

Table 7: State Dependence: Check

$$P(w_{it} = 1) = \mathbf{1}\{x_{it}\beta + \gamma w_{i,t-1} + \alpha_i + \epsilon_{it}\}$$

	HRE	XTRE	XTFE
	(1)	(2)	(3)
LAG	1.463 (.103)	1.402 (.096)	-.475 (.315)
logc	.62 (.1)	.613 (.1)	-.17 (.534)
logr	27.081 (7.58)	28.466 (7.574)	35.514 (27.112)
logfinw	.296 (.014)	.291 (.014)	.565 (.056)
educ0	-.805 (.327)	-.814 (.325)	-3.7 (2.157)
educ1	-.641 (.299)	-.648 (.297)	-1.747 (2.074)
educ2	-.445 (.298)	-.43 (.296)	-2.396 (2.065)
educ3	.035 (.311)	.052 (.309)	-1.563 (1.815)
live1	-.136 (.133)	-.148 (.133)	-.233 (.825)
live2	.05 (.108)	.03 (.109)	-.154 (.519)
live3	.279 (.115)	.285 (.116)	.554 (.422)
malehead	-.079 (.095)	-.057 (.095)	-.726 (.722)
logQ	.212 (.056)	.215 (.056)	-.545 (2.262)
cons	-10.677 (1.186)	-10.441 (1.187)	
N*T	4936	4936	740
LogL	-555.421	-550.87	-99.906

Note: Standard errors are in parentheses; Heckman (1981b) Random-Effects (HRE), Random-Effects Probits (XTRE), and Fixed-Effects Conditional Logit (XTFE).

Table 8: State Dependence: ATM

$$P(w_{it} = 1) = \mathbf{1}\{x_{it}\beta + \gamma w_{i,t-1} + \alpha_i + \epsilon_{it}\}$$

	HRE	XTRE	XTFE
	(1)	(2)	(3)
LAG	1.585 (.102)	1.89 (.052)	-.068 (.149)
logc	.852 (.086)	.645 (.062)	1.038 (.23)
logr	13.576 (4.601)	14.528 (4.286)	17.136 (12.364)
logfinw	.059 (.008)	.046 (.007)	.092 (.019)
educ0	-.823 (.232)	-.611 (.18)	.508 (1.094)
educ1	-.517 (.145)	-.409 (.108)	-.178 (.896)
educ2	-.174 (.129)	-.137 (.103)	-.142 (.851)
educ3	-.013 (.125)	-.039 (.103)	-.155 (.763)
live1	-.003 (.103)	-.025 (.087)	.101 (.373)
live2	.024 (.076)	.027 (.065)	-.386 (.261)
live3	.171 (.073)	.151 (.064)	.039 (.212)
malehead	-.019 (.074)	-.006 (.06)	.058 (.336)
logQ	.17 (.049)	.101 (.033)	.18 (.771)
cons	-11.316 (1.037)	-8.832 (.726)	
N*T	4936	4936	1612
LogL	-1871.261	-1702.557	-462.283

Note: Standard errors are in parentheses; Heckman (1981b) Random-Effects (HRE), Random-Effects Probits (XTRE), and Fixed-Effects Conditional Logit (XTFE).

Table 9: State Dependence: ATM conditional on Check

$$P(w_{it}^{atm} = 1 | w_{it}^{check} = 1) = \mathbf{1}\{x_{it}\beta + \gamma w_{i,t-1}^{atm} + \alpha_i + \epsilon_{it}\}$$

	HRE	XTRE	XTFE
	(1)	(2)	(3)
LAG	1.453 (.129)	1.894 (.055)	-.188 (.167)
logc	.779 (.097)	.542 (.069)	.977 (.263)
logr	9.618 (5.205)	11.11 (4.722)	11.806 (13.578)
logfinw	.033 (.01)	.022 (.008)	.058 (.022)
educ0	-.911 (.282)	-.615 (.206)	.491 (1.204)
educ1	-.521 (.167)	-.356 (.114)	-.149 (.995)
educ2	-.2 (.147)	-.126 (.107)	-.024 (.92)
educ3	-.017 (.142)	-.049 (.107)	.138 (.82)
live1	.025 (.122)	-.024 (.096)	.19 (.42)
live2	-.007 (.09)	-.003 (.071)	-.492 (.292)
live3	.117 (.084)	.099 (.07)	-.074 (.238)
malehead	.019 (.09)	.01 (.067)	.271 (.378)
logQ	.169 (.059)	.071 (.036)	.236 (.847)
cons	-9.885 (1.156)	-7.013 (.806)	
e(N)	3936	3936	1368
e(sigma-u)	.731	.0009	
e(ll)	-1606.015	-1449.555	-391.904

Note: Standard errors are in parentheses; Heckman (1981b) Random-Effects (HRE), Random-Effects Probits (XTRE), and Fixed-Effects Conditional Logit (XTFE).

Table 10: Honoré and Kyriazidou Estimator

$$Check : P(w_{it} = 1) = \mathbf{1}\{x_{it}\beta + \gamma w_{i,t-1} + \alpha_i + \epsilon_{it}\}$$

	HK7	HK6	HK5	HK4	HK3
logc	-0.533 (0.341)	-0.533 (0.345)	-0.524 (0.348)	-0.503 (0.352)	-0.478 (0.368)
logr	-6.408 (13.416)	-5.907 (13.586)	-5.229 (13.780)	-4.177 (14.070)	-2.424 (14.751)
logfinw	0.057 (0.042)	0.054 (0.043)	0.050 (0.044)	0.045 (0.044)	0.041 (0.046)
logQ	0.030 (0.198)	0.027 (0.203)	0.022 (0.209)	0.019 (0.216)	0.028 (0.230)
malehead	0.410 (0.403)	0.418 (0.411)	0.423 (0.418)	0.420 (0.424)	0.398 (0.439)
γ	0.963 (0.339)	0.939 (0.345)	0.919 (0.351)	0.902 (0.360)	0.891 (0.377)
bandwidth	4.210	3.609	3.007	2.406	1.804
N	1234	1234	1234	1234	1234
Final N	112	112	112	112	112
T	5	5	5	5	5

Table 11: Honoré and Kyriazidou Estimator

$$ATM : P(w_{it} = 1) = \mathbf{1}\{x_{it}\beta + \gamma w_{i,t-1} + \alpha_i + \epsilon_{it}\}$$

	HK7	HK6	HK5	HK4	HK3
logc	0.529 (0.443)	0.501 (0.453)	0.475 (0.462)	0.446 (0.468)	0.412 (0.472)
logr	26.791 (22.315)	28.167 (22.844)	29.055 (23.365)	29.063 (23.868)	27.611 (24.565)
logfinw	0.076 (0.035)	0.073 (0.035)	0.069 (0.036)	0.064 (0.037)	0.060 (0.037)
logQ	8.260 (3.479)	8.377 (3.560)	8.481 (3.644)	8.556 (3.731)	8.559 (3.854)
malehead	-0.003 (0.762)	-0.004 (0.787)	-0.001 (0.808)	0.013 (0.826)	0.051 (0.855)
γ	2.062 (0.235)	2.065 (0.241)	2.070 (0.247)	2.077 (0.250)	2.086 (0.253)
bandwidth	4.210	3.609	3.007	2.406	1.804
N	1234	1234	1234	1234	1234
Final N	300	300	300	300	300
T	5	5	5	5	5

Table 12: Honoré and Kyriazidou Estimator

$$CATM : P(w_{it}^{atm} = 1 | w_{it}^{check} = 1) = \mathbf{1}\{x_{it}\beta + \gamma w_{i,t-1}^{atm} + \alpha_i + \epsilon_{it}\}$$

	HK7	HK6	HK5	HK4	HK3
logc	0.801 (0.477)	0.783 (0.484)	0.764 (0.490)	0.742 (0.494)	0.714 (0.497)
logr	21.723 (23.837)	23.246 (24.233)	24.237 (24.595)	24.369 (24.979)	23.111 (25.671)
logfinw	0.041 (0.040)	0.040 (0.040)	0.037 (0.041)	0.034 (0.042)	0.029 (0.043)
logQ	6.966 (3.590)	7.059 (3.640)	7.132 (3.691)	7.165 (3.752)	7.109 (3.862)
malehead	-0.537 (0.667)	-0.541 (0.683)	-0.541 (0.696)	-0.532 (0.710)	-0.506 (0.732)
γ	2.039 (0.250)	2.038 (0.254)	2.039 (0.257)	2.043 (0.258)	2.050 (0.260)
bandwidth	4.279	3.667	3.056	2.445	1.834
N	984	984	984	984	984
Final N	257	257	257	257	257
T	5	5	5	5	5