Will that be Cash, Check, or Debit? The Decision to Use Alternative Payment Methods: State Dependence or Unobserved Heterogeneity?

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Abstract

This paper investigates the household decision to adopt alternative payment technologies (financial innovation); examples of financial innovation are interest-bearing checking accounts, credit cards, and ATM cards. The obvious advantage of these payments tools is that they allow households to economize on their money holdings while still providing liquidity services. Through technological progress, the use of paper and coin currency has become almost unnecessary. However, studies by Humphrey, Pulley, and Vesala (1996), Evans and Schmalensee (1999), and Stavins (2001) have shown that large segments of the population in Europe, North America, and Japan have yet to adopt financial innovation. This paper looks at these issues by using the Bank of Italy Survey of Household Income and Wealth and applying discrete-choice dynamic panel data techniques. Identifying the root cause of adoption (or lack of) is a non-trivial task. One of the major task is to distinguish between true state dependence and unobserved heterogeneity. Preliminary evidence indicates that state dependence plays a role in the adoption decision.

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

The introduction of financial innovation, such as interest-bearing bank accounts and debit cards, has resulted in a significant increase in personal efficiency, reducing the time and cost involved with money transactions. Another benefit it that it allows households to circumvent the inflation tax; by depositing money into a bank account which pays a nominal interest rate, households ensure that their 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. A cross-country study by Humphrey, Willesson, Bergendahl, and Lindblom (2003) estimate that the annual savings to shifting from paper-based to electronic-based system is about one percent of GDP. However, studies by Humphrey, Pulley, and Vesala (1996), Evans and Schmalensee (1999), and Stavins (2001) have shown that large segments of the population in Europe, North America, and Japan have yet to adopt financial innovation. With the myriad of benefits associated with financial innovation, why is it that some households are hesitant to adopt it?

Theoretical models of financial innovation such as Ireland (1995), Lacker and Schreft (1996), and Uribe (1997) predict that episodes of high inflation will cause the rate of financial innovation to increase. 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, the *extensive margin*; then conditional on this adoption decision the household decides how much to allocate to each payment method, the *intensive margin*.

Modelling both the extensive and intensive margins has yielded many interesting insights into monetary economics. As Mulligan and Sala-i-Martin (2000) note that 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 provides only a snapshot of the role of fixed costs.

Attanasio, Guiso, and Jappelli (2002) add a temporal component by studying 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) they estimate 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:

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

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 ratios 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 to avoid the inflation tax. Although technological progress has greatly simplified the knowledge required to adopt financial innovation, the cost of learning for some households may still be non-trivial.

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. Attanasio, Guiso, and Jappelli (2002) find that the fixed cost of adopting an ATM card are quite low, ranging from 14.3 to 28.1 euros (in 2000 figures). They also calculate the direct financial adoption cost from a sample of representative Italian banks and found it to be about 6.2 euros. As a rough measure the time and psychic fixed cost that households must incur is the difference between the estimated fixed cost and actual financial adoption cost (8.1 to 21.9 euros).

Why do such low financial adoption costs result in such low adoption rates of financial innovation? An explanation of this phenomenon focuses on the heterogeneity between the households. Up to now the studies involving household financial innovation use only cross-sectional methods; there has been 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. The static specification is unsatisfying since it ignores the dynamic nature of the decision to adopt financial innovation. Table 10 and 11 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.

In alternative fields longitudinal or panel data has proven to be quite fruitful in 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 refute the findings of cross-sectional studies. One of the significant contributions of this paper is to utilize discrete-choice dynamic panel data methods in the study of financial innovation. The SHIW has a panel component but Attanasio, Guiso, and Jappelli (2002) ignore this feature of the data and treat 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, and the presence of a male head of household. These finding beg the question, why do poorer households in Italy have low adoption rates of financial innovation?

Answering this question has many policy implications. A calibration study by Erosa and Ventura (2002) demonstrates inflation is a regressive tax when households do not participate on the extensive margin. The results are particularly interesting since inflation in Italy was quite high (six to eight percent) in the beginning of the 1990's. Using Italian data would be an ideal test to see if the inflation tax is important empirically. 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. For example, the British government regularly advertises on Virgin Radio, a popular mainstream radio station, to espouse the convenience of receiving monthly assistance payments electronically.

An alternative explanation for 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 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 over 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. The data used in this study, taken from the Bank of Italy Survey of Household Income and Wealth, is described in Section

3. Section 4, the decision to adopt financial innovation is empirically implemented. 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. Finally, Section 6 concludes with some remarks and ideas on future work.

2 Dynamic Discrete Choice Panel Data Models

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

$$(2) \quad \begin{aligned} w_{it}^* &= \underbrace{x_{it}\beta}_{\text{observables}} + \underbrace{\gamma w_{i,t-1}}_{\text{state dependence}} + \underbrace{\alpha_i}_{\text{unobserved heterogeneity}} + \underbrace{u_{it}}_{\text{error term}}, \quad i = 1 \ldots N, t = 1 \ldots T, \\ w_{it} &= \begin{cases} 1 & \text{if } w_{it}^* > 0, \\ 0 & \text{if } w_{it}^* \leq 0, \end{cases} \\ \text{and } v_{it} &= \alpha_i + u_{it}. \end{aligned}$$

Here 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, observations are of a repeated 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 estimates 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 it is 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. The issue of the *incidental parameter* is particularly problematic in large N and short T panels. Also, these dynamic discrete choice models are nonlinear, which complicates estimation. 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. The fixed effects estimator is usually preferred to handle the initial conditions while the random effects is better for the incidental parameters problem. 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 of these estimators will be provided.

2.1 The Parametric Likelihood and the Random Effects Estimator

The *random effects* estimator is often referred to as a 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 involves a first-order Markov process with no exogenous variables:

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

- *Exogenous initial conditions:*
  For this case the joint probability of w_{it} for a given α_i is:

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

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

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

- *Equilibrium process:*
  For this case the the limiting marginal probabilities are:

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

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

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

  The likelihood function for the random effects is:

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

With the random-effects the maximum likelihood estimates (MLE) of β_0, γ, and σ_α^2 are consistent if either $N \to \infty$ or both N and $T \to \infty$. The weakness of the likelihood approach is that if the parametric assumptions are rejected, the estimates will be inconsistent. To avoid inconsistent estimators when these 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 relationship between w_{i0} and α_i must be considered. Let $f(w_{i0}|\alpha)$ be the marginal probability of w_{i0} given α_i. For the random-effects model the likelihood is:

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

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

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

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, as shown by Lee (1997). Alternatively, Bayesian techniques can be used to obtain an *exact* estimators using Markov-Chain Monte-Carlo methods, McCulloch and Rossi (1994) provide an example of this approach.

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 $t = 1 \ldots T$.

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.

The random-effects/parametric likelihood with either estimation method 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.

2.2 The Conditional Logit or Fixed-Effects Estimator

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 $(y_{i0} \ldots y_{iT})$ is of the form:

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

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

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:

$$\text{(12)}\quad P(A) = P_0(\alpha_i)^{w_{i0}}[1 - P_0(\alpha_i)]^{1-w_{i0}} \frac{1}{1 + \exp(\gamma w_{i,0} + \alpha_i)} \frac{\exp(\alpha_i)}{1 + \exp(\alpha_i)} \frac{\exp[(\gamma + \alpha_i)w_{i3}]}{1 + \exp(\gamma + \alpha_i)},$$
$$\text{(13)}\quad P(B) = P_0(\alpha_i)^{w_{i0}}[1 - P_0(\alpha_i)]^{1-w_{i0}} \frac{\exp(\gamma w_{i,0} + \alpha_i)}{1 + \exp(\gamma w_{i,0} + \alpha_i)} \frac{1}{1 + \exp(\alpha_i)} \frac{\exp(\alpha_i w_{i3})}{1 + \exp(\alpha_i)}.$$

The conditional probabilities are then:

$$\begin{aligned}
\text{(14)}\qquad P(A|A \cup B) &= P(A|w_{i0}, w_{i1} + w_{i2} = 1, w_{i3}) \\
&= \frac{\exp(\gamma w_{i3})}{\exp(\gamma w_{i3}) + \exp(\gamma w_{i0})} \\
&= \frac{1}{1 + \exp[\gamma(w_{i0} - w_{i3})]} \\
\text{(15)}\qquad P(B|A \cup B) &= P(B|w_{i0}, w_{i1} + w_{i2} = 1, w_{i3}) \\
&= 1 - P(A|A \cup B) \\
&= \frac{\exp[\gamma(w_{i0} - w_{i3})]}{1 + \exp[\gamma(w_{i0} - w_{i3})]}
\end{aligned}$$

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

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

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:

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

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

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

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 the case, $T > 3$, please refer to Honoré and Kyriazidou (2000).

One of the major advantages of the conditional approach is that the initial conditions do 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 effects 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

The estimators discussed allow the extent of state dependence and unobserved heterogeneity to be quantified. 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:

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

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

This test can be implemented by estimating the following relationship:

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

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

3 Italian Household Characteristics

The dataset used in this study is the Italian *Survey of Household Income and Wealth* (SHIW), constructed by the Bank of Italy, as part of the Bank of Italy Historical Database of the Survey of Italian Household Budgets from 1977-2000. The SHIW has undergone large changes during this period. For example, starting with the 1987 survey the Bank of Italy started to collect information regarding household wealth. This paper utilizes the surveys from 1991, 1993, 1995, 1998, and 2000. The 1987 and 1989 waves are not included since the panel component of these surveys is quite small. The panel component for 1991-2000 contains 1236 households. Another drawback for using the early surveys is that the questions regarding financial innovation in the 1987 and 1989 are quite poor i.e. ATM information was not collected until 1991.

The interest rate and ATM/banking concentration data is taken from the Bank of Italy Monetary Statistics survey. Currently the dataset only contains information for the 20 administrative regions as opposed to the study by Attanasio, Guiso, and Jappelli (2002) which has the data for the 95 provinces. The Bank of Italy does not allow external users to access provincial data. For a more detailed discussion of the data please refer to the appendix A.

3.1 Currency and Financial Innovation

The SHIW consists of multiple cross-sections with a panel component. The panel component of the SHIW suffers from severe attrition. A study by Ugo, Giraldo, and Rettore (2002) studies the effects of attrition on the results of discrete-choice dynamic panel data estimators. They find that even though attrition is severe the estimation techniques are not adversely affected. This paper will not consider these issues. As a check the descriptive statistics from the multiple cross-sections and panel component are both reported. It is acknowledged that the households that are in the panel component are more wealthier, better educated, and more likely to adopt financial innovation.

3.1.1 Multiple Cross-sections

Table 1 reports the usage pattern of financial technology; the raw and unweighted frequencies are reported. The fraction of households that have a bank account (includes savings and postal accounts) has been constant at about 85 percent. ATM usage has grown by almost 78 percent in the nine years. The growth in ATM usage has mainly come from households who already have a bank account. In 1991, only one-third of households with bank accounts used an ATM. By 2000, the adoption rates increased with about 61 percent of households with bank accounts using an ATM.

Table 2 and 3 reports weighted sample means of household wealth and cash management. There was a dramatic decrease, about 52 percent, in the amount of currency held by households after 1991. Changes in nondurable consumption cannot explain this trend as it fluctuates during the period sample. There is a negative correlation between deposits (includes bank and post office deposits, CDs, and repos) and financial wealth (deposits plus government securities and equities) with currency held. One possible reason for the decrease in money-holdings is due to the increase in the number of trips to the ATM. The number of trips to the bank has remained constant but trips to the ATM has increased by 46 percent from 1991 to 2000. The increase in the usage of financial technology cannot account the fall in money-holdings for households that did not have a bank account. For these households the decrease is tied with dramatic decrease in their already low levels of financial wealth. Another indication of this asymmetric effect is reflected in how households received their income. For households that adopted financial innovation the share of income received in currency fell while direct deposits increased. The non-participating households share of income received in cash remained constant.

3.1.2 Balanced Panel Sample

The balanced panel component, hereafter BP, comprises about 15 percent of the actual sample. The advantage of using the panel is that the household behaviour can be tracked through the five surveys and the issue of entry and exit of households into the various payment methods can be investigated. Table 4 is constructed in order to give an indication how representative the BP is compared to the full sample.

Table 5 and 6 summarizes the currency and financial innovation statistics. It seems that the proportion of households using checks is much higher, 90 percent, in the BP. The rate of ATM adoption and usage of direct deposit is much higher in all periods although the spread between the two groups narrows in later surveys. The balanced panel households appear to hold more money relative to the population. These households also seem to have relatively stable consumption and wealth profile.

Using the BP the transition probabilities (the change in a single categorical variable over time) for the probability of having a bank account and/or ATM. Table 7 and 8 indicates that once a household has undergone financial innovation the probability of abandoning this technology is quite small. Table 9 allows for the state where a household has a bank account and no ATM card. The stylized fact that one can glean from this table is that households transitions are in step-wise fashion. Households first decide to adopt bank account and then get an ATM card instead of doing everything at one time. The exit probabilities are quite small and maybe statistically insignificant but they also has the same pattern.

3.2 Interest Rates: Time and Regional Variation

A unique dataset that the Bank of Italy constructs is the deposit interest rates in different areas of Italy. The AGJ dataset contained the dataset on a provincial level however this study will only use regional data. The difference is that instead of 95 different rates at certain point in time only 20 are observable. The behaviour of nominal interest rates has been dramatic, see Figure 1. In the early part of the 1990's they rose and then fell to historic lows by 2000. A major reason for this decrease is the entrance of Italy into the European Monetary Union and the Maastricht Treaty.

Another interesting feature is the regional variation in nominal deposit interest rates. Figure 2 demonstrates this variation with kernel density graphs. One of the major reasons for these differences is that Italy is a decentralized country owing to its history. These variations are systemic in the Italian banking sector. The study by Hester, Calcagnini, and de Bonis (2001) gives a broader perspective on the market structure of the Italian banking system. For all intents and purposes this paper takes these differences as given.

4 Empirical Specification and Estimation

The previous sections have discussed the econometric issues involved with estimating dynamic discrete choice models and describes the data that will be used in this study. This section casts the model of financial innovation into an econometric framework, using the choices of Italian households in the SHIW.

4.1 Determinants of Financial Innovation

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. Previous household choices (w_{t-1})
5. 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. Two forms of financial innovation will be considered: one, the decision to adopt a bank account and second is the decision to adopt an ATM card. A feature of this decision process is that the necessary condition to adopt an ATM is to also have a bank account. This stepwise decision is not directly modelled rather they are treated as separate decisions. To avoid any problems the decision to adopt an ATM card will be conditioned on households who have always had a bank account. This issue is discussed in more detail when the results are presented.

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 was 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.

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 fewer 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 in the HK estimator, as discussed earlier.

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 10; 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 11. This table indicates that out of possible 984 households 322 adopted an ATM card and retained possession of it throughout the sample period. 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 12 and point to evidence 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 Tables 13, 14, and 15. 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 estimator 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

Dynamic discrete choice models indicate 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. The presence of true state dependence implies that fixed costs prevent households from adopting financial innovation. This result indicates that there maybe a role for financial institutions and governments to encourage households to adopt financial innovation.

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 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 look at this problem using numerical dynamic optimization models. Examples of this approach are Rust (1987), Hotz and Miller (1993), Aguirregabiria and Mira (2002), and Ching, Imai, and Jain (2003). The advantage of using these class models is that: first, they model households decisions as forward-looking behaviour. Second, since the decision rules are based on optimization model the Lucas Critique can be circumvented. As a result the solved decision rules can be used for policy analysis and counterfactual exercises. For interested readers, a brief model is provided in the appendix B.

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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:

Bank of Italy: Survey of Household Income and Wealth
Household Participation in 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 houshold 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 houshold 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 questionaire 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.

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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 >= 51646 TO < 129114 EUROS
   04         FROM >= 129114 TO < 258228 EUROS
   22         FROM >= 25823 TO < 51646 EUROS
   24         FROM >= 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

$$\begin{aligned} OLD_{jt} &\equiv TDB20620 : CLASSE\_PARZ = 16, \\ NEW_{jt} &\equiv TDC20012 : VOCESOTVOC = 035001038. \end{aligned}$$

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.

B A Model of Financial Innovation

In this model 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 costs. 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.

B.1 Dynamic Optimization Problem

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

$$\max U_t = \sum_{t=0}^{\infty} \delta^t \mathrm{E}_t u(c_t), \tag{B.1}$$

subject to the following budget constraint:

$$\begin{aligned} a_{t+1} &= \phi_t a_t + h_t(1-\phi_t)(1+r_t)a_t + y_t - c_t - s(\phi_t a_t, c_t) \\ &- (\pi_t \phi_{t-1} a_t)(1-h_{t-1}) - \max[(h_t - h_{t-1})\kappa, 0]. \end{aligned} \tag{B.2}$$

Where c_t is consumption, δ is the discount rate, and h_t is the binary choice variable which takes value one if the household has adopted financial innovation and otherwise is equal to zero. The assets that the 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 the 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:

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

B.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:

$$V(h_{t-1}, \phi_{t-1}, a_t, Z_t) = \max[V^0(h_{t-1}, \phi_{t-1}, a_t, Z_t), V^1(h_{t-1}, \phi_{t-1}, a_t, Z_t)], \tag{B.3}$$

where superscript 0 and 1 denote the period t no-adopt and adopt states. To gain some insight into the problem 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.

B.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:

$$V(0, 1, a_t, Z_t) = \max[V^0(0, 1, a_t, Z_t), V^1(0, 1, a_t, Z_t)]. \tag{B.4}$$

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

$$\underbrace{u[a_t + y_t - a_{t+1} - s(a_t, c_t) - \pi_t a_t, 0, Z_t] + \delta \mathrm{E}_t V(0, 1, a_t, Z_{t+1})}_{\text{did not adopt financial innovation}} < \tag{B.5}$$
$$\underbrace{u[\phi_t a_t + (1-\phi_t)(1+r_t)a_t + y_t - a_{t+1} - s(\phi_t a_t, c_t) - \pi_t a_t - \kappa, 1, Z_t] + \delta \mathrm{E}_t V(1, 1, a_t, Z_{t+1})}_{\text{did adopt financial innovation}}.$$

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

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

Inverting these monotonic utility functions then approximating the difference yields:

$$r_t a_t(1-\phi_t) + s(\phi_t a_t, c_t) - s(a_t, c_t) - k > \varphi\{(\delta \mathrm{E}_t[V(0, 1, a_t, Z_{t+1}) - V(1, 1, a_t, Z_{t+1})]\}^{-1}, \tag{B.6}$$

or

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

B.2.2 Households who did adopt financial innovation

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

$$V(1, \phi_{t-1}, a_t, Z_t) = \max[V^0(1, \phi_{t-1}, a_t, Z_t), V^1(1, \phi_{t-1}, a_t, Z_t)]. \tag{B.7}$$

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:

$$\text{(B.8)} \quad \underbrace{u[a_t + y_t - a_{t+1} - s(a_t, c_t), 0, Z_t] + \delta \mathrm{E}_t V(0, \phi_{t-1}, a_t, Z_{t+1})}_{\text{Un-adopt financial innovation}} <$$
$$\underbrace{u[\phi_t a_t + (1 - \phi_t)(1 + r_t)a_t + y_t - a_{t+1} - s(\phi_t a_t, c_t), 1, Z_t] + \delta \mathrm{E}_t V(1, \phi_{t-1}, a_t, Z_{t+1})}_{\text{Retain financial innovation}}.$$

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

$$\text{(B.9)} \quad \underbrace{r_t a_t(1 - \phi_t) + s(\phi_t a_t, c_t) - s(a_t, c_t)}_{\text{Benefit of Retaining financial innovation}} >$$
$$\underbrace{\varphi\{\delta \mathrm{E}_t[V(0, \phi_{t-1}, a_t, Z_{t+1}) - V(1, \phi_{t-1}, a_t, Z_{t+1})]\}^{-1}}_{\text{Difference in expected utility}}.$$

C Figures and Tables

All figures and tables are provided in the following pages.

Figure 1: Interpolated Regional Interest Rates

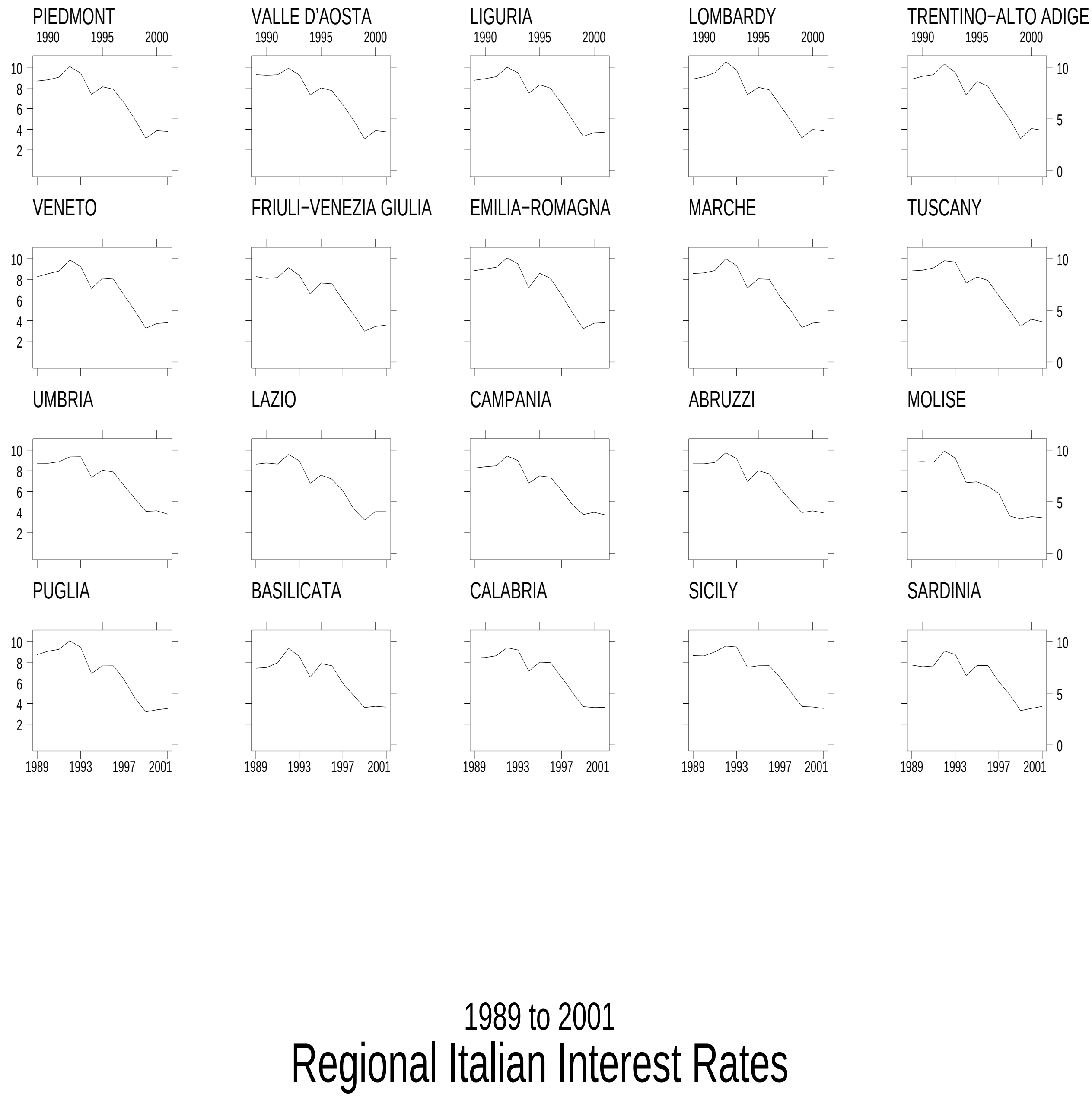

Figure 2: Kernel Densities of Regional Interest Rates

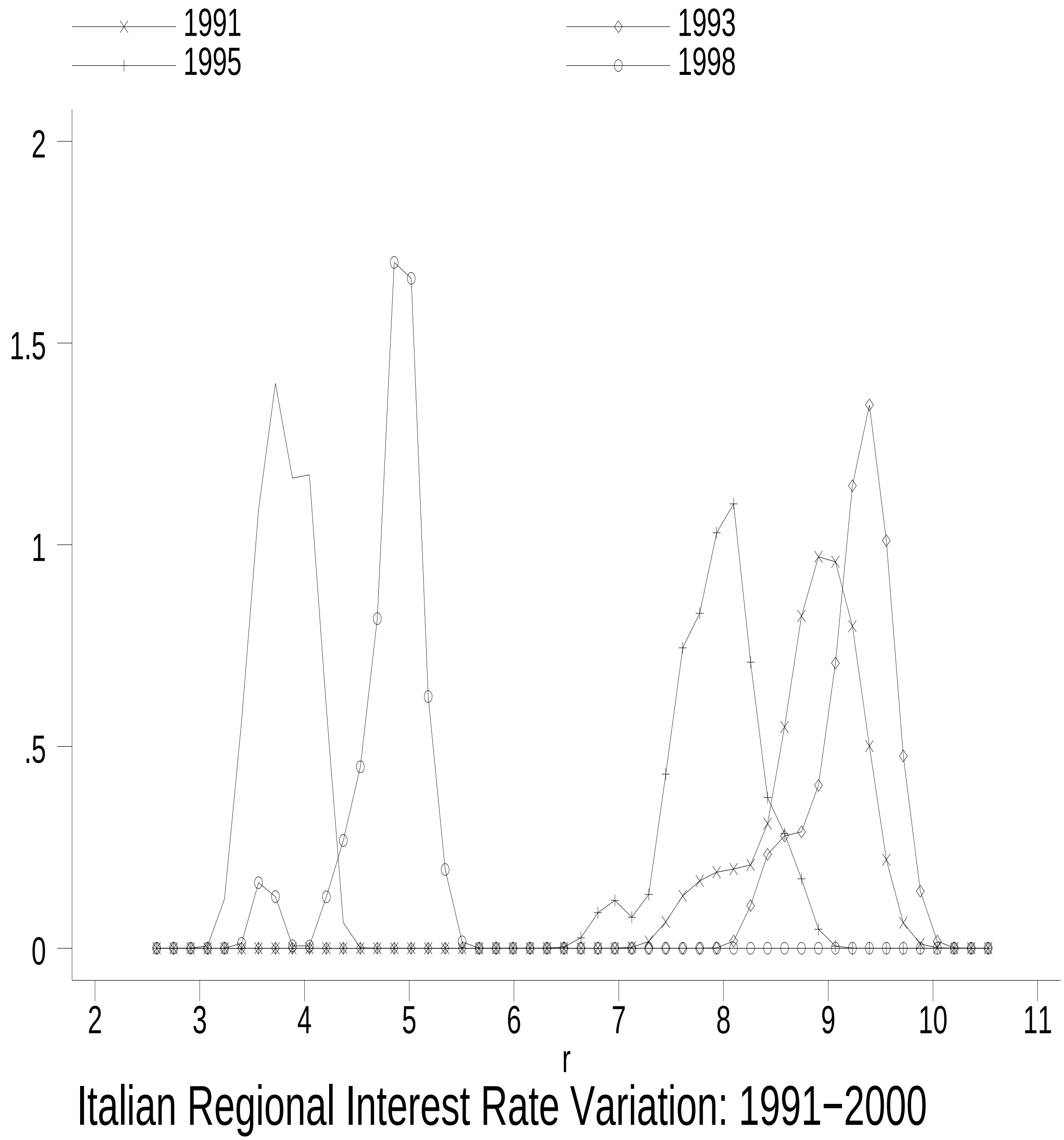

Table 1: Payment Instrument Usage

Raw Frequencies

1991

CHECK	ATM NO	ATM YES	Total
NO	1209	0	1209
YES	4643	2336	6979
Total	5852	2336	8188

1993

CHECK	ATM NO	ATM YES	Total
NO	1226	0	1226
YES	4109	2754	6863
Total	5335	2754	8089

1995

CHECK	ATM NO	ATM YES	Total
NO	1273	0	1273
YES	3573	3289	6862
Total	4846	3289	8135

1998

CHECK	ATM NO	ATM YES	Total
NO	1010	0	1010
YES	2494	3643	6137
Total	3504	3643	7147

2000

CHECK	ATM NO	ATM YES	Total
NO	1238	0	1238
YES	2542	4221	6763
Total	3780	4221	8001

Weighted Frequencies

1991

CHECK	ATM NO	ATM YES	Total
NO	0.135	0.000	0.135
YES	0.572	0.293	0.865
Total	0.707	0.293	1.000

1993

CHECK	ATM NO	ATM YES	Total
NO	0.149	0.000	0.149
YES	0.507	0.344	0.851
Total	0.656	0.344	1.000

1995

CHECK	ATM NO	ATM YES	Total
NO	0.151	0.000	0.151
YES	0.450	0.400	0.849
Total	0.600	0.400	1.000

1998

CHECK	ATM NO	ATM YES	Total
NO	0.144	0.000	0.144
YES	0.371	0.485	0.856
Total	0.515	0.485	1.000

2000

CHECK	ATM NO	ATM YES	Total
NO	0.154	0.000	0.154
YES	0.325	0.521	0.846
Total	0.479	0.521	1.000

Note: Weighted Frequencies are calculated using sample weights.

Table 2: Currency, Wealth, and Financial Innovation

Variable	**1991**	**1993**	**1995**	**1998**	**2000**
Fraction with a bank account	0.865	0.851	0.849	0.856	0.846
Fraction using ATMs	0.293	0.344	0.400	0.485	0.521
Deposits	8,786	8,001	7,513	9,888	12,810
No ATM	7,597	6,683	5,838	7,883	9,868
ATM	11,654	10,512	10,028	12,021	15,517
No Bank Account	478	146	130	199	301
Bank Account	10,083	9,375	8,823	11,520	15,088
Bank Account and No ATM	9,278	8,604	7,752	10,866	14,401
Financial Wealth	16,817	18,379	16,900	21,021	27,292
No ATM	11,994	12,597	11,361	12,945	14,170
ATM	28,449	29,401	25,220	29,607	39,363
No Bank Account	602	158	287	311	782
Bank Account	19,349	21,568	19,850	24,508	32,119
Bank Account and No ATM	14,686	16,252	15,076	17,851	20,513
Nondurable consumption	19,553	17,405	15,568	16,702	17,294
No ATM	17,133	14,746	12,752	12,993	12,782
ATM	25,391	22,474	19,797	20,644	21,445
No Bank Account	12,059	10,189	9,165	10,015	10,094
Bank Account	20,724	18,669	16,705	17,828	18,605
Bank Account and No ATM	18,332	16,086	13,955	14,150	14,056
Currency/consumption ratio	0.035	0.025	0.028	0.027	0.025
No ATM	0.040	0.029	0.034	0.034	0.035
ATM	0.023	0.017	0.019	0.019	0.017
No Bank Account	0.054	0.036	0.041	0.038	0.041
Bank Account	0.032	0.023	0.025	0.025	0.023
Bank Account and No ATM	0.037	0.028	0.031	0.033	0.032
Observations	8188	8089	8135	7147	8001

Note: Summary statistics are calculated using sample weights.

Table 3: Cash Management

Variable	**1991**	**1993**	**1995**	**1998**	**2000**
Currency	563	370	373	368	356
No ATM	583	384	396	388	396
ATM	513	344	339	346	318
No Bank Account	590	335	371	357	376
Bank Account	559	377	374	369	352
Bank Account and No ATM	582	399	405	401	406
Average withdrawal at Bank	495	612	465	493	463
No ATM	486	616	459	487	480
ATM	520	606	473	498	450
Bank Account and No ATM	486	616	459	487	480
Average withdrawal at ATM	263	227	197	219	220
Minimum Currency	135	132	91	126	130
No ATM	133	137	94	149	146
ATM	139	124	86	109	120
Total Number trips to bank (yearly basis)	17	15	12	15	16
To Bank No ATM	18	15	13	19	18
To Bank with ATM	15	15	11	11	14
Total Number of trips to ATM	35	40	39	46	52
Fraction of income received in currency	0.463	0.456	0.448	0.360	0.380
No ATM	0.576	0.602	0.623	0.549	0.599
ATM	0.190	0.178	0.186	0.160	0.179
No Bank Account	0.864	0.884	0.909	0.799	0.868
Bank Account	0.400	0.381	0.367	0.286	0.292
Bank Account and No ATM	0.508	0.519	0.528	0.452	0.472
Fraction of income received via direct deposit	0.334	0.368	0.393	0.473	0.505
No ATM	0.227	0.225	0.223	0.269	0.285
ATM	0.593	0.639	0.649	0.689	0.707
No Bank Account	0.000	0.000	0.000	0.005	0.024
Bank Account	0.386	0.432	0.463	0.552	0.592
Bank Account and No ATM	0.281	0.291	0.298	0.372	0.408
Observations	8188	8089	8135	7147	8001

Note: Summary statistics are calculated using sample weights.

Table 4: Demographic Characteristics of Survey versus Balanced Panel

Variable	**1991**		**1993**		**1995**		**1998**		**2000**	
No Education	0.08	0.05	0.10	0.06	0.10	0.06	0.07	0.06	0.07	0.04
Elementary	0.35	0.32	0.34	0.31	0.33	0.31	0.27	0.29	0.29	0.29
Middle School	0.27	0.31	0.28	0.31	0.27	0.30	0.27	0.29	0.26	0.30
High School	0.22	0.24	0.22	0.25	0.24	0.26	0.30	0.28	0.28	0.29
Bachelor	0.08	0.08	0.07	0.08	0.07	0.07	0.09	0.08	0.09	0.09
Rural Area	0.07	0.07	0.10	0.10	0.11	0.10	0.13	0.12	0.14	0.14
Suburbs	0.41	0.43	0.34	0.32	0.30	0.30	0.30	0.30	0.30	0.27
Semicenter	0.29	0.27	0.31	0.32	0.32	0.32	0.31	0.30	0.33	0.32
Center	0.23	0.24	0.25	0.27	0.27	0.28	0.26	0.28	0.23	0.27
Male Head	0.81	0.86	0.74	0.80	0.74	0.79	0.76	0.77	0.67	0.70
Age	53	51	54	52	54	54	54	56	55	58
Income Earners	1.69	1.75	1.77	1.81	1.80	1.87	1.78	1.89	1.73	1.85
Observations	8188	1236	8089	1236	8135	1236	7147	1236	8001	1236

Note: Cross-section sample statistics are calculated using sample weights.

Table 5: Currency, Wealth, and Financial Innovation - Balanced Panel

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

Table 6: 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
No Education	0.730	0.712	0.580	0.645	0.691
Elementary	0.848	0.843	0.820	0.824	0.824
Junior High School	0.930	0.934	0.932	0.930	0.913
High School	0.973	0.974	0.997	0.977	0.969
College	0.989	0.990	0.978	0.990	0.990
Fraction using ATMs	0.344	0.405	0.464	0.539	0.566
No Education	0.063	0.068	0.087	0.066	0.055
Elementary	0.175	0.194	0.258	0.303	0.297
Junior High School	0.335	0.447	0.500	0.591	0.611
High School	0.554	0.624	0.679	0.746	0.775
College	0.611	0.635	0.717	0.817	0.867
Average withdrawal at Bank	499	583	505	569	450
Bank Account	499	583	505	569	450
Bank Account and No ATM	503	623	503	559	479
Average withdrawal at ATM	262	226	203	236	220
Minimum Currency	135	142	108	147	158
No ATM	141	157	120	192	192
ATM	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
No ATM	0.53	0.55	0.588	0.535	0.519
ATM	0.19	0.20	0.166	0.147	0.148
No Bank Account	0.86	0.82	0.852	0.863	0.833
Bank Account	0.36	0.36	0.340	0.267	0.251
Bank Account and No ATM	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
No ATM	0.25	0.26	0.26	0.33	0.38
ATM	0.64	0.65	0.68	0.72	0.76
Bank Account	0.43	0.46	0.51	0.59	0.66
Bank Account and No ATM	0.30	0.31	0.33	0.41	0.49
Observations	1236	1236	1236	1236	1236

Table 7: Transition Probabilities

	No ATM	ATM	Total
No ATM	0.83	0.17	1
ATM	0.10	0.90	1
Total	0.51	0.49	1

Table 8: Transition Probabilities

	No Check	Check	Total
No Check	0.64	0.36	1
Check	0.04	0.96	1
Total	0.10	0.90	1

Table 9: Transition Probabilities

	No Check	Check and No ATM	ATM	Total
No Check	0.64	0.30	0.06	1
Check and No ATM	0.07	0.73	0.20	1
ATM	0.01	0.09	0.90	1
Total	0.10	0.41	0.49	1

Table 10: 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 11: 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 12: 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	.434
	(.162)	(.102)
llogr	-28.719	-17.275
	(7.265)	(3.832)
llogfinw	.12	.03
	(.014)	(.011)
leduc0	.139	-.838
	(.719)	(.407)
leduc1	.182	-.307
	(.673)	(.328)
leduc2	.324	-.164
	(.649)	(.304)
leduc3	.564	.294
	(.606)	(.275)
llive1	-.182	-.043
	(.245)	(.159)
llive2	.079	.121
	(.173)	(.112)
llive3	.226	.115
	(.161)	(.1)
lmalehead	.068	-.064
	(.234)	(.153)
llogQ	.769	1.416
	(.452)	(.29)
leta	-.004	.008
	(.014)	(.009)
cons	-11.098	-16.585
	(1.909)	(1.477)
N*T	4936	4936
LogL	-580.124	-1983.731

Note: Standard errors in parentheses; Only the lag of the exogenous variables are reported.

Check: households who have an interest-bearing bank account

ATM: households who have interest-bearing bank account and an ATM card.

Table 13: 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	1.402	-.475
	(.103)	(.096)	(.315)
logc	.62	.613	-.17
	(.1)	(.1)	(.534)
logr	27.081	28.466	35.514
	(7.58)	(7.574)	(27.112)
logfinw	.296	.291	.565
	(.014)	(.014)	(.056)
educ0	-.805	-.814	-3.7
	(.327)	(.325)	(2.157)
educ1	-.641	-.648	-1.747
	(.299)	(.297)	(2.074)
educ2	-.445	-.43	-2.396
	(.298)	(.296)	(2.065)
educ3	.035	.052	-1.563
	(.311)	(.309)	(1.815)
live1	-.136	-.148	-.233
	(.133)	(.133)	(.825)
live2	.05	.03	-.154
	(.108)	(.109)	(.519)
live3	.279	.285	.554
	(.115)	(.116)	(.422)
malehead	-.079	-.057	-.726
	(.095)	(.095)	(.722)
logQ	.212	.215	-.545
	(.056)	(.056)	(2.262)
cons	-10.677	-10.441	.
	(1.186)	(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); Quadratic time trend and Age of head of the household variables are significant but are unreported.

Table 14: 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	1.89	-.068
	(.102)	(.052)	(.149)
logc	.852	.645	1.038
	(.086)	(.062)	(.23)
logr	13.576	14.528	17.136
	(4.601)	(4.286)	(12.364)
logfinw	.059	.046	.092
	(.008)	(.007)	(.019)
educ0	-.823	-.611	.508
	(.232)	(.18)	(1.094)
educ1	-.517	-.409	-.178
	(.145)	(.108)	(.896)
educ2	-.174	-.137	-.142
	(.129)	(.103)	(.851)
educ3	-.013	-.039	-.155
	(.125)	(.103)	(.763)
live1	-.003	-.025	.101
	(.103)	(.087)	(.373)
live2	.024	.027	-.386
	(.076)	(.065)	(.261)
live3	.171	.151	.039
	(.073)	(.064)	(.212)
malehead	-.019	-.006	.058
	(.074)	(.06)	(.336)
logQ	.17	.101	.18
	(.049)	(.033)	(.771)
cons	-11.316	-8.832	.
	(1.037)	(.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); Quadratic time trend and Age of head of the household variables are significant but are unreported.

Table 15: 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	1.894	-.188
	(.129)	(.055)	(.167)
logc	.779	.542	.977
	(.097)	(.069)	(.263)
logr	9.618	11.11	11.806
	(5.205)	(4.722)	(13.578)
logfinw	.033	.022	.058
	(.01)	(.008)	(.022)
educ0	-.911	-.615	.491
	(.282)	(.206)	(1.204)
educ1	-.521	-.356	-.149
	(.167)	(.114)	(.995)
educ2	-.2	-.126	-.024
	(.147)	(.107)	(.92)
educ3	-.017	-.049	.138
	(.142)	(.107)	(.82)
live1	.025	-.024	.19
	(.122)	(.096)	(.42)
live2	-.007	-.003	-.492
	(.09)	(.071)	(.292)
live3	.117	.099	-.074
	(.084)	(.07)	(.238)
malehead	.019	.01	.271
	(.09)	(.067)	(.378)
logQ	.169	.071	.236
	(.059)	(.036)	(.847)
cons	-9.885	-7.013	.
	(1.156)	(.806)	
N*T	3936	3936	1368
LogL	-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); Quadratic time trend and Age of head of the household variables are significant but are unreported.

Table 16: Honoré and Kyriazidou Estimator

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

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

Note: Standard errors in parentheses; N is the total households in the sample but Final N is the number of households that are included in the semi-parametric conditional logit estimation.

Table 17: Honoré and Kyriazidou Estimator

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

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

Note: Standard errors in parentheses; N is the total households in the sample but Final N is the number of households that are included in the semi-parametric conditional logit estimation.

Table 18: Honoré and Kyriazidou Estimator

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

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

Note: Standard errors in parentheses; N is the total households in the sample but Final N is the number of households that are included in the semi-parametric conditional logit estimation.