Dynamics of Consumer Adoption of Financial Innovations:

The Case of ATM Cards

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Abstract: Consumer technology adoption has long been a research topic in Marketing and Economics. One interesting stylized fact is that usage of new technologies by the elderly is consistently much lower than that by other age groups. Previous literature tries to rationalize this fact by arguing that the elderly have negative attitudes toward new technologies, or it is relatively more difficult for them to learn and use new technologies. If one estimates individuals' adoption costs in a static choice model, these reasons would translate into higher adoption costs for the elderly. However, there is one potential explanation that has been neglected in the previous literature: the elderly have much shorter life horizons than the young, and consequently their total discounted benefits from adoption could also be much smaller. In order to capture this factor, we explicitly model consumers to be forward-looking and solve a finite horizon dynamic programming problem when deciding whether to adopt a new technology. We apply this framework to the case of ATM cards. To measure monetary benefits per period from ATM card adoption, we also explicitly model how consumers make cash withdrawal decisions. We estimate the structural parameters of our model by using a micro-level panel dataset, which consists of detailed demographic information, individuals' adoption decisions of ATM cards and cash withdrawal patterns, and the number of ATM machines and interest rates over time, as provided by the Bank of Italy. The estimation results allow us to measure the relative importance of adoption costs and total discounted benefits in influencing consumers' ATM card adoption decisions. We find evidence that the elderly do *not* have larger adoption costs for ATM cards in Italy -- the lower ATM card adoption rate among the elderly can be explained in terms of differences in total discounted benefits of adoption across age groups. By conducting counterfactual experiments, we quantify how consumers' ATM adoption decisions would be affected by changing (i) the amount of subsidies, (ii) interest rates, and (iii) number of ATMs.

Keywords: Technology Adoption, Adoption Cost, Optimal Stopping, Elderly People, ATM Cards, Cash Demand Model

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1 Introduction

Consumer technology adoption has long been a research topic in Marketing and Economics. One interesting stylized fact is that usage of new technologies (e.g., calculators, computers, video recorders, cable television, and automated teller machines (ATMs)) by the elderly is consistently much lower than that by other age groups (Kerschner and Chelsvig (1984), Gilly and Zeithaml (1985)).[2] Previous literature tries to rationalize this fact by arguing that either the elderly have negative attitudes toward new technologies, or it is relatively difficult for them to learn and use new technologies (Adams and Thieben (1991), Hatta and Liyama (1991), Rogers et al. (1996)). If one estimates individuals' initial adoption costs in a static choice model, these reasons would translate into higher adoption costs (both physiological and psychological) for the elderly. However, one potential explanation has been neglected in the previous literature: the elderly have much shorter life horizons than the young, and consequently their total discounted benefits from adoption could also be much smaller. Ignoring the differences in total discounted benefits from adopting a new technology could lead to biased estimates in adoption costs for various age groups. To capture this factor, in this paper we explicitly model consumers to be forward-looking and solve a finite horizon dynamic programming problem when deciding whether they should adopt a new technology. Our goal is to use this framework to measure the relative importance of adoption costs and total discounted future benefits in influencing adoption decisions.

We apply this framework to the case of ATM cards. There are three reasons why ATM cards provide a particularly interesting case to study consumers' adoption decisions of a new technology. First, the costs, especially non-pecuniary learning costs, are typically incurred at the time of adoption and usually cannot be compensated by the benefits that immediately follow adoption[3]. By and large, as in any durable goods purchase case, the benefits from adopting an ATM card are benefit flows, which are received throughout the life of the acquired ATM technology. Without considering people's forward-looking behavior, a static choice model would underestimate the average adoption cost to a large extent. Second, the ATM provides a typical example that the elderly tried and adopted to a lesser degree than the non-elderly (Gilly and Zeithaml (1985), Kerschner and Chelsvig (1984), Rogers et al. (1996)). Similar results are found in our reduced-form regressions even

[2] I am not referring to those technologies specially designed to aid the elderly.
[3] There may be an ongoing fee for using an ATM card, but typically it is much less than the initial cost and can be fully covered by the benefits received in each period.

after controlling for other personal characteristics, such as education, gender, income, employment status, and geographic area. Without a dynamic model to take into account older people's shorter life horizons, we may conclude that older people have larger adoption costs. Third, some adoption decisions had to be made in an uncertain and limited information situation, especially in the introductory stages of the ATM technology. For example, consumers might worry about the reliability of the ATM technology or the availability of the ATM network. Many consumers would thus intentionally postpone their adoption decisions until there was enough information about the technology and there were enough ATMs nearby. All these features are common for many new technologies, and hence the model developed here should also be applicable to other cases, albeit with minor modifications.

We estimate the structural parameters of our model using a unique micro-level panel dataset provided by the Bank of Italy. The dataset consists of detailed demographic information (e.g., age, income, consumption, gender, etc.), individuals' adoption decisions of ATM cards and cash withdrawal patterns, the number of ATM machines and interest rates over time, and the average survival probabilities for different ages. Most importantly, the information on age and survival probabilities allows us to incorporate consumers' different life horizons in our model, and hence recover their adoption costs more accurately.[4] Moreover, the information on income, consumption, cash withdrawal patterns, both before and after ATM card adoption, and interest rates over time, allows us to model individuals' cash withdrawal decisions using a cash demand model. In particular, we are able to calibrate this model and use it to measure the monetary benefits per period from adopting ATM cards conditional on individuals' observed characteristics. When combining this cash demand model with the dynamic model of adoption decisions, we are also able to measure adoption costs in monetary terms.

To the best of our knowledge, this is the first estimated dynamic structural model that: (i) provides an estimate of adoption costs in monetary terms, (ii) focuses on adoption decisions for different age groups; (iii) studies adoption decisions of a financial innovation. Because of the "graying" of the marketplace in today's world, studying the behavior and decision making process of older people is becoming increasingly important. Marketers also are interested in this segment more

[4] In Appendix 1, we use a simple example to show why a static model underestimates the average initial adoption cost and an infinite horizon model overestimates the average adoption cost. The intuition for identification is also discussed in the example.

than before because the elderly population has been growing and becoming stronger in terms of total purchasing power. The estimation results of this model have important managerial implications in terms of how to accelerate adoption decisions made by the elderly. For example, having a more precise estimate of adoption costs for different age groups allows banks to use first-time sign-up bonuses more effectively to induce the elderly to adopt a financial innovation.

Our results can be summarized as follows. After taking the expected total discounted benefits into account, we find evidence that the elderly do *not* have larger adoption costs for ATM cards in Italy. The lower ATM card adoption rate among the elderly can be explained in terms of differences in total discounted benefits of adoption across age groups. In the model with two latent segments, we find that the adoption costs are €142.50 and €207.54 in 2002 euros. By conducting counterfactual experiments, we quantify how consumers' ATM adoption decisions would be affected by changing (i) the amount of subsidies offered to the elderly, (ii) interest rates, and (iii) number of ATMs.

The remainder of the paper is structured as follows. Related literature is discussed in Section 2. Section 3 outlines relevant institutional details about ATMs and the banking system in Italy. Section 4 describes the unique micro-level panel data that we employ in this work. Section 5 presents the model. The estimation algorithm and some identification issues are discussed in Section 6. Section 7 shows the estimation results and findings from several counterfactual experiments. Section 8 presents the conclusions.

2 Literature Review

2.1 Measuring Adoption Costs in a Dynamic Structural Model

The model that we develop in this paper is related to the one presented in Swanson et al. (1997), who also argue that the elderly have shorter life horizons, and hence have less incentives to adopt new technologies. However, since their paper is a theoretical one, they do not estimate their model or measure the relative importance of adoption costs and total expected discounted benefits.

This paper is also related to the work of Ryan and Tucker (2007), who study technology adoption and communications choice decisions of a multinational bank's employees in an infinite horizon dynamic model. In their model, the length of a period is very short and hence an infinite horizon dynamic programming model provides a good proxy to the environment. However, their data does not allow them to measure the benefits of adopting the new technology in monetary terms. As a result, unlike our paper, they can only measure adoption costs in a relative sense instead of in monetary terms.

Another related paper is by Song and Chintagunta (2003), who study consumer adoption decisions of a new durable product. They assume that the benefits of adopting a new product come from a composite quality index. In contrast, we use a cash demand model to explicitly measure the monetary benefits of adopting ATM cards, based on interest rates and cash withdrawal patterns. This is why our framework is able to recover adoption costs in monetary terms.

Finally, we are aware of two papers, in which dynamic models are used to measure consumer switching costs: Goettler and Clay (2007) use micro-level data to estimate switching costs in a model of consumer learning and tariff choice; Shcherbakov (2007) uses aggregate level data to measure consumer switching costs in the US television industry. Both of them find substantial consumer switching costs.

2.2 ATM Adoption

ATM adoption itself is not a new topic in economics. Much of the existing literature examines banks' ATM adoption decisions (for example, Hannan and McDowell (1984, 1987), Saloner and Shepard (1995), Ishii (2005), Ferrari et al. (2007)). However, since the ATM market is a two-sided market, banks' decisions on whether to install more ATM machines depend on how many consumers adopt ATM cards (and vice versa). Surprisingly, there is little research analyzing consumers' ATM card adoption decisions.[5] To our knowledge, there are only three empirical papers that provide a quantitative study of consumers' ATM card adoption decisions (Attanasio et al. (2002), Huynh (2007), Riccuarelli (2007)) and all of them use a static choice model. However, as argued in the introduction, consumers' ATM card adoption decisions are not myopic decisions. A dynamic model is a must to capture consumers' forward-looking adoption decisions.

[5] A lack of consumer-level data might be one important reason for this.

3 Institutional Details

3.1 ATMs in Italy

ATMs were first introduced to Italy in the 1970s (Canato and Corrocher (2004)). Bancomat, the Italian inter-banking cash dispenser project, was promoted by the Italian Society for Interbanking Automation starting in 1983 (Orlandi (1989)). During the time period we study in this paper, Bancomat was the only Italian ATM network that allowed customers at all Italian banks in the system to use any ATM in the system. An ATM card is also called a Bancomat card in Italy.

Hester et al. (2001) provide a good discussion of the evolution of ATMs and the Italian banking system. According to them, because of privatization, changing regulations, reduced restrictions on branching, and the rapid technical progress in data processing, the Italian banking system underwent substantial restructuring since 1988. At the same time, there was a rapid expansion in branches and ATMs throughout Italy. Between 1991 and 1999, the number of bank branches rose from 18,332 to 27,134 and the number of ATMs rose from 11,601 to 30,266. Figure A1 in the appendix indicates that ATMs and branches had been growing at different rates in the five major geographic areas of Italy (Northwest, Northeast, Central, South, and Islands). Figure A2 shows that in all areas the ratio of ATMs to branches had increased. In 1991 the ratio of ATMs to branches was highest in the Northwest, which includes financial centers like Milan and Turin, and lowest in the Islands, which is the poorest area of Italy. By 1999, the ratio of ATMs to branches was almost constant in the Italian peninsula; only the islands of Sardinia and Sicily lagged in this ratio.

Figure A3 in the appendix shows the overall adoption rate from 1991 to 2004. The numbers are calculated from the Bank of Italy's Survey of Household Income and Wealth (SHIW). Generally speaking, the adoption rate has been steadily increasing over time, with a 31.9% adoption rate in 1991 and 57.8% of households having at least one ATM card in 2004.

3.2 Some Facts about the Banking System in Italy

Most Italian banks charge an annual service fee for ATM cards, but it has never been a significant amount: Attanasio et al. (2002) show that the average yearly fee was 6.2 euros on a sample of 38 banks. There are no additional service charges when a customer uses an ATM card issued by the bank owning an ATM.

The normal bank account for day-to-day transactions in Italy is a cheque or current account. All cheque accounts in Italy are interest bearing, and interest is received quarterly. An ATM card needs to be linked to a cheque account before it can be used to withdraw cash.

In Italy, bank opening hours vary according to the bank and location. In general, banks are open from 08:30 until 13:30, and then again for an hour and a half from 14:30 until 16:00. Banks are generally closed on weekends and holidays. On the day before a holiday, banks are often closed in the afternoon as well.

4 Data

The data used in this paper come from four different sources.

4.1 Bank of Italy Survey of Household Income and Wealth (SHIW)

The SHIW is a comprehensive socio-economic survey; this database contains information regarding:

- Individual characteristics and occupational status,
- Sources of household income,
- Consumption expenditures.

These surveys were conducted on an annual basis from 1977 to 1984, and then again in 1986. They then were conducted bi-annually from 1987 to 2004 (replacing 1997 with 1998). We select a panel from 1991 to 2004 as the sample used for estimation. 1991 is the first year that ATM card information appears in the Bank of Italy's public database and the 2004 survey is the latest SHIW wave that is available. The key questions for this study in the survey include the following:

ATM card:
"Did you or any other member of your household have an ATM card?"
Average amount of withdrawal at an ATM:
"What was the average amount per withdrawal?"

There are 694 households observed from 1991 through 2004. 387[6] of these households had a bank account, but did not possess an ATM card in 1991. Of the 893 households observed from 1993 through 2004, 483 had a bank account, but did not have an ATM card in 1993. Of the 1010 households observed from 1995 through 2004, 534 were bank account holders, but non-adopters of ATM cards in 1995. Figure 4 shows the composition of the panel households selected for estimation. There are two reasons to fix the panel households from 1995 and only select non-adopters in their first observation periods. First, we find it rare in this panel that households abandon ATM cards after adopting them. Therefore, we will model ATM card adoption as an optimal stopping problem[7], while keeping a long time horizon for all panel households. Second, the provincial level residence location data that we obtained from Luigi Guiso is limited to pre-1998 households. The Bank of Italy's public database does not contain residence location information at the provincial level.

Figure 1: Panel

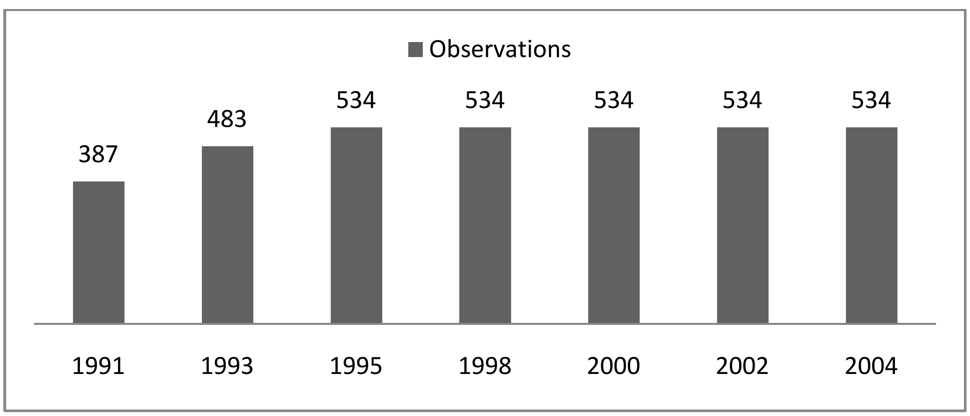


Table 1 summarizes the cumulative adoption rate of this panel.

Table 1: Cumulative Adoption Rate of ATM Cards (1991*-2004)

Year	1991	1993	1995	1998	2000	2002	2004
Adoption Rate	0	0.1387	0.2397	0.4363	0.5318	0.6236	0.6648

[6] I also exclude a few outliers with an unreasonably high income/consumption level or irregular adoption patterns (for example, non-adoption, adoption, non-adoption, adoption…) from the panel, which account for less than 5% of the total observations.

[7] For the same modelling reason, the total number of "valid" observations for the structural model is not 387+483+534*5=3,540. It is actually 387+416+406+301+250+201=1,961, after omitting households' first observations and their post-adoption observations.

Observations (panel)	387	483	534	534	534	534	534

* ATM card information before 1991 was not included in the Bank of Italy's public database.

Table 2 shows the summary statistics of some key variables. Generally speaking, this is a sample of an old population with the average age of the household head at 52 in 1991 and 62 in 2004, with standard deviation at around 13-14. Therefore, this dataset is quite suitable for testing the shorter life horizon hypothesis (also check Figure Series A4 for age dispersions). Both household income and consumption of non-durables have a slightly upward trend. The percentage of male household heads has a decreasing trend, probably reflecting the demise of male heads and female longevity. This also indicates that households did change heads over time and household head demographics are time varying. 55.62% of households live in the north or in the central area of Italy. The remaining 44.38% live in the south or in the islands area. Comparatively speaking, this is a poorly educated sample. Less than 5.5% of household heads hold a bachelor's degree or above. Around 20% of household heads have a high school diploma and about 30% have a middle school diploma. Almost 40% of the heads have only received elementary school education and this is the largest segment of the panel population. On average, more than 5% of the heads have not received any education at all[8].

Table 2: Summary Statistics of Main Variables*

Variable	1991	1993	1995	1998	2000	2002	2004
Age (household head)	52.0956 (13.5214)	53.1367 (13.8939)	54.5225 (13.5967)	56.8858 (13.6345)	58.2097 (13.6782)	60.1199 (13.6558)	61.9214 (13.8924)
Household income	47.2688 (22.9061)	46.5080 (24.5015)	47.2081 (24.9661)	51.0605 (28.0614)	51.9912 (28.6416)	50.2374 (27.0574)	50.9209 (27.1699)
Consumption of non-durables	32.1393 (13.2241)	32.9264 (13.9453)	34.3390 (14.6396)	33.3956 (14.7588)	34.3983 (14.7183)	33.5241 (15.0404)	35.7546 (15.9624)
Male head	0.8527 (0.3549)	0.7950 (0.4041)	0.7809 (0.4140)	0.7491 (0.4340)	0.6592 (0.4744)	0.6273 (0.4840)	0.6236 (0.4849)
Living area	Percent						
North or Centre	55.62						
South or Islands	44.38						

[8] The corresponding percentages are 17% (pre-primary and primary education), 32% (lower secondary education), 37% (upper secondary education), and 14% (post-secondary education) for 25-to-64-year-olds in Italy, by highest level of education attained. (OECD Indicators (2007))

Highest educational qualification achieved (household head)	Percent						
None	4.91	6.42	6.93	7.68	5.81	4.87	4.49
Elementary school	38.50	39.34	39.33	36.52	36.89	37.45	37.83
Middle school	33.59	30.64	30.52	29.21	29.03	29.78	29.03
High school	19.90	19.67	19.29	21.72	23.22	22.85	23.41
Bachelor's degree and above	3.10	3.93	3.93	4.87	5.06	5.06	5.24
Observations	387	483	534	534	534	534	534

* Income and Consumption of non-durables are measured in 1,000,000 Lire (2002). Numbers in brackets are standard deviations.

Figure 2 depicts the adoption level by age over time. We can clearly see that age is a negative factor in predicting ATM card adoptions - seniors over 65 have a much lower adoption rate than people aged less than 50. Figure 3 shows the adoption rate by education. Also, it is clear that education level is positively related to ATM card adoption. Figure Series A5 displays the adoption rate by both age and education in a wave-by-wave manner. It shows similar patterns conditional on age and education.

Figure 2: Cumulative ATM Card Adoption Rate by Age

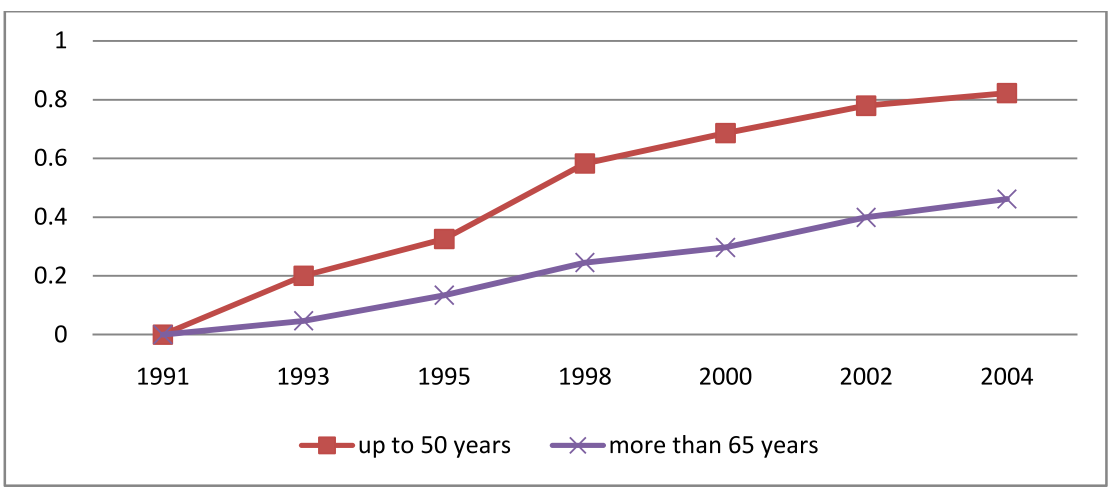
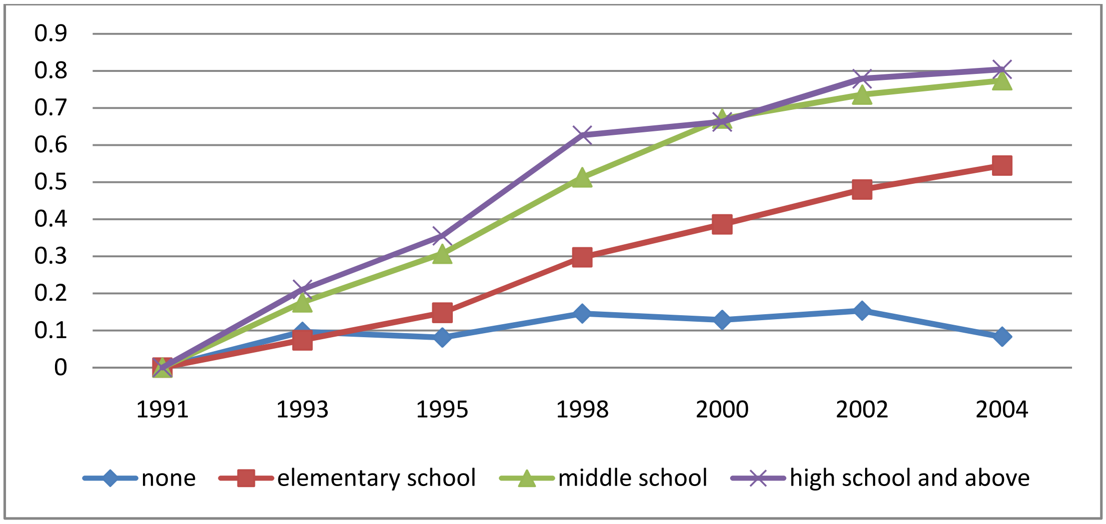


Figure 3: Cumulative ATM Card Adoption Rate by Education



4.2 Interest Rate

The nominal interest rate[9] on current account deposits is also drawn from the Bank of Italy's public database, which is available at http://bip.bancaditalia.it/4972unix/homebipeng.htm.

The time-series interest rate variation includes an increase in the early part of the 1990s and then a steady decrease up to 2004. This variation is mainly caused by Italy's entrance into the European Monetary Union. Since the interest rate is at the regional level, we only show the average value over Italy's 20 regions in Table 4 (for more details, please see p. 62, Technical Appendix of Huynh (2007)).

Table 3: Interest Rate

Year	1991	1993	1995	1998	2000	2002	2004
Interest Rate (mean)	8.872	10.274	6.829	3.811	1.862	1.647	0.916
Interest Rate (standard deviation)	0.489	0.401	0.263	0.206	0.190	0.170	0.115
Observations (number of regions)	20, interest rate varies by region in Italy						

4.3 ATM and Banking Data

Before 1998, the data on the number of ATMs was drawn from another special survey from the Bank of Italy. The Bank of Italy also provides provincial information about the number of ATMs and POS terminals from 1997 to 2006. Giorgio Calcagnini provided banking concentration

[9] Interest income is subject to a withholding tax in Italy. The withholding tax rate is 30% before 1997 and 27% since 1998. The flat rate withholding tax is deducted from nominal interest rates in the empirical estimations.

data from 1990 to 2005. As expected, both the number of ATMs and the number of bank branches have been increasing over time. These data can help control influences from the supply side. The number of ATMs, the number of POS terminals, and the number of bank branches are all highly correlated and reduced form regression results show that only the number of ATMs is significant when we include all three variables. Consequently, we only use the number of ATMs in the structural estimation.

Table 4 shows the number of ATMs per 1,000 population. Because the ATM data is at the provincial level and there are more than 90 provinces in Italy (the number was 109 as of 2006), we only show the average number over the provinces that the panel households lived in.

Table 4: Number of ATMs per 1,000 Population

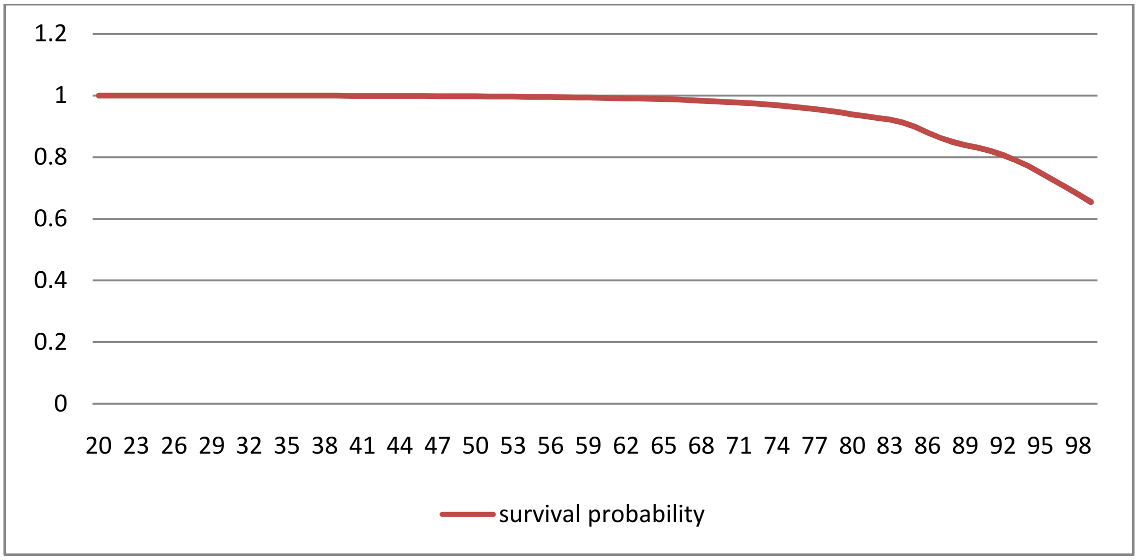
Year	1991	1993	1995	1998	2000	2002	2004
Number of ATMs per 1,000 Population (mean)	0.141	0.208	0.246	0.497	0.573	0.648	0.646
Number of ATMs per 1,000 Population (standard deviation)	0.100	0.125	0.150	0.226	0.227	0.235	0.236
Observations (number of provinces)	91	92	91	95	95	95	95

4.4 Population and Survival Probability Data

National and provincial level data about population and age-conditional survival probability are obtained from the website of the Italian Institute of Statistics (ISTAT): http://demo.istat.it/index_e.html

Figure 4 shows the 2004 Italian national level survival probability conditional on age (the probability of surviving until $t + 1$ at age t). The survival probability is obviously a non-linear function of age.

Figure 4: Survival probability



5 Model

Before delving into the mathematical model, it is useful to briefly discuss the benefits and costs associated with adopting an ATM card. The benefits are incremental benefits compared to the traditional way of withdrawing money from a human teller at a bank counter. The costs are "the costs of change".[10]

Benefits

The benefits from adoption mainly lie in reduced transaction cost (versus withdrawing money at a bank counter), more interest savings (can put more money in an interest-bearing bank account) and increased convenience (24-hour ATMs vs. daytime human tellers). The means of measuring the adoption benefit is explained in the cash demand model shown below.

Costs

There are three types of costs involved with adopting an ATM card: the initial adoption cost (mainly learning cost and hassle cost), the ongoing annual fee, and the usage-based transaction fee.

[10] "Diffusion can be seen as the cumulative or aggregate result of a series of individual calculations that weigh the incremental benefits of adopting a new technology against the costs of change, often in an environment characterized by uncertainty (as to the future evolution of the technology and its benefits) and by limited information (about both the benefits and costs and even about the very existence of the technology)." (Hall and Khan (2003))

Although we do not have detailed data on either the annual fee or the transaction fee, this should not be a serious problem. A bank customer can use an ATM card for free at ATMs owned by the bank issuing the ATM card, therefore, to a big extent consumers can manage to avoid transaction fees. As discussed in section 3.2, the annual fee has never been expensive and the average yearly fee was only 6.2 euros (Attanasio et al. (2002)).

5.1 Adoption Benefits: A Cash Demand Model[11]

In order to quantitatively measure the cost savings from adopting an ATM card, we use an extension of the Baumol (1952) - Tobin (1956) cash demand model to calculate the demand for currency. It is a cash inventory management model where the consumer chooses the average amount of withdrawal, m, to minimize the sum of transaction costs and interest losses, TC. Interest losses are the forgone interest from holding cash rather than putting it in an interest-bearing bank account. The objective function is shown in the following equation:

(1) $$\min_m TC_j = wT_j(\frac{c}{m}) + R(\frac{m}{2}),$$

where w is the unit time cost of transaction (opportunity cost of time); T_j measures the technology-specific transaction time of each withdrawal (T_1 for ATM and T_0 for no ATM, $T_1 < T_0$); c is the consumption financed by cash in each time period, so $\frac{c}{m}$ is the average number of withdrawals in each period; R is the interest rate. The first term, $wT_j(\frac{c}{m})$, captures the total transaction cost in each period. The second term, $R(\frac{m}{2})$, measures interest losses because the average cash inventory in hands is $\frac{m}{2}$. There is a trade-off between reducing transaction costs and avoiding interest losses: a larger m means less transactions, but more interest losses in each period. Simple algebra gives us the optimal amount of cash withdrawal and the minimized total cost:

(2) $$m_j^* = \sqrt{2wT_jc/R} = \sqrt{2T_j} * \sqrt{wc/R}$$

(3) $$TC_j^* = \sqrt{2wT_jcR} = \sqrt{2T_j} * \sqrt{wcR}.$$

[11] This model is usually called the money demand model. In order to distinguish it from the money demand model in monetary economics, I name it the cash demand model.

Thus, the total cost saving from adoption per period can be represented by the difference between the minimized total cost without an ATM card (TC_0^*) and the minimized total cost with an ATM card (TC_1^*):

(4) $$\Delta TC = TC_0^* - TC_1^* = (\sqrt{2T_0} - \sqrt{2T_1}) * \sqrt{wcR}$$ [12]

Empirically, w can be approximated by annual income ($y_{i,t}$) and c is best measured by the consumption of non-durable goods ($c_{i,t}$). Suppose w=$\lambda * y_{i,t}$, and c=$\mu * c_{i,t}$, where λ and μ are constants. ΔTC can then be expressed as a variable directly proportional to $\sqrt{y_{i,t}c_{i,t}R_{i,t}}$.

5.2 ATM Card Adoptions: An Optimal Stopping Problem

In the data most panel households would stick to an ATM card once they adopted it (also see p. 24, Technical Appendix of Huynh (2007)) - there are rare occurrences of households first adopting an ATM card and then discarding it in our panel, so it is reasonable to model the adoption decision as an optimal stopping problem.

Depending on the adoption status ($a_{i,t}$) and the state variables ($S_{i,t}$), the utility function for household i in time t can be shown as:

(5) $$U(a_{i,t}, S_{i,t}) =$$

$$\left\{ \begin{array}{c} U_{01}(S_{i,t}) = U(\Delta TC_{i,t}, n_{i,t}) + \psi_0 \frac{t-1}{t} - F_{i,t} + e_{i1t}, \text{if } a_{i,t} = 1 \text{ and } \forall s < t, a_{i,s} = 0 \\ U_{11}(S_{i,t}) = U(\Delta TC_{i,t}, n_{i,t}) + \psi_0 \frac{t-1}{t} + e_{i1t}, \text{if } \exists s < t, a_{i,s} = 1 \\ U_{00}(S_{i,t}) = e_{i0t}, \text{ if } \forall s \leq t, a_{i,s} = 0 \end{array} \right\},$$

where subscript 1 means adoption and 0 means non-adoption; U_{01} is the current period utility of a new adopter; U_{11} is the current period utility of an old adopter; U_{00} is the current period utility of a non-adopter; $\Delta TC_{i,t}$ is the cost saving from adoption defined in the previous subsection; $n_{i,t}$ is the number of bank ATMs per 1,000 population; $\psi_0 \frac{t-1}{t}$[13] captures the time trend of the ATM

[12] A potential drawback of this formula is that when $R = 0$, $\Delta TC = 0$. In the empirical implementation, I set the minimum value of R to be 0.5%, which is consistent with the nominal interest rate in the period 1991-2004.
[13] A linear time trend is also attempted, but the model fit is much worse.

technology and an increasingly attractive ATM technology means ψ_0>0[14]; $F_{i,t}$ is the one-time lump sum adoption cost; e_{i1t} and e_{i0t} are error terms.

In our empirical estimations, we use a linear functional form for $U(\Delta TC_{i,t}, n_{i,t})$:

(6) $$U(\Delta TC_{i,t}, n_{i,t}) = b_{TC} * \Delta TC_{i,t} + b_n * n_{i,t}$$

$$= \underbrace{b_{TC} * (\sqrt{2\lambda\mu T_0} - \sqrt{2\lambda\mu T_1})}_{\tilde{b}_{TC}} * \sqrt{y_{i,t} c_{i,t} R_{i,t}} + b_n * n_{i,t}.$$

The Bellman equation for household i in time t can be written as:

(7) $$V(S_{it}) = \max_{\mathrm{a}} \mathbb{E}\{U(a_{i,t}, S_{i,t}) + z_{i,t+1}\beta \int V(S_{i,t+1}) dF(S_{i,t+1}|a_{i,t}, S_{i,t})\},$$

where $z_{i,t+1}$ is the survival probability of household i's head from time t to $t+1$. At the terminal period, we assume $z_{i,t+1}$=0 and $U(a_{i,t}, S_{i,t})$=0.

Specifically, the Bellman equation for the optimal choice of potential adopter i is:

(8) $$V_0(S_{i,t}) = \max\{V_{01}(S_{i,t}), V_{00}(S_{i,t})\}.$$

And,

(9) $$V_{01}(S_{i,t}) = U_{01}(S_{i,t}) + z_{i,t+1}\beta \int V_{11}(S_{i,t+1}) dF(S_{i,t+1}|S_{i,t})$$

is the value of adopting an ATM card in time t.

(10) $$V_{00}(S_{i,t}) = U_{00}(S_{i,t}) + z_{i,t+1}\beta \int V_0(S_{i,t+1}) dF(S_{i,t+1}|S_{i,t})$$

is the value of still waiting in time t.

(11) $$V_{11}(S_{i,t}) = U_{11}(S_{i,t}) + z_{i,t+1}\beta \int V_{11}(S_{i,t+1}) dF(S_{i,t+1}|S_{i,t})$$

is the value of holding an ATM card in time t.

Since we do not allow ATM cards to be abandoned, there is no expression of $V_{10}(S_{i,t})$.

[14] It is possible that the initial adoption cost is decreasing over time. I do not distinguish the two stories (increasing attractiveness vs. decreasing adoption cost) and I interpret the adoption cost as the average adoption cost.

The likelihood increment for household i in time t is then:

(12)
$$L_{i,t} = \Pr[V_{01}(S_{i,t}) > V_{00}(S_{i,t})] * I_{i,t-1}(0) * [1 - I_{i,t}(0)] +$$
$$\Pr[V_{01}(S_{i,t}) \leq V_{00}(S_{i,t})] * I_{i,t-1}(0) * I_{i,t}(0),$$

where

(13)
$$\Pr[V_{01}(S_{i,t}) > V_{00}(S_{i,t})] =$$
$$\Pr[U_{01}(S_{i,t}) + z_{i,t+1}\beta \int V_{11}(S_{i,t+1}) dF(S_{i,t+1}|S_{i,t}) >$$
$$U_{00}(S_{i,t}) + z_{i,t+1}\beta \int V_0(S_{i,t+1}) dF(S_{i,t+1}|S_{i,t})];$$

(14)
$$I_{i,s}(0) = \begin{cases} 1, if\ a_{i,s} = 0 \\ 0, if\ a_{i,s} = 1 \end{cases}.$$

Individual Heterogeneity: A Concomitant Variable Latent Class Model

We incorporate unobserved individual heterogeneity by using a concomitant variable latent class segmentation (see Dayton and McReady (1988), Gupta and Chintagunta (1994)): if household i belongs to segment r, the initial adoption cost would be:

(15) $$F_{i,t} = F_{0,r} + \alpha_1 * (age_{i,t} - 50 | age_{i,t} > 50) + \alpha_2 * (age_{i,t} | age_{i,t} \leq 50).$$

By using the above expression, we allow the adoption cost to vary upon age. The reason for using 50 as a cut-off point is largely due to data patterns (see Figure 2 for the adoption rate by age and age histograms in Figure Series A4). We also tried 60/65 as the cut-off point and experimented with a quadratic specification in static model estimations. Qualitative results do not change and the goodness of fit of these alternative models is generally more inferior. Also, note that we only allow $F_{0,r}$ to vary across different latent segments and this is just a simplification.

The probability that household i belongs to segment r is represented by a logistic formula:

(16)

$$\pi_{i,r} = \frac{\exp(\gamma_{0,r} + \gamma_{X,r} * X_{i,t})}{1 + \sum_{r=1}^{r=R_s-1} \exp(\gamma_{0,r} + \gamma_{X,r} * X_{i,t})},$$

where $X_{i,t}$ are demographic variables of the household head. Since some households in the surveys did change household heads over time, $X_{i,t}$ cannot be simplified to X_i.

Finally, the unconditional likelihood function can be expressed as:

(17)

$$\prod_{i}^{I}\prod_{t}^{T}\sum_{r}^{R_S}(L_{i,t} * \pi_{i,r})$$

Variables and the Evolution of State Variables

State variables ($S_{i,t}$):

time or survey wave (t), age ($age_{i,t}$), number of bank ATMs per 1,000 population ($n_{i,t}$), income ($y_{i,t}$), consumption of non-durables ($c_{i,t}$), interest rate ($R_{i,t}$), age-specific survival probability ($z_{i,t+1}$)

Control variable ($a_{i,t}$):

adoption decision

Household head demographics ($X_{i,t}$):

education, gender, location[15]

The evolution of state variables:

first-order Markov process for $n_{i,t}$, $c_{i,t}$, $y_{i,t}$[16];

deterministic process for age with an upper bound Age=102[17];

---

[15] Other variables like employment status, marital status, number of income earners in the household, number of household members, and size of the city, are also experimented on in the static choice models. Since none of them is significant, they are dropped from the structural model to lessen the computational burden.

[16] $y_{i,t}$ should also depend on the number of income earners in the household and the number of income earners should be correlated with age. Unfortunately, the number of income earners cannot be predicted well based on the age of household members. Besides, regression analysis about $y_{i,t}$ based on the first order Markov process assumption gives us a high R^2. Consequently, I keep this AR(1) assumption for $y_{i,t}$.

[17] Rust and Phelan (1997) make the same assumption for terminal age; the oldest household head in my panel was 97.

I.I.D. type-1 extreme value distribution for $e_{i,t}$.

We assume the time trend $\psi_0 \frac{t-1}{t}$ and the interest rate $R_{i,t}$ are totally exogenous from each household head's perspective. When household heads forecast the future, the time trend and the interest rate are beyond their expectations, therefore, their projections of the time trend and the future interest rate are approximated by the current period $\psi_0 \frac{t-1}{t}$ and $R_{i,t}$, respectively. There are two reasons to make this assumption. First, in reality, it is usually hard to predict the speed of technology improvement. ATM technology is no exception, hence $\psi_0 \frac{t-1}{t}$ cannot be predicted; for the interest rate, it is unreasonable to assume that ordinary people are able to predict its direction correctly. In fact, even professional economists make more wrong predictions than right ones[18]. In other words, individuals are assumed to be forward-looking to calculate discounted future benefits, but they are not capable of correctly forecasting the direction of interest rates and the level of future technology advancement. Second, it can lessen the computational burden. For example, if the time trend can be expected, each age group would have a unique set of value functions, which would make the already tremendous state space even larger[19].

6 Empirical Strategy

6.1 Estimation

There are three comprehensive review papers in which the estimation of a dynamic discrete choice model is discussed: Eckstein and Wolpin (1989), Rust (1994), and most recently, Aguirregabiria and Mira (2007). In this paper, the estimation is carried out in two stages (Rust (1987), Rust and Phelan (1997)). In the first stage, we recover consumer beliefs about the evolution processes of most state variables (transition probabilities) by imposing rational expectation and exclusion restrictions (independence of state variables). In the second stage, we estimate a formal dynamic model to recover consumers' preference parameters and their adoption costs (with latent

[18]Starting in 1982, the *Wall Street Journal* conducted polls asking economists for biannual interest rate forecasts and predictions. It was found that not only were these economists not even close in forecasting actual interest rates, they could not even predict the direction in which interest rates would move. In fact, in their forecasts, experts accurately predicted the direction of interest rates less than one third of the time. (Sjuggerud (2005))

[19] If there are m different age groups, the dimension of the new state space would be m times the original dimension. Similarly, if there are k interest rates, the dimension of the new state space would be k times the original one.

class segmentation). Since the model is a finite-horizon dynamic one, the value function is calculated by the backward solving method.

6.2 Identification

In general, the discount rate in a dynamic discrete choice model cannot be non-parametrically identified (Rust (1994), Magnac and Thesmar (2002)). In this paper, we therefore estimate two versions of the model by fixing β set at 0.90 and 0.85, respectively.

The large variation in age in our sample and non-linear survival probabilities are the two key ways to control for different life horizons and identify age-specific adoption costs. To measure the adoption cost in monetary values, it is necessary to make some transformations. To continue from section 5.1, w can be approximated by annual income ($y_{i,t}$) and c is measured by the consumption of non-durable goods ($c_{i,t}$). Suppose w=$\lambda * y_{i,t}$, and c=$\mu * c_{i,t}$, where λ and μ are constants. Then,

(18) $$m_j^* = \sqrt{2\lambda\mu T_j} * \sqrt{y_{i,t}c_{i,t}/R_{i,t}}$$

(19) $$\Delta TC = TC_0^* - TC_1^* = (\sqrt{2\lambda\mu T_0} - \sqrt{2\lambda\mu T_1}) * \sqrt{y_{i,t}c_{i,t}R_{i,t}}$$

We need to know $\sqrt{2\lambda\mu T_j}$ in order to calculate ΔTC. Fortunately, the Bank of Italy's unique dataset provides information about an individual household's withdrawal behaviour, both before and after adopting an ATM card. Specifically, we have m_0^*, m_1^*, $y_{i,t}$, $c_{i,t}$, and $R_{i,t}$. Therefore, we can separately estimate $\sqrt{2\lambda\mu T_0}$ and $\sqrt{2\lambda\mu T_1}$. Plugging these two scalars into the expression for ΔTC, we can measure monetary cost savings from adoption. Intuitively, based on households' different withdrawal patterns and using calibration, we can infer total monetary cost savings from ATM card adoption.

7 Estimation Results and Counterfactual Experiments

7.1 Estimation Results

Step 1

We discretize the main continuous state variables, namely, number of bank ATMs per 1,000 population ($n_{i,t}$), household income ($y_{i,t}$) and consumption of non-durables ($c_{i,t}$). Assuming each of these variables conforms to an AR(1) process, we estimate the equations governing their evolution. Households are assumed to have rational expectations, so they have a good understanding of these stochastic processes. The estimated equations are shown below:

(20) $$n_{i,t}=0.1142+0.9191*n_{i,t-1}+e_n,\ e_n \sim N(0,\ 0.1139)$$

(21) $$y_{i,t}=0.9528*y_{i,t-1}+e_y,\ e_y \sim N(0,\ 19.4462)$$

(22) $$c_{i,t}=0.9657*c_{i,t-1}+e_c,\ e_c \sim N(0,\ 11.6134).$$

Table A1 in the appendix contains estimation details. Their R^2, which ranges from 0.82 to 0.9, indicates that AR(1) is a good approximation of the evolution process.

Step 2

We first estimate a series of static reduced form logit models with different specifications. Based on the estimation results of the static models (they are put in a separate technical appendix), we select significant variables and some commonly used demographic variables that should appear in dynamic models. In total, we estimated 12 (3*2*2) dynamic models based on: (1) model with one latent segment, two latent segments or three latent segments; (2) a discount rate of 0.85 or 0.9; (3) a linear or concave time trend. To be concise, we only show the results of models with a concave time trend. Table A2 shows results of models with one segment; Table 5 presents results of models with 2 segments; Table A3 contains results of models with 3 segments.

Table 5: models with two segments

	β=0.85, dynamic model		β=0.9, dynamic model		static model	
parameter	estimate	s.d.	estimate	s.d.	estimate	s.d.
ψ_0 (time trend)	**3.2062****	0.9509	**2.6646****	0.7558	**6.1296****	1.0652
$\tilde{b}_{TC}$ (adoption benefit)	**0.1163****	0.0222	**0.0981****	0.0164	**0.1701****	0.0184
b_n (# of ATMs)	**1.7198***	0.7247	**1.4794***	0.6424	**0.7806***	0.3136
$F_{0,1}$ (adoption cost in segment 1)	**11.9547****	3.0041	**14.3346****	3.3096	**6.4956****	2.0075
$\text{Log}(F_{0,2}-F_{0,1})$ (log(adoption cost difference))	**1.6968****	0.204	**1.8596****	0.1758	0.0234	1.7567

α_1 (age-specific adoption cost, age>50)	-0.0004	0.0295	-0.0776+	0.0426	**0.0644****	0.0094
α_2 (age-specific adoption cost, age<50)	-0.0154	0.0173	-0.0193	0.018	0.0038	0.0069
γ_0	-0.813	0.7779	-0.823	0.564	-3.782	6.9018
γ_{sex}	0.1204	0.2432	0.13	0.2423	0.7056	6.78
γ_{north}	-0.3386	0.2759	-0.2623	0.2705	-9.378	25.37562
γ_{edu1} (none)	**-1.3618***	0.6545	**-1.5603***	0.6544	-5.5401	32.5692
γ_{edu2} (elementary)	-0.5514+	0.3069	**-0.6453***	0.3	-0.0139	0.9562
γ_{edu3} (middle school)	0.0376	0.2674	0.0235	0.277	-3.1446	7.541
-ll	816.833		819.467		820.089	
N	1961		1961		1961	
AIC	**1659.666**		1664.934		1666.178	
BIC	**1676.468**		1681.736		1682.980	

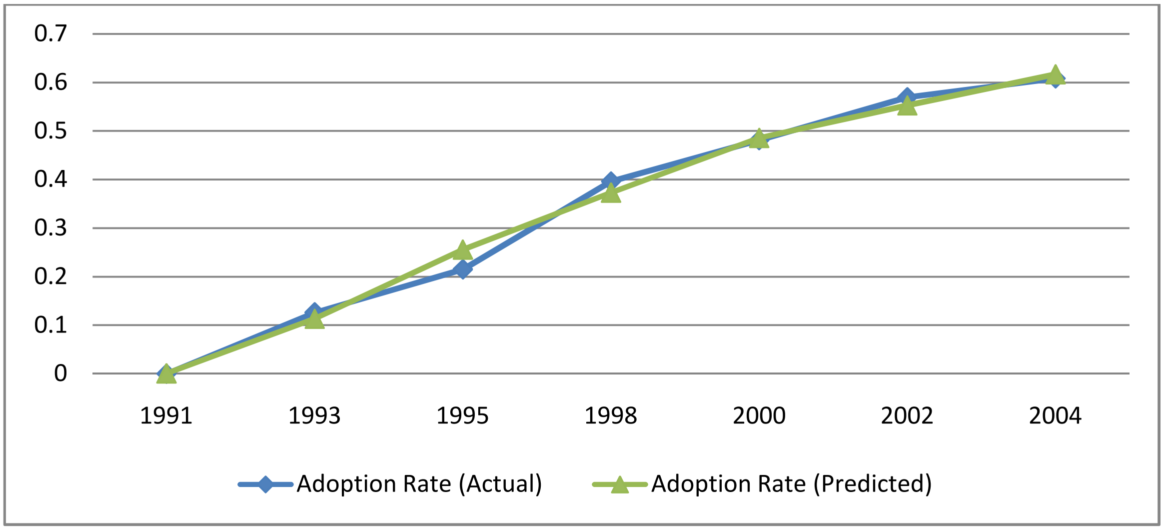
Which model performs the best?

We can select the best model from the twelve candidates along the above mentioned three dimensions: (1) segment: both AIC and BIC favour dynamic models with two latent segments; (2) time trend: similarly, in terms of goodness-of-fit statistics, specifications with the concave time trend outperform specifications with the linear time trend to a large extent; (3) discount rate: clearly, models with a 0.85 discount rate are superior to models with a 0.9 discount rate according to the model selection criteria. Overall, the results show that the best model is the dynamic model with two latent segments and a discount rate of 0.85. Therefore, the remaining result discussions and counterfactual experiments are mainly based on this specification.

Goodness of fit of the best model

As shown in Figure 5, the dynamic model with two latent segments and a 0.85 discount rate fits the overall adoption rate over time very well.

Figure 5: Cumulative adoption rate: actual and predicted



Do the elderly have a larger adoption cost?

The most striking finding from the estimation is that older people do *not* have a larger adoption cost and this result is robust across different dynamic models. In the two-segment 0.85-discount-rate model, the coefficient for seniors' age-specific (age>50) adoption cost, α_1, is not significant. α_1 is even negative and marginally significant in the 0.9 discount rate dynamic models. In contrast, α_1 is always significantly positive in the static models we tried.

This result might seem to be surprising. One possible explanation involves taking into account the opportunity cost of time. In the survey, many senior household heads were unemployed, probably due to retirement. For example, according to the 2004 SHIW survey, 59.4% of household heads aged between 51 and 65 were unemployed and the percentage was 98.9% for heads over 65 years in age. Unemployed seniors had more free time to spend and thus they had a lower opportunity cost of time. Even though seniors might have more difficulties to learn how to use ATM technology, because their unit time cost is lower, their total adoption cost may not be higher than that of younger people.

We view this as evidence that seniors' lower adoption rate is mainly driven by their lack of incentives to adopt, not because they have a larger adoption cost. In other words, the lower adoption rate of the elderly can be largely rationalized by their shorter life horizons. There are many reports about how old people lag behind in today's "information revolution" world. For example, according to a *New York Times* article (2004), only 22 percent of Americans over 65 went online, compared with 75 percent of those aged 30 to 49. Why don't seniors take advantage of new technologies, such as computers and the Internet? This paper offers a potential answer: even though seniors may be able to foresee the benefits of these new technologies, because of the much smaller discounted total benefits, it might not be worthwhile for them to exert the effort to learn them.

How important are the adoption benefits measured in the cash demand model?

We construct a unique measure of adoption benefits, ΔTC, in a cash demand model. The coefficient of ΔTC, $\tilde{b}_{TC}$, is very significant and robust across all the models. This supports the validity of using this cash demand model and indicates that ΔTC is indeed a good measure of adoption benefits. Because ΔTC is a direct measure of cost savings from adopting an ATM card, it is more concrete than the composite quality index used in the durable goods literature.

How large are the adoption costs, in euros?

As discussed in section 6.2, in order to obtain monetary adoption costs, we need to do some calibration and first disentangle b_{TC} from $\tilde{b}_{TC} = b_{TC} * (\sqrt{2\lambda\mu T_0} - \sqrt{2\lambda\mu T_1})$. To do so, we put together the amount of ATM withdrawal (m_1^*) for every ATM adopter and the amount of bank counter withdrawal (m_0^*) for every non-adopter across time. We also calculate the square root of each household's income*consumption of non-durables/interest rate - $\sqrt{y_{i,t}c_{i,t}/R_{i,t}}$ in the cash demand model. The summary statistics are shown in Table 6.

Table 6: summary statistics of withdrawal patterns

Variable (1,000 Lire)	Mean	Std. Dev.	Min	Max	Observations
m_1^* (amount of withdrawal at an ATM)	459.0951	294.581	52.59712	3287.858	868
$\sqrt{y_{i,t}c_{i,t}/R_{i,t}}$	388.1708	196.3116	55.1366	1191.619	868
m_0^* (amount of withdrawal at a bank counter)	1103.107	1081.906	73.63596	23604.31	1628
$\sqrt{y_{i,t}c_{i,t}/R_{i,t}}$	230.4905	140.1507	20.5744	1324.367	1628

Running two OLS regressions,

(23) $$m_1^* = \sqrt{2\lambda\mu T_1} * \sqrt{y_{i,t}c_{i,t}/R_{i,t}} + \varepsilon_1$$

(24) $$m_0^* = \sqrt{2\lambda\mu T_0} * \sqrt{y_{i,t}c_{i,t}/R_{i,t}} + \varepsilon_0,$$

we get the estimates for $\sqrt{2\lambda\mu T_1}$ (0.9807) and $\sqrt{2\lambda\mu T_0}$ (3.6650), respectively.

Table 7: OLS regressions to estimate $\sqrt{2\lambda\mu T_1}$ and $\sqrt{2\lambda\mu T_0}$

Variable (1,000 Lire)	m_1^*	m_0^*
$\sqrt{y_{i,t}c_{i,t}/R_{i,t}}$	0.9807 (0.0265)**	3.6650 (0.1091)**
Observations	868	1628
R-squared	0.61	0.41

Plugging these two scalars into the expression of $\tilde{b}_{TC}$, We can get b_{TC}. Since ΔTC is measured in 1,000 Lire, dividing the estimates of the non-age specific adoption costs ($F_{0,1}$ and $F_{0,2}$) by b_{TC}, we can get the equivalent monetary adoption costs. In the dynamic model with two latent segments and a 0.85 discount rate, $b_{TC}=\frac{\tilde{b}_{TC}}{\sqrt{2\lambda\mu T_0}-\sqrt{2\lambda\mu T_1}}=0.0433$. The adoption cost is thus $\frac{F_{0,1}}{b_{TC}}$=275,924 Lire (€142.50 in 2002 euros) for the first segment, and $\frac{F_{0,2}}{b_{TC}}$=401,864 Lire (€207.54 in 2002 euros) for the second segment. The numbers in the static counterpart are much smaller. The static model in table 5 shows that b_{TC} is 0.0634, and the non-age specific adoption costs are €52.92 and €61.25, respectively, for two latent segments.

Given that most Italian banks did charge an annual fee for the ATM card and the average rate was 6.2 euros in Attanasio et al. (2002), the estimated monetary adoption costs in the dynamic model appear reasonable, especially after considering the learning cost and the hassle cost. However, since the sample employed for estimation in this paper is for a poorly educated population, it is possible that the adoption costs are exaggerated. These numbers should therefore be interpreted with this caveat in mind.

The impacts of time trend and the development of the ATM network

A positive and significant time trend is found in the estimation results. Given that ATM technology has been improving all the time in terms of both security and versatility, we expect to find a positive trend. The availability of ATMs (number of ATMs per 1,000 population) also has a positive effect on adoption. Because the time trend and the number of ATMs are highly correlated (correlation coefficient > 0.7), the number of ATMs is not very significant in some specifications.

Who belongs to which segment?

Consistent with common wisdom, education turns out to be the most important predictor as to which segment each household belongs to. Household heads with a lower level of education[20], namely, none or elementary school, are much more likely to belong to the segment with a larger adoption cost. Living in the north or south doesn't affect an individual's likelihood to fall into a given segment.

In adoption cost households with a male head are not different from households with a female head. This is not consistent with previous research, which shows that men are more likely to adopt technology (for example, Kerschner and Chelsvig (1984)). One possible reason why we do not find that gender matters is that we use the same survival probabilities for both men and women. Therefore, a confounding effect could arise: women have longer life expectancies and thus bigger adoption benefits than men; on the other hand, men have a higher tendency to try new technologies and thus smaller adoption costs than women. To separate out these two factors, we allow for gender-specific survival probabilities[21] and re-estimate the model with a 0.85 discount rate and two latent segments. The estimation results are shown in Table 8.

[20] Whether the household head has a spouse, and the spouse's education level are also tried in the static model estimation, but they are found to be not significant.

[21] Please refer to Figure A6 for gender-specific survival probability curves.

Table 8: model with gender-specific survival probabilities

β=0.85	dynamic model, universal survival probabilities		dynamic model, gender-specific survival probabilities	
parameter	estimate	s.d.	estimate	s.d.
ψ_0 (time trend)	**3.2062****	0.9509	**4.2508****	1.5245
$\tilde{b}_{TC}$ (adoption benefit)	**0.1163****	0.0222	**0.1225****	0.023
b_n (# of ATMs)	**1.7198***	0.7247	**1.2078***	0.6315
$F_{0,1}$ (adoption cost in segment 1)	**11.9547****	3.0041	**12.3759****	3.6627
Log$(F_{0,2} - F_{0,1})$ (log(adoption cost difference))	**1.6968****	0.204	**1.9825****	0.2901
α_1 (age-specific adoption cost, age>50)	-0.0004	0.0295	-0.0128	0.0328
α_2 (age-specific adoption cost, age<50)	-0.0154	0.0173	-0.0118	0.0155
γ_0	-0.813	0.7779	**-1.9937****	0.6593
γ_{male}	0.1204	0.2432	0.6676+	0.3799
γ_{north}	-0.3386	0.2759	-0.1333	0.3344
γ_{edu1} (none)	**-1.3618***	0.6545	**-1.5344***	0.7421
γ_{edu2} (elementary)	-0.5514+	0.3069	**-0.713***	0.3323
γ_{edu3} (middle school)	0.0376	0.2674	0.0296	0.2966
-ll	816.833		817.764	
N	1961		1961	
AIC	**1659.666**		1661.528	
BIC	**1676.468**		1678.330	

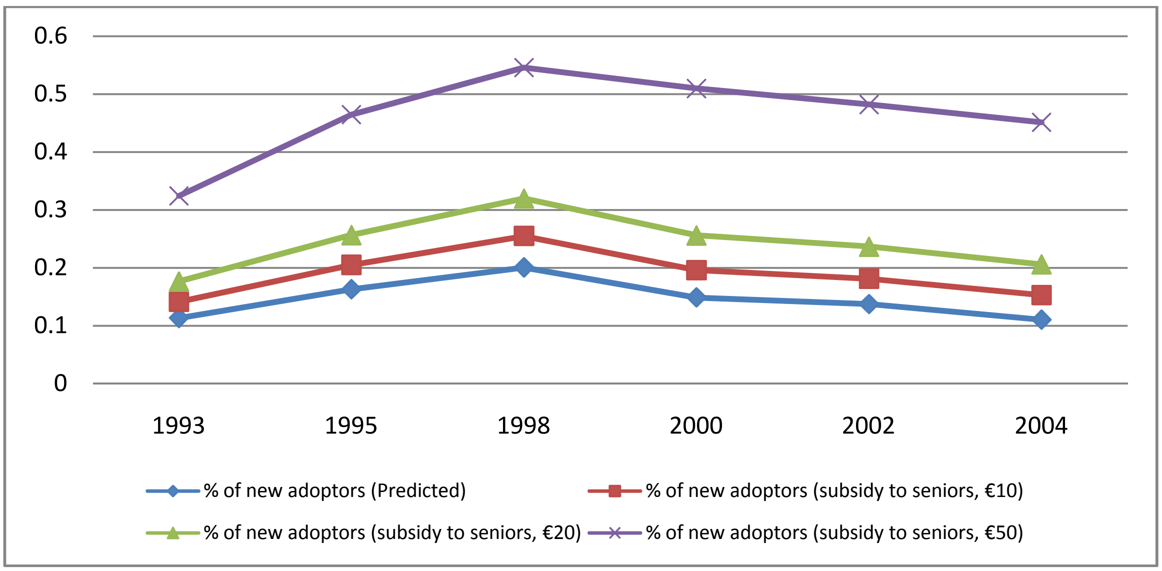
Most of the results are just consistent with the counterpart without gender-specific survival probabilities. Interestingly, in the new specification, the co-efficient for gender is now positive and marginally significant, which means that after controlling for different life expectancies, men are more likely to have a smaller adoption cost. We also view this as a validation of the main model.

7.2 Counterfactual Experiments

In this section we use the parameter estimates in the two-segment 0.85 discount rate model to analyze households' adoption decisions. Specifically, we examine the impact of 1) a subsidy to seniors, 2) an increase/decrease in the number of ATMs, 3) an increase/decrease in the interest rate, on adoption. We mainly use the percentage of new adopters in each period over the previous period non-adopters to represent adoption. We also compare the overall cumulative adoption rate in section 7.2.1.

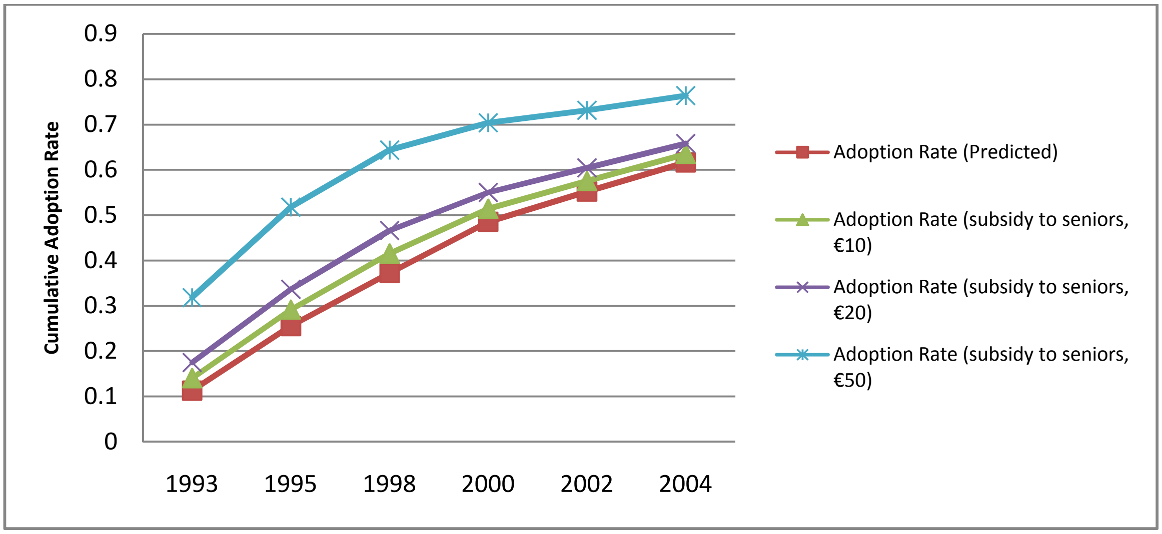
7.2.1 The effect of a subsidy to the elderly group on the % of new adopters and the cumulative adoption rate

Figure 6: Counterfactual Experiment: a subsidy to seniors



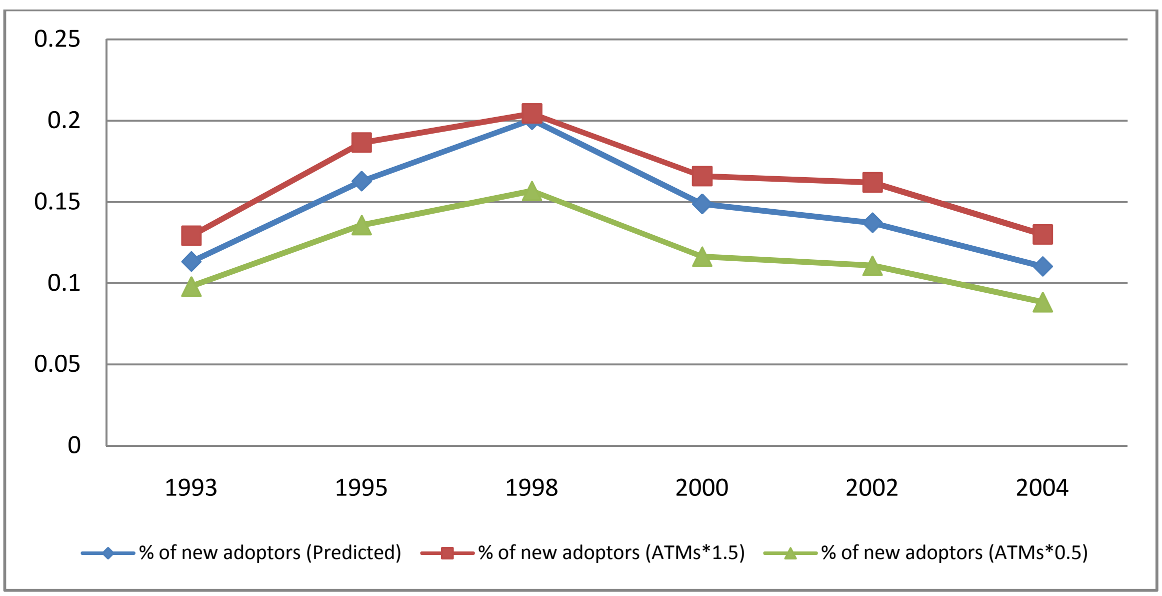
Since it is mainly the elderly that have a low adoption rate, a subsidy targeting at the elderly group (age > 50) is very effective: a €10 subsidy to the elderly can increase the average percentage of new adopters to 18.9%; a €20 subsidy can raise the number to 24.2%; a €50 subsidy can make it 46.3%! Figures 7 and 8 show the impact of different amounts of subsidies to seniors on the percentage of new adopters and the overall cumulative adoption rate, respectively.

Figure 7: Counterfactual Experiment: a subsidy to seniors



7.2.2 The effect of an increase/decrease in the ATM number on the % of new adopters

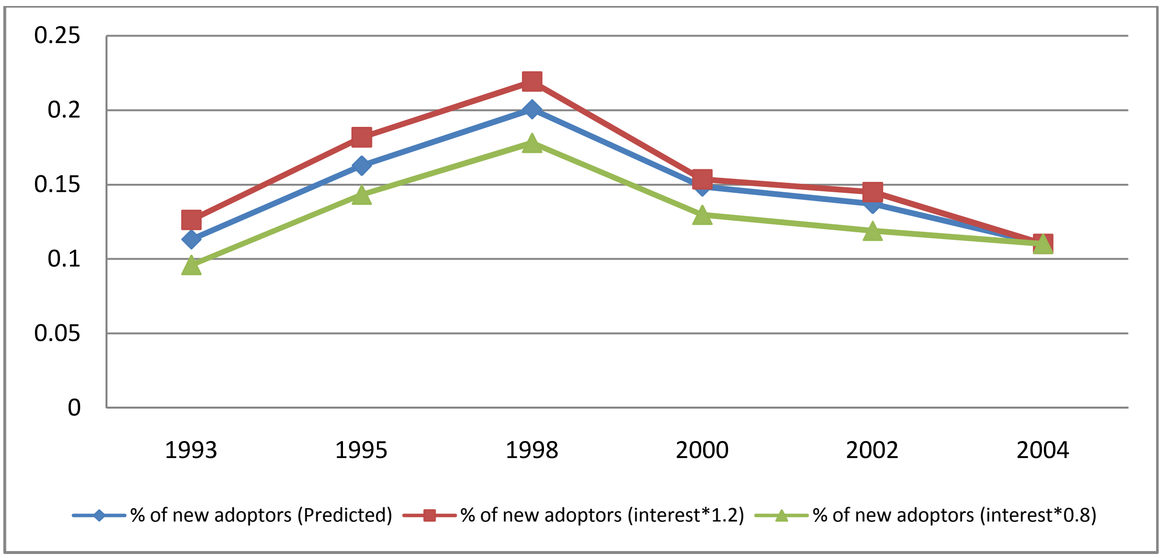
Figure 8: Counterfactual Experiment: ATM points increase/decrease by 50%



Installing more ATMs can attract more customers to adopt the ATM card, but the impact is not very big. A 50% increase in the number of ATMs can result in an on average 13.0% increase in the percentage of new adopters, while a 50% decrease in the number of ATMs can roughly decrease the percentage of new adopters by 18.8%. Depending on the cost of installing one ATM, the subsequent maintenance cost, and competitors' strategies, banks can decide how many new ATMs to install in the future. It should be noted that we currently do not allow the number of ATMs to lower the time costs of withdrawal. If this feature is incorporated, it is possible that the effect of this experiment could be stronger. Another related experiment that we are investigating is to change the growth rate of ATMs. This would allow us to examine the role of expectation.

7.2.3 The effect of an interest rate change on the % of new adopters

Figure 9: Counterfactual Experiment: interest rate increase/decrease by 20%



A higher interest rate would make it more costly to hold cash in hands, thus giving people more incentives to adopt an ATM card; a lower interest rate would have the opposite effect. But the magnitudes are not symmetric: as shown in Figure 9, a 20% interest rate increase would induce 6.9% more non-adopters to adopt an ATM card, whereas a 20% interest rate cut would have made 10.8% of new adopters decide not to adopt. Banks might want to learn the side effect of a promotional interest rate increase: it can not only encourage people to deposit more, but it can also make non-adopters more likely to consider getting an ATM card.

8 Concluding Remarks

This paper is motivated by a stylized fact of consumers' adoption decisions - the elderly have a much lower adoption rate of new technologies. Different reasons are offered in the literature and these can be summarized as the elderly having a larger adoption cost. A larger adoption cost is one explanation, and a shorter life horizon is another. Without a dynamic model taking people's limited life horizons into account, these two reasons cannot be separated out. This paper provides the first attempt to disentangle these two reasons by allowing for age-specific adoption costs and incorporating people's different life horizons in a finite horizon dynamic model. The findings are striking: the elderly do *not* have a larger adoption cost, so their lower adoption rate is probably caused by their shorter remaining life horizons. With the help of a Baumol-Tobin type cash inventory management model, we recover the initial adoption costs in 2002 euros and we find that a static choice model underestimates the average adoption cost to a big extent.

Two limitations should be noted. First, we use a very simple calibration method to transform adoption costs into monetary values, without considering time trend and individual heterogeneity. Consequently, we can only interpret the estimated adoption costs as average costs. Future research can make the calibration more flexible at the expense of a heavier computational burden. Second, it might be worthwhile to more finely discretize the state space and allow for normally distributed random coefficients by using, for example, the interpolation and simulation method proposed by Keane and Wolpin (1994).

Appendix 1

The intuition for identification and why only a finite-horizon dynamic model can correctly estimate the initial adoption cost

Suppose in the data we observe two individuals, Tom and Jerry. In 2000, both of them were 70 years old. Tom adopted an ATM card in 2000, but Jerry did not. Suppose we can measure that Tom's annual adoption benefit was \$10, while Jerry's potential adoption benefit was \$8. Let us further assume that the initial adoption cost F, was the same for both of them.

What kind of interval estimate of F can we get? In a static model, Tom and Jerry are assumed to be myopic – they compare only their current benefit with the initial adoption cost. Because Tom adopted but Jerry did not, we would infer that F is between \$8 and \$10. In an infinite horizon model with a 0.9 discount rate, we would conclude that F is between \$80 and \$100, because we implicitly assume that people would live forever by using an infinite horizon model. Realistically speaking, people would not be so myopic as to consider only a one-period benefit, or be so naïve as to assume that they could live forever. They must realize that they can enjoy the adoption benefit for many years, but not without an end. Suppose the terminal age is 80. After re-calculating their discounted future benefits, we could say that the initial adoption cost is between \$44 and \$57.

This is a very simple model with only two individuals and no stochastic factors involved. But the basic intuition has been clearly shown – we can back out the initial adoption cost if we can measure individuals' adoption benefits and if we know their adoption decisions. In addition, a static model tends to underestimate the initial adoption cost and an infinite horizon dynamic model tends to overestimate the initial adoption cost. Only a finite-horizon dynamic model can correctly estimate the initial adoption cost.

Appendix 2

Empirical evidence supporting the existence of learning cost in adopting ATM cards

In 2000 Survey, a special set of questions are asked:

If no-one in the household has a bank debit card or a credit card – or, if a card is not used at least three times a month

Why don't you use debit cards or credit cards/why don't you use them very much? ***(more than one answer is possible)***

- service is complicated to use 1 (41.2%)
- fears of mistakes or fraud 2 (16.0%)
- used in the past and not satisfied 3 (3.5%)

- too costly 4 (16.6%)
- the shopkeeper did not accept the card 5 (0.5%)
- loss of discounts 6 (0.92)
- don't consider cards necessary.. 7 (13.3%)
- prefer to use cash.. 8 (5.8%)
- other ***(please specify):*** ________________________________ 9 (7.8%)

As one can see, at 42.2%, "service is complicated to use" is the primary reason why many Italians don't or seldom use ATM cards or credit cards. At 16.0%, "fears of mistakes or fraud" is another important reason why people are afraid to use the new payment instruments. This evidence suggests that learning cost is the major barrier preventing people from adopting these new instruments.

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Table A1: AR(1) process for main state variables

State Variables	$n_{i,t}$	$y_{i,t}$ (1,000 Lire)	$c_{i,t}$ (1,000 Lire)
$t-1$	0.9191 (0.0185)	0.9528 (0.00644)	0.9657 (0.00586)
Constant	0.1142 (0.00863)	n.a.	n.a.
σ	0.1139	19.4462	11.6134
R^2	0.8210	0.8794	0.9003
Range	[0:0.1:1.5]	[0:15:150]	[0:10:100]
Number of grid points	16	11	11

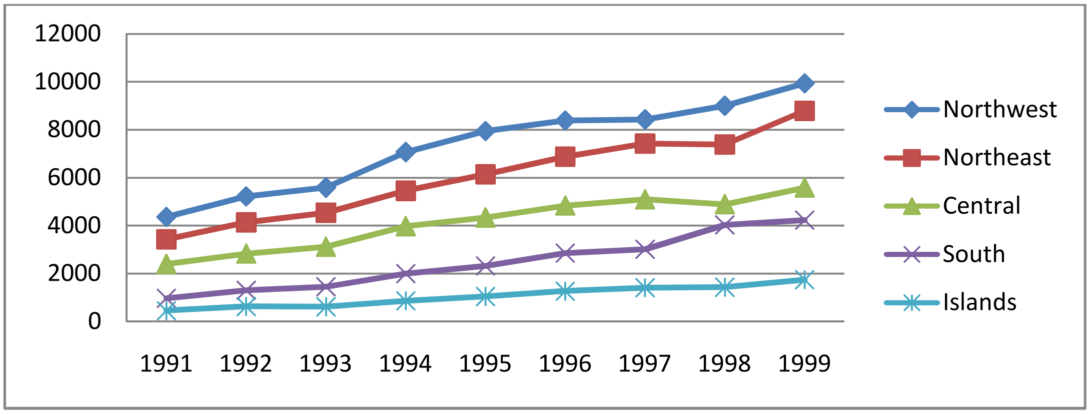
Table A2: models with one segment

	β=0.85, dynamic model		β=0.9, dynamic model	
parameter	estimate	s.d.	estimate	s.d.
ψ_0 (time trend)	**2.6844****	0.4996	**2.2861****	0.4101
$\tilde{b}_{TC}$ (adoption benefit)	**0.0902****	0.0103	**0.0794****	0.009
b_n (# of ATMs)	**0.9018****	0.324	**0.7935***	0.3204
$F_{0,1}$ (adoption cost in segment 1)	**13.0829****	1.5635	**16.3025****	1.8322
α_1 (age-specific adoption cost, age>50)	-0.0217	0.0182	**-0.1036****	0.0257
α_1 (age-specific adoption cost, age<50)	**-0.0227***	0.0115	**-0.033***	0.013
-ll	829.489		839.948	
N	1961		1961	
AIC	1670.978		1691.896	
BIC	1678.733		1699.651	

Table A3: models with three segments

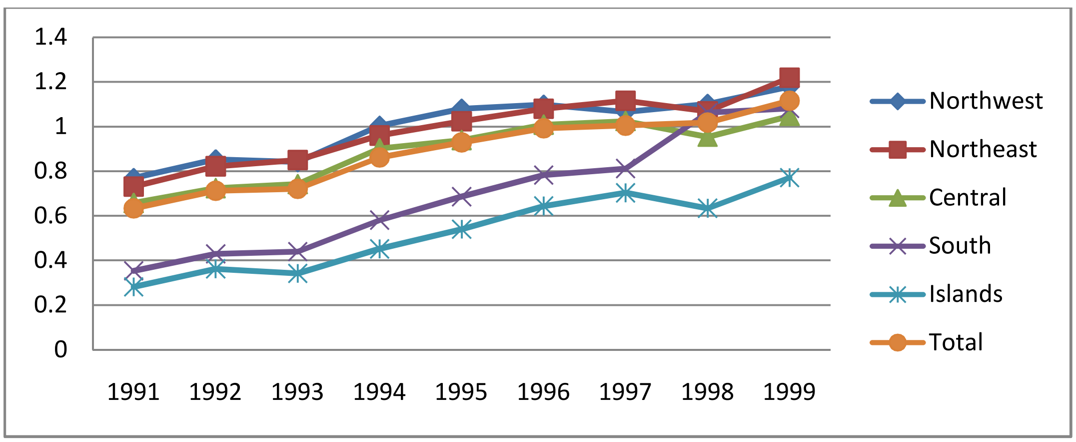
	β=0.85, dynamic model		β=0.9, dynamic model	
parameter	estimate	s.d.	estimate	s.d.
ψ_0 (time trend)	**3.1638****	0.8882	**2.5156****	0.6651
$\tilde{b}_{TC}$ (adoption benefit)	**0.1156****	0.0193	**0.0977****	0.0136
b_n (# of ATMs)	**1.8292****	0.6494	**2.0032****	0.6764
$F_{0,1}$ (adoption cost in segment 1)	**11.8927****	2.2483	**14.303****	2.9898
Log$(F_{0,2} - F_{0,1})$ (log(adoption cost difference between segments 2 and 1))	-0.6188	3.2667	**1.8029****	0.5583
Log$(F_{0,3} - F_{0,2})$ (log(adoption cost difference between segments 3 and 2))	**1.6386****	0.173	0.0725	7.743
α_1 (age-specific adoption cost, age>50)	0.0016	0.0289	-0.0635	0.0426
α_2 (age-specific adoption cost, age<50)	-0.0133	0.0163	**-0.0233***	0.0095
γ_{01}	-0.531	0.5411	0.8386	3.8343
γ_{sex1}	0.1734	0.5409	-0.1535	0.3659
γ_{north1}	**-2.5596***	1.2623	2.2363	24.5916
$\gamma_{edu1,1}$ (none)	**-2.1159****	0.3795	-2.8384	2.8238
$\gamma_{edu2,1}$ (elementary)	-2.5364	1.6958	-1.9436	3.7252
$\gamma_{edu3,1}$ (middle school)	-1.0292	0.8105	-1.1051	3.8374
γ_{02}	**-2.4221***	1.2248	0.9751	8.7846
γ_{sex2}	0.0383	0.3259	-0.6911	0.7078
γ_{north2}	0.3974	0.522	4.7594	24.8495
$\gamma_{edu1,2}$ (none)	-1.0373	0.6794	-3.4609	10.3246
$\gamma_{edu2,2}$ (elementary)	0.9774	0.8415	-3.154	10.9491
$\gamma_{edu3,2}$ (middle school)	1.3812+	0.8191	-2.4499	8.8966
-ll	811.437		812.383	
N	1961		1961	
AIC	1662.874		1664.766	
BIC	1688.724		1690.616	

Figure A1: Number of ATMs in Italy, 1991-1999



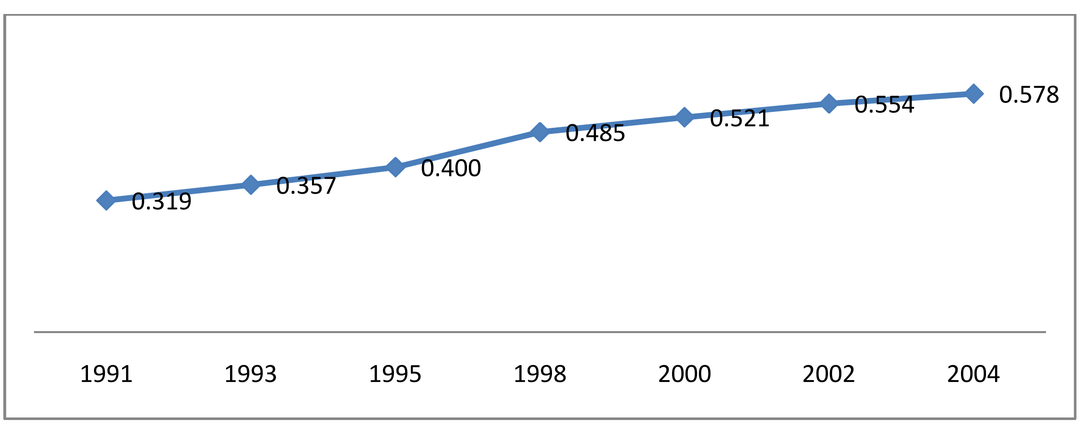
Source: Hester et al (2001)

Figure A2: Ratio of ATMs to Branches, 1991-1999



Source: Hester et al (2001)

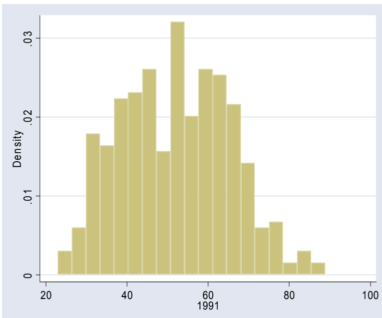
Figure A3: Cumulative Adoption Rate of ATM Card, 1991-2004



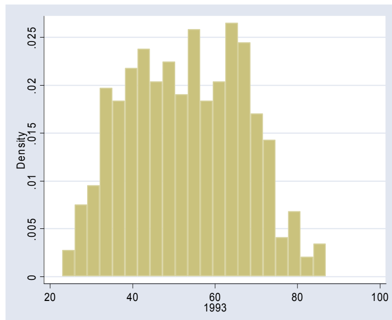
Source: SHIW 1991-2004

Figure Series A4

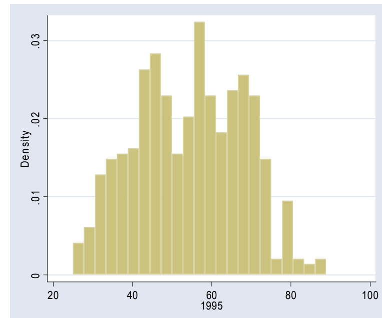
Age histograms for the panel (1991-2004)



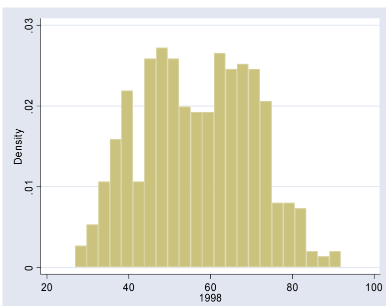
Age Histogram: 1991



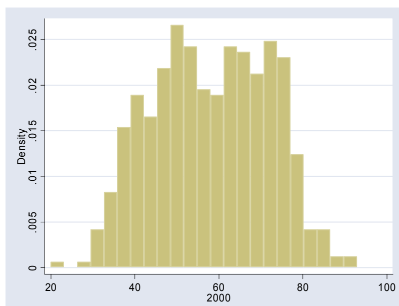
Age Histogram: 1993



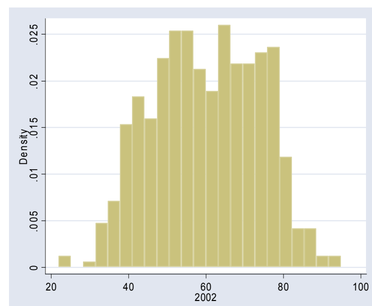
Age Histogram: 1995



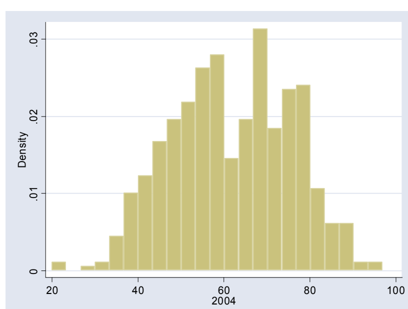
Age Histogram: 1998



Age Histogram: 2000



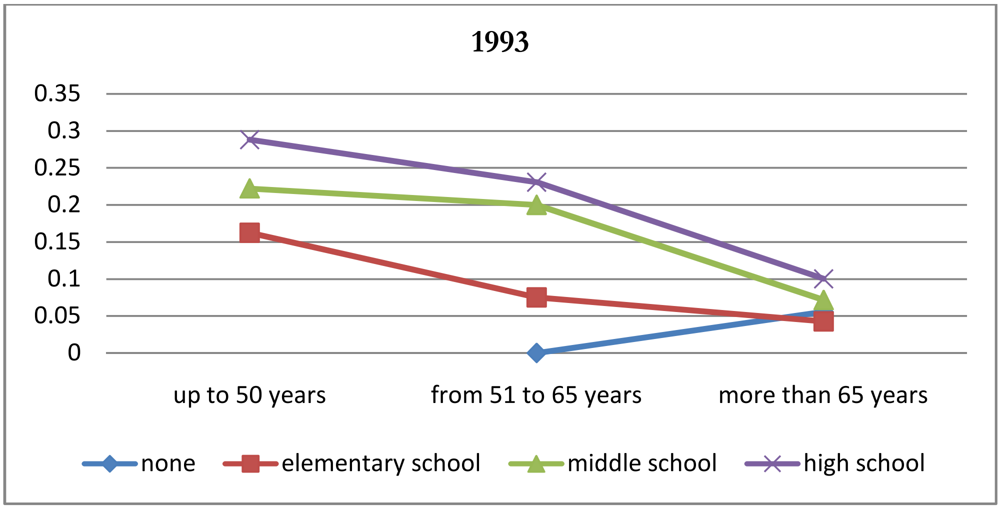
Age Histogram: 2002

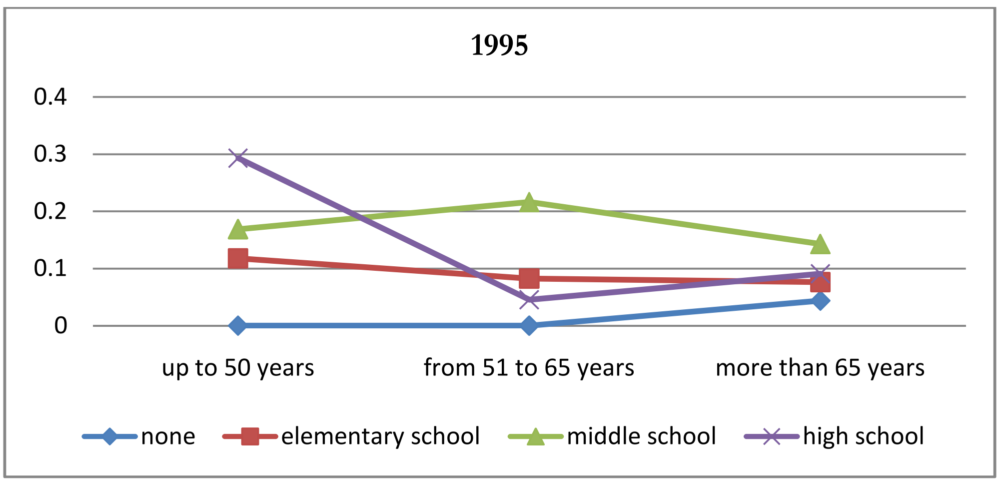


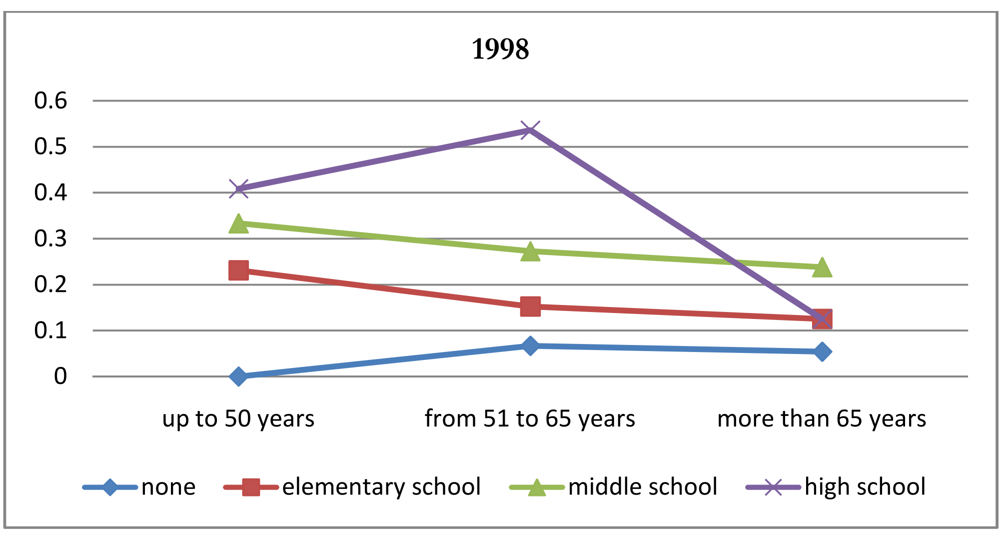
Age Histogram: 2004

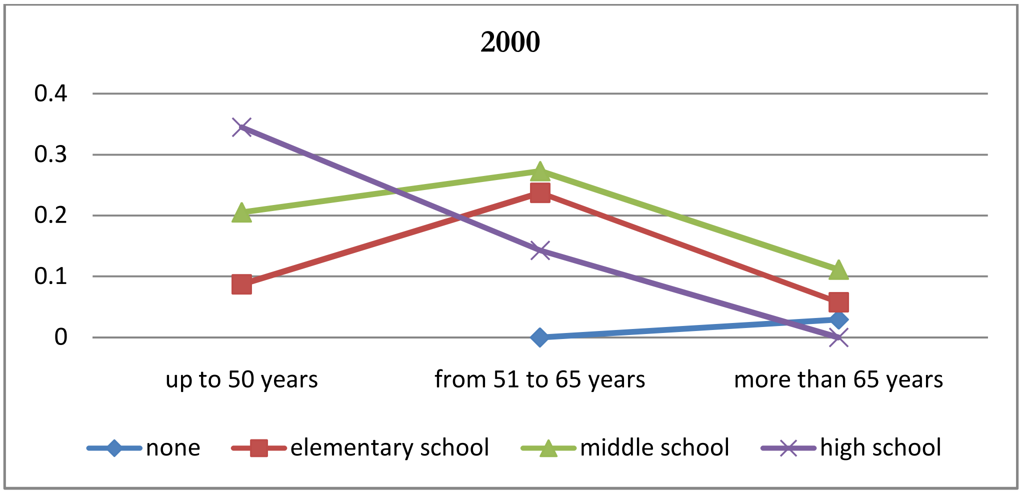
Figure Series A5

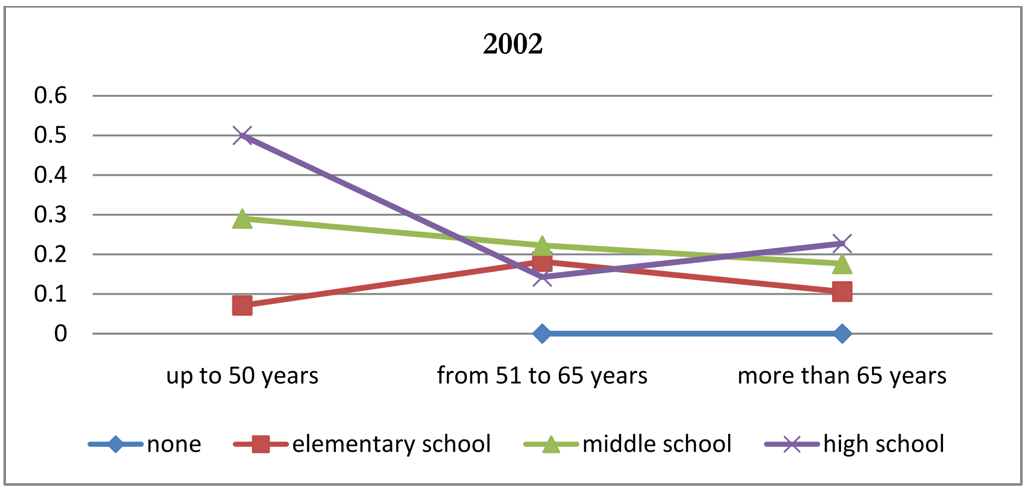
% of new adopters over non-adopters in the previous period by age and education (1993-2004)








2000
0.4
0.3
0.2
0.1
0
up to 50 years
from 51 to 65 years
more than 65 years
none
elementary school
middle school
high school


2002
0.6
0.5
0.4
0.3
0.2
0.1
0
up to 50 years
from 51 to 65 years
more than 65 years
none
elementary school
middle school
high school

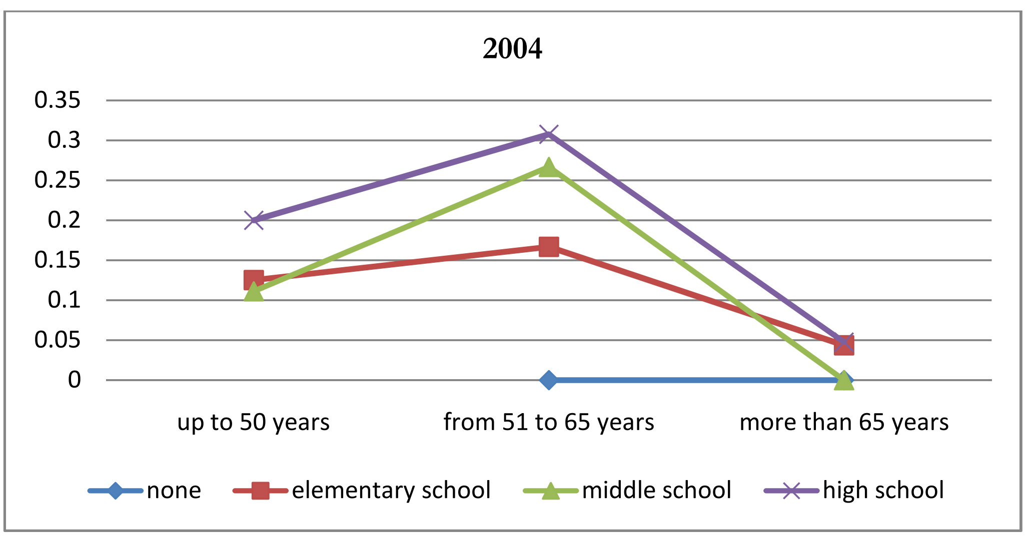

2004
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
up to 50 years
from 51 to 65 years
more than 65 years
none
elementary school
middle school
high school

Figure A6: Gender-specific survival probabilities