Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Dynamics of Consumer Adoption of Financial Innovation: The Case of ATM Cards

Botao Yang, Andrew T. Ching

To cite this article:
Botao Yang, Andrew T. Ching (2014) Dynamics of Consumer Adoption of Financial Innovation: The Case of ATM Cards. Management Science 60(4):903-922. http://dx.doi.org/10.1287/mnsc.2013.1792

MANAGEMENT SCIENCE
Vol. 60, No. 4, April 2014, pp. 903–922
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.2013.1792

Dynamics of Consumer Adoption of Financial Innovation: The Case of ATM Cards

Botao Yang
Marshall School of Business, University of Southern California, Los Angeles, California 90089,
botao.yang@marshall.usc.edu

Andrew T. Ching
Rotman School of Management, University of Toronto, Toronto, Ontario M5S 3E6, Canada,
andrew.ching@rotman.utoronto.ca

We develop a structural consumer life-cycle model to investigate consumers' adoption and usage decisions of ATM cards. If consumers are forward-looking with a known discount factor, our framework can control for the heterogeneous life span faced by consumers of different ages, and hence measure adoption costs more accurately. Moreover, our framework can recover the monetary value of total adoption costs. To estimate our model, we use an Italian panel data set, which contains information on consumers' adoption decisions for ATM cards, and their cash withdrawal patterns before and after adoption. Our results suggest that one could significantly overestimate adoption costs for the elderly when ignoring their shorter life span. Our policy experiments show that a sign-up bonus targeted to the elderly could be much more effective if implemented as a limited-time offer rather than a permanent offer. Interestingly, if the sign-up bonus is permanent, younger consumers may strategically postpone adoption.

Keywords: financial innovation; adoption costs; ATM cards; cash demand model; consumer life-cycle model; limited time promotional offer; permanent promotional offer; dynamic programming
History: Received July 16, 2010; accepted June 20, 2013, by Pradeep Chintagunta, marketing. Published online in *Articles in Advance* November 13, 2013.

1. Introduction

The adoption of financial innovation[1] has been an important part of household finance in the past forty years. For instance, by adopting new financial instruments like ATM cards, credit or debit cards, consumers can manage their transaction balances more efficiently. ATMs have significantly reduced the transaction cost of withdrawing cash from a bank account; credit/debit cards have significantly reduced the need to carry cash for daily transactions. If consumers adopt these financial innovations, they can invest more in an interest-bearing asset and reduce the cost of inflation. This in turn can influence the aggregate demand for money and the social costs of inflation. Although this important implication is well recognized and documented (e.g., Attanasio et al. 2002, Alvarez and Lippi 2009), the literature seldom investigates consumers' adoption decisions of financial innovations. Papers that investigate this issue typically use a reduced-form approach to identify the determinants of adoption decisions. These papers have generated many useful insights, but they also suffer from one potential limitation: they do not consider the possibility that consumers can be forward-looking and take the future flow of benefits of adopting the new technology into account. The estimated costs of adopting a new technology can be very different depending on how consumers consider future benefits. Because of this potential shortcoming, these models may generate misleading predictions about how consumers might change their adoption decisions under new marketing environments or public policies.

In light of these implications, the first objective of this paper is to develop a structural framework to analyze forward-looking consumers' adoption decisions of a financial innovation and estimate their adoption costs. To achieve this goal, we assume consumers make their adoption decisions to maximize their total discounted future utility; we formulate the problem using dynamic programming. We use our model to study the consumer decision of ATM card adoption, one of the most important financial innovations in the past three decades.[2] To estimate

[1] Financial innovation is a broadly defined term. In addition to innovations related to new technologies that reduce transaction costs, the term commonly refers to new types of securities. Tufano (2003) provides an excellent survey of this literature.

[2] Paul Volcker, a former chairman of the Federal Reserve, commented in the *Wall Street Journal*'s (2009) Future of Finance Initiative that the ATM was the peak of financial innovation.

our model, we use a unique microlevel data set from the Bank of Italy. In addition to demographic characteristics and ATM card adoption decisions, the data contain detailed information about cash management decisions at the household level. Such information allows us to model how consumers manage cash before and after adopting ATM cards and impute the per period monetary benefits of adopting the innovation even if consumers choose not to adopt in a given period. This allows us to recover the monetary value of total adoption costs.

The Bank of Italy's unique data set, together with our model, also allows us to shed new light on a stylized fact of technology adoption behavior: Adoption rates of many new technologies (e.g., calculators, computers, video recorders, and ATMs) by the elderly are consistently much lower than those by younger age groups (e.g., Kerschner and Chelsvig 1984, Gilly and Zeithaml 1985). Previous literature tries to rationalize this fact by arguing that either the elderly have psychological resistance toward new technologies (technophobia), or that it is relatively difficult for them to learn how to use new technologies (e.g., Adams and Thieben 1991, Hatta and Liyama 1991, Rogers et al. 1996). However, one potential explanation has been neglected: the elderly have a much shorter remaining life span than the young, and consequently their total discounted benefits from adoption could also be much smaller. Ignoring differences in total discounted benefits from adopting a new technology could lead to biased estimates in adoption costs for different age groups and misleading policy implications.

To address this potential problem, the second objective of this research is to show how to use our framework to quantify the costs of adopting ATM cards by age. If we assume that consumers understand how age affects longevity, and that their discount factor (from future benefits of an ATM card) is known, we can use our structural model to control for heterogeneous expected discounted benefits from adoption, and hence measure adoption costs more accurately.[3] To illustrate what our model can accomplish, we fix the discount factor to a value (which is 0.943) calculated from consumers' responses to a survey question on when to cash a lottery, and estimate the rest of the parameters. For this discount factor, we find that total adoption costs remain relatively constant for people over age 50. However, if we assume consumers are myopic (i.e., discount factor = 0), estimated adoption costs would increase with age for people over age 50. Our results suggest that *if* consumers are forward-looking, ignoring this could lead to serious bias in the estimates of adoption costs.

The third research objective is to use our model to study the impact of a sign-up bonus that targets the elderly. It is common for companies to use a sign-up bonus to encourage consumer adoption of new technologies. To shed light on this promotion strategy, we conduct counterfactual experiments where banks give consumers who are age 50 and older a sign-up bonus for adopting ATM cards. We consider two ways to implement the sign-up bonus: (i) limited-time offer, and (ii) permanent offer (i.e., an offer with no expiration date). We argue that the limited-time offer would not change consumer expectations about future adoption costs, but the permanent offer would. Using our model, we show that these two marketing promotion strategies can lead to dramatically different outcomes: (1) the limited-time offer is much more effective in increasing adoption rates in the older group of consumers; (2) adoption rates for consumers who are younger than age 50 drop under the permanent offer. This is because the permanent offer creates an option value for consumers to postpone adopting. In particular, the permanent offer gives younger consumers an incentive to delay adopting ATM cards until they reach age 50. Our counterfactual experiments suggest that if consumers are forward-looking, ignoring their strategic delay behavior may cause banks to miscalculate net benefits of their marketing promotion campaigns.

To the best of our knowledge, this is the first dynamic structural model of technology adoption that (i) provides a framework that could potentially control for consumers' heterogeneous life horizon when measuring their adoption costs over their life cycle, (ii) models usage decisions of old and new technologies, and (iii) investigates the impacts of two ways of implementing a sign-up bonus to a particular age group: limited-time offer and permanent offer. Although the model appears to be tailored for ATM card adoption, with suitable modifications one can still apply our basic framework to study consumer adoption decisions of other financial innovations such as credit cards, debit cards, or other new payment instruments.

The remainder of this paper is structured as follows. Related literature is discussed in §2. Section 3 outlines relevant institutional details about ATMs and the banking system in Italy. Section 4 describes the

[3] One important limitation of this research needs to be highlighted. Unfortunately, like most empirical applications of dynamic programming models, our model does not have exclusion restrictions that can help identify consumers' discount factor (Magnac and Thesmar 2002, Fang and Wang 2012). Because of this limitation, we need to assume a discount factor; we do not attempt to test whether reduced adoption rates with age are attributable to higher adoption costs or shorter remaining life horizon. To achieve such identification, one needs to first carry out additional research to measure how consumers discount the future benefits generated by the new technology of interest.

microlevel panel data used in the estimation. Section 5 presents the model. The estimation algorithm, identification issues, and results are discussed in §6. Section 7 presents the conclusions.

2. Literature Review

2.1. Adoption of Financial Innovations

Here we study consumers' adoption decisions of financial innovations that reduce transaction costs for an individual's cash management. These financial innovations include ATMs (e.g., Attanasio et al. 2002, Huynh 2007), credit/debit cards (e.g., Borzekowski et al. 2008), online banking (e.g., Bauer and Hein 2006), and the automated clearing house (ACH) electronic payment system (e.g., Gowrisankaran and Stavins 2004, Ackerberg and Gowrisankaran 2006), etc. Among these papers, the paper by Bauer and Hein (2006) is more closely related to ours. They investigate whether risk aversion is a determining factor in consumers' adoption of online banking. They find evidence that this factor plays a key role in younger consumers' adoption decisions, but is not statistically significant in explaining older consumers' adoption behavior. Our research complements theirs by showing that shorter remaining life spans can be a plausible explanation for why older consumers are hesitant to adopt.[4]

Note that all of the above-mentioned papers use the static reduced-form approach to study consumer adoption decisions. They do not explicitly consider consumer expectations about future benefits generated by new technology. Therefore, it is difficult to perform certain policy experiments (e.g., limited-time offer versus permanent offer) based on their estimation results. Because our dynamic structural model explicitly takes consumers' forward-looking behavior into account, it is better suited for policy experiments that will change consumers' expectations about the future.

2.2. Dynamic Adoption Decision Models

There are several studies in marketing that also use the discrete choice dynamic programming framework and individual level data to study consumers' technology adoption decisions (e.g., Sriram et al. 2010, Ryan and Tucker 2012).[5] Unlike our modeling framework, their frameworks cannot recover the monetary value of total adoption costs; hence, they are less suitable for evaluating the impact of giving a specific amount of a sign-up bonus (or other monetary incentives) on adoption decisions.

Another main difference between our model and those in the existing literature is that we use a life-cycle model where consumers face a finite horizon, while the papers discussed above use an infinite horizon model.[6] Our consumer life-cycle model helps us improve the current understanding of adoption decisions for different age groups, an area that has been understudied in the previous literature. If we combine our model with other methods to calibrate consumers' discount factors, we could investigate whether the shorter life horizon faced by the elderly could be a plausible explanation for why they are reluctant to adopt new technologies.[7]

More broadly, the model is related to the health investment literature (e.g., Fang et al. 2007, Khwaja 2010). Their main point is that, from a dynamic perspective, better insurance may increase one's life expectancy, and consequently enhance one's incentive to invest in health. This dynamic effect counteracts the usual "moral hazard" story in static models that insurance induces more risky behavior. We share the idea that the longer the expected planning horizon (life span in our cases), the greater the incentive to invest in the improvement of one's welfare in the future. Ratchford (2001) also argues that as consumers become older, the return to new investments in knowledge becomes smaller. Yet Ratchford (2001) does not investigate this hypothesis empirically.

3. ATM/Banking System in Italy

ATMs were first introduced to Italy in the 1970s (Canato and Corrocher 2004). Bancomat, the Italian interbanking cash dispenser project, was promoted by the Italian Society for Interbanking Automation starting in 1983 (Orlandi 1989). During the time period studied in this paper, Bancomat was the only ATM network in Italy that allowed customers of all Italian banks to use any ATM in the network.[8] Many Italian

[4] The importance of ATMs has also attracted researchers to examine banks' ATM adoption decisions (e.g., Hannan and McDowell 1984, 1987; Saloner and Shepard 1995; Ishii 2007; Ferrari et al. 2010).

[5] Another line of literature uses aggregate level data to study adoption decisions of durable goods (e.g., Gordon 2009, Gowrisankaran and Rysman 2012, Nair 2007, Song and Chintagunta 2003), and experienced goods (e.g., Ching 2010a, Chen et al. 2013).

[6] Strictly speaking, every consumer should face a finite horizon problem as they cannot live forever. But an infinite horizon model could be a good proxy when the length of a period is short (e.g., day or week). Here an infinite horizon model would not be a good approximation because the length of a period in our data is two years. This modeling choice is driven by the slow diffusion of ATM cards, and the fact that our main data source is from a biannual survey. Note also that it is common for structural econometricians who study consumer life-cycle decisions to use a finite horizon dynamic programming framework (see, e.g., Keane et al. 2011).

[7] This hypothesis is also mentioned in Swanson et al. (1997). Their focus is different from ours. Instead of estimating adoption costs, their goal is to understand how consumer adoption of new technologies affects economic growth using a theoretical model. Consequently, the details of their model are very different from ours.

[8] For a more detailed discussion about the evolution of ATMs and branches in Italy, see Hester et al. (2001).

Table 1 Retail Trade, Debit Card Transactions, and Credit Card Transactions (Million Euros)

Year	1999	2000	2001	2002	2003	2004	2005	2006	2007
Italy retail trade value	687,525	697,523	716,356	735,889	738,225	754,206	748,384	757,452	761,114
All debit card POS transactions	14,792	18,855	23,059	32,427	27,899	31,667	33,633	35,181	36,880
All credit card POS transactions	18	22	25	28	30	36	40	42	45

Sources. Italian Institute of Statistics and Bank of Italy.

banks charge a small annual service fee for ATM cards. According to Attanasio et al. (2002), the average annual fee was €6.2 (1995 base) on a sample of 38 banks. There are no additional service charges when a customer uses an ATM owned by the bank which issues the ATM card. The normal bank account for day-to-day transactions in Italy is a checking account, which also serves as a savings account. Note that all checking accounts in Italy are interest bearing, and interest is received quarterly. An ATM card needs to be linked to a checking account before it can be used to withdraw cash. In Italy, banks are usually open from 08:30 to 16:00, with a one-hour break between 13:30 and 14:30; they are generally closed on weekends and holidays. On the day before a holiday, banks are often closed in the afternoon as well. Their restricted hours suggest that ATM cards could significantly reduce the transaction costs of withdrawing cash for many consumers.

Most ATM cards in Italy have the point of sale (POS) functionality, which means they can be used as debit cards at places like shopping malls and supermarkets, as long as merchants are equipped with POS terminals to process debit transactions. Table 1 shows the Italy retail trade value, debit card POS transactions and credit card POS transactions from 1999 to 2007. The proportion of retail trade sales paid by debit cards is very small. For example, in 2004, the total retail trade value in Italy was €754,206 million, while the debit card POS transactions were €31,677 million, accounting for 4.2% of the total retail trade. Even if we take into account that only ATM card holders can make debit card payments at POS terminals, the percentage remains small.[9] The values of credit card transactions are even smaller than those of debit card transactions.

The above evidence indicates that consumers in Italy seldom use the POS function of ATM cards. Moreover, credit card payments were uncommon in Italy for the period studied in this paper, i.e., 1991–2004 (Rolfe 2005). This is consistent with a recent comment by Lyman (2009), "Italy, for the most part, remains a cash economy." These institutional details are important when we implement our cash demand model in §6. They explain why we use consumption of nondurable goods as a proxy for consumption financed by cash.

[9] The ATM card adoption rate was 57.8% in 2004. If we suppose that 57.8% of the total retail trade sales came from those adopters in 2004, the percentage becomes $31{,}667/(754{,}206 * 0.578) = 7.3\%$.

4. Data

The data used in this paper combine four different data sets: (i) Survey of Household Income and Wealth, (ii) interest rate data at the regional level, (iii) number of ATMs at the provincial level, and (iv) population and survival probability data. The information in items (i)–(iii) is obtained from the Bank of Italy; data in item (iv) is obtained from the Italian Institute of Statistics.

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

The SHIW is a comprehensive socio-economic survey. This database contains information regarding: (1) individual characteristics and occupational status, (2) sources of household income, and (3) consumption expenditures.

These surveys were conducted annually from 1977 to 1985, and then biannually from 1987 to 1995 and from 1998 to 2004. We selected a panel from 1991 to 2004 as the sample used for estimation; 1991 is the first year that ATM card information appears in the SHIW, and 2004 is the latest year of data that is available to the public. The key questions for this study in the survey include the following:

1. *ATM card*: "Did you or any other member of your household have an ATM card?"

2. *Average amount of withdrawal at an ATM/bank counter*: "What was the average amount per withdrawal?"

Although the total number of households in this survey is around 8,000 in each wave, most are not included in our study because they do not satisfy our selection criteria. A household belongs to our sample if (i) anyone in the household has bank accounts; (ii) all are nonadopters of ATM cards in their first observed periods; (iii) we observe which province they live in; (iv) we observe them through 2004; and (v) they do not abandon ATM cards after adoption. We set these criteria for the following reasons. Requirement (i) is a necessary condition for a household to apply for ATM cards. Requirement (ii) stems from the focus of this research, i.e., studying

Table 2 Summary Statistics of Main Variables

Variable	1991	1993	1995	1998	2000	2002	2004
Age of household head	52.10	53.14	54.52	56.89	58.21	60.12	61.92
	(13.52)	(13.89)	(13.60)	(13.63)	(13.68)	(13.66)	(13.89)
Annual household income	47.27	46.51	47.21	51.06	51.99	50.24	50.92
	(22.91)	(24.50)	(24.97)	(28.06)	(28.64)	(27.06)	(27.17)
Annual consumption of nondurables	32.14	32.93	34.34	33.40	34.40	33.52	35.75
	(13.22)	(13.95)	(14.64)	(14.76)	(14.72)	(15.04)	(15.96)
Male head dummy	0.85	0.80	0.78	0.75	0.66	0.63	0.62
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 or above	3.10	3.93	3.93	4.87	5.06	5.06	5.24
Observations	387	483	534	534	534	534	534

Notes. We report means for all key variables except education. Numbers in parentheses are standard deviations, which are not reported for dummy variables. Income and consumption of nondurables are measured in 500 euros (2002).

adoption decisions. We use requirement (iii) because our data on the number of ATMs are broken down at the provincial level. Requirement (iv) ensures that we have a reasonably long panel of households. We set requirement (v) because there are very few households that abandoned ATM cards after adoption. Although a model that allows households to switch back to nonadoption is more general, it will significantly increase the size of the state space for the dynamic programming problem. Moreover, such incidences are rare not only for ATM cards, but also for other new technologies. This is shown by the fact that most of the previous research considers the adoption of new technology as an optimal stopping problem (e.g., Ryan and Tucker 2010, Song and Chintagunta 2003, Sriram et al. 2010). We also exclude a few outliers with relatively high income/consumption levels from the panel.[10] The total number of households excluded because of (v) or because they are outliers is only 22.

There are 387 households that satisfy these criteria in the 1991 survey. In addition, there are 96 and 51 new households in the 1993 and 1995 waves, respectively, that satisfy the criteria and which are included in our sample. Note that there are new households added in each wave of the SHIW, but none of them satisfies requirement (iii) after 1995 because our provincial level residence location data is limited to pre-1998 households.[11] Altogether, there are 534 households in our sample.

Table 2 shows the summary statistics of some key variables. The sample average age of the household head increases from 52 (in 1991) to 62 (in 2004) with standard deviations varied from 13.5 to 13.9. This shows that the data have significant variation in age, and therefore should be suitable for estimating a consumer life-cycle model. Both household income and consumption of nondurables show a slightly upward trend. The percentage of male household heads decreases, probably reflecting the demise of male heads and the longer average life span of females. This also indicates that some households may have changed heads over time. Of the total households, 55.62% are in the north or the central area of Italy, and 44.38% are in the south or islands area. The overall educational level of household heads in our sample is quite low in any given year: at most 5.24% hold a bachelor's degree or above; around 20% have a high school diploma; about 30% have a middle school diploma; almost 40%, the largest segment of the panel population, received an elementary school education; more than 5% received no education at all.

Table 3 summarizes the cumulative adoption rate of this panel. Because we only select nonadopters in 1991, the adoption rate is zero in that year. After

Table 3 Cumulative Adoption Rate of ATM Cards (1991–2004, Panel Households Only)

Year	1991	1993	1995	1998	2000	2002	2004
Adoption rate for all panel households	0	0.139	0.240	0.436	0.532	0.624	0.665
Adoption rate for household head under age 50 in 1991	0	0.185	0.297	0.535	0.628	0.717	0.760
Adoption rate for household head over age 65 in 1991	0	0.044	0.120	0.224	0.270	0.362	0.418

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

[10] We use the cutoffs €75,000 for annual income and €50,000 for annual consumption.

[11] Note that the size of one province in Italy is comparable to that of a county in the United States.

Table 4 Summary Statistics of Cash Withdrawal Behavior

Variable	1991	1993	1995	1998	2000	2002	2004
Fraction with a bank account	100	100	100	100	100	100	100
Fraction using ATMs	0	13.9	24.0	43.6	53.2	62.4	66.5
Average withdrawal at a bank	482.06	610.47	634.43	554.86	492.10	534.58	603.37
No ATM card	482.06	630.96	622.16	564.87	527.40	561.81	521.53
With ATM card	n.a.	467.98	679.42	538.53	441.83	507.02	679.50
Average withdrawal at an ATM	n.a.	220.11	240.53	234.78	244.87	226.73	251.49
Total number of trips (yearly basis)	18	15	11	16	19	15	18
To the bank (*no ATM card*)	18	16	11	19	21	15	19
To the bank (*with ATM card*)	n.a.	13	11	13	17	15	17
To the ATM	n.a.	29	28	36	58	42	43
Fraction of no. of withdrawals made at ATM (s)	n.a.	0.747	0.681	0.753	0.786	0.745	0.775
Number of households	387	483	534	534	534	534	534

Note. Average withdrawals are measured in 2002 euros.

that, the adoption rate increases by about 10% every two years (except for the 20% increase from 1995 to 1998, and the 4% increase from 2002 to 2004). Note that household heads over age 65 have a much lower adoption rate than those under age 50. This is consistent with the stylized fact reported in the technology adoption literature (e.g., Gilly and Zeithaml 1985).

Table 4 reports the sample means of some variables of interest that are related to cash management from 1991 to 2004 using our sample. All monetary variables are measured in euros using 2002 as the base year. Table 4 shows that the diffusion of ATM cards is relatively slow among consumers in our sample: It increases from 13.9% (1993) to 66.5% (2004). Note that (i) the average withdrawal at an ATM is much lower than that at a bank counter, and (ii) ATM card adopters make twice as many trips to an ATM compared to the number of trips to a bank for nonadopters. Note also that although ATM card adopters mainly use ATMs to withdraw cash (around 75% of total cash withdrawals), they still withdraw cash from bank counters. Table 5 shows the cash withdrawal behavior within households before and after adopting an ATM card. ATM adopters withdraw a smaller amount of cash on average after adopting an ATM card. These summary statistics provide preliminary evidence that consumers are doing some cost minimization based on the withdrawal technology available to them. Because ATMs reduce the transaction time per withdrawal, consumers choose to make more withdrawals and withdraw less cash each time. This allows them to maintain higher average balances in their accounts and hence earn more interest.

Table 5 Cash Withdrawal Behavior Within Household Before and After Adoption

Variable	No. of obs.	Mean	Std. dev.
Average bank counter withdrawal before adoption – Average bank counter withdrawal after adoption	283	−10.82	684.76
Average bank counter withdrawal before adoption – Average ATM withdrawal after adoption	288	300.04	307.24
Average bank counter withdrawal before adoption – Weighted average withdrawal after adoption	306	191.19	360.33

Note. Average withdrawals are measured in 2002 euros.

Following this argument, consumers with higher consumption of nondurables should benefit more by using ATMs because they need more cash to finance their consumption. Moreover, consumers who have higher income should gain more by adopting ATMs because they have higher opportunity cost of time. Therefore, in terms of adoption behavior, we expect that households with higher consumption of nondurables and higher income are more likely to adopt ATM cards. Our data support this implication. The average annual consumption of nondurables (income) for new adopters is about €3,000–€5,000 (€5,000–€10,000) higher than that of nonadopters.

4.2. Other Data Sources: Interest Rates, Number of ATMs, Survival Probabilities

To control for the opportunity cost of time, we use data on interest rates and ATM density (measured by the number of ATMs per 1,000 population). The nominal interest rate on current account deposits is drawn from the Bank of Italy's public database, which is available at http://bip.bancaditalia.it/4972unix/homebipeng.htm. The number of ATMs by province is provided by the Bank of Italy. Note that the interest rate varies across the 20 regions in Italy. Table 6 shows the average interest rate and average ATM density.[12] The average interest rate increases from 8.9% in 1991 to 10.3% in 1993 and then steadily

[12] 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 estimation.

Table 6 **Interest Rate and Average Number of ATMs per 1,000 Population**

Year	1991	1993	1995	1998	2000	2002	2004
Interest rate	8.872 (0.489)	10.274 (0.401)	6.829 (0.263)	3.811 (0.206)	1.862 (0.190)	1.647 (0.170)	0.916 (0.115)
No. of ATMs per 1,000 population	0.141 (0.100)	0.208 (0.125)	0.246 (0.150)	0.497 (0.226)	0.573 (0.227)	0.648 (0.235)	0.646 (0.236)

Notes. Numbers in parentheses are standard deviations. There are 20 regions in Italy and interest rate is region-specific. There were more than 90 provinces in Italy between 1991 and 2004; the number of ATMs is province-specific.

decreases to 0.9% in 2004.[13] The standard deviation of interest rates decreases from 0.489 in 1991 to 0.115 in 2004, indicating that it differs across regions. The ATM density increases steadily from 0.14 in 1991 to 0.65 in 2002, and then remains at 0.65 in 2004. Note that the standard deviation of the ATM density increases from 0.100 to 0.236, indicating that it becomes more disparate across provinces over time.

Because we use a life-cycle model to study the data, we use age-specific survival probability to control for the expected life horizon. We obtain the data from the Italian Institute of Statistics (http://demo.istat.it/index_e.html). Figure 1 shows the 2004 Italian national level survival probability conditional on age (the probability of surviving until $t+1$ at age t). It is a decreasing and nonlinear function of age.

5. Model

Before explaining the mathematical model, we briefly discuss the benefits and costs associated with adopting an ATM card. The benefits from adopting an ATM card mainly come from the reduced transaction cost of withdrawing cash, more interest earned (as one can afford to make more withdrawals and put more savings in an interest-bearing bank account on average), and increased convenience (24-hour ATMs versus daytime human tellers). On the other hand, there are two types of costs involved with adopting an ATM card: (i) monetary costs including ongoing annual and transaction fees, and (ii) nonmonetary costs including learning, hassle, psychological costs, etc. Note that bank customers can use their ATM cards at their own banks for free. Therefore, it seems that to a large extent, consumers can manage to avoid transaction fees. Although we do not observe the amount of annual fees paid by each household, this should not pose a major problem because we are interested in recovering total adoption costs (i.e., monetary plus nonmonetary adoption costs). Next we discuss the model in detail.

[13] For more details, see the technical appendix of Huynh (2007).

5.1. Adoption Benefits: A Cash Demand Model

To quantitatively measure the cost savings from adopting an ATM card, we use an extension of the Baumol–Tobin cash demand model (Baumol 1952, Tobin 1956).[14] It is a cash inventory management model where a consumer chooses the average amount of withdrawal, m, to minimize the sum of transaction costs and interest losses, TC.[15] Interest losses are the forgone interest from holding cash rather than putting it in an interest-bearing bank account (recall that checking accounts are interest-bearing and the highest observed nominal interest rate is 10.3% in 1993). The objective function is shown in the following equation:

$$\min_m TC_j = w \cdot T_j \cdot \left(\frac{c_j}{m}\right) + R \cdot \left(\frac{m}{2}\right), \tag{1}$$

where $j=0$ means without ATM cards and $j=1$ means with ATM cards; w is the unit time cost of transaction (opportunity cost of time); T_j is the transaction time of each withdrawal given technology j (note that $T_0 > T_1$); c_j is the consumption financed by cash in each time period given technology j, so c_j/m is the average number of withdrawals in each period; and R is the interest rate. The first term, $w \cdot T_j \cdot (c_j/m)$, captures the total transaction costs in each period. The second term, $R \cdot (m/2)$, measures interest losses because the average cash inventory in hands is $m/2$. There is a trade-off between reducing transaction costs and avoiding interest losses: a larger m means a smaller number of withdrawal transactions, but more interest losses in each period. Simple algebra gives us the optimal amount of cash withdrawal and the minimized total cost:

$$m_j^* = \sqrt{2w \cdot T_j \cdot c_j / R} = \sqrt{2T_j} \cdot \sqrt{w \cdot c_j / R}, \tag{2}$$

$$TC_j^* = \sqrt{2w \cdot T_j \cdot c_j \cdot R} = \sqrt{2T_j} \cdot \sqrt{w \cdot c_j \cdot R}. \tag{3}$$

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^*):

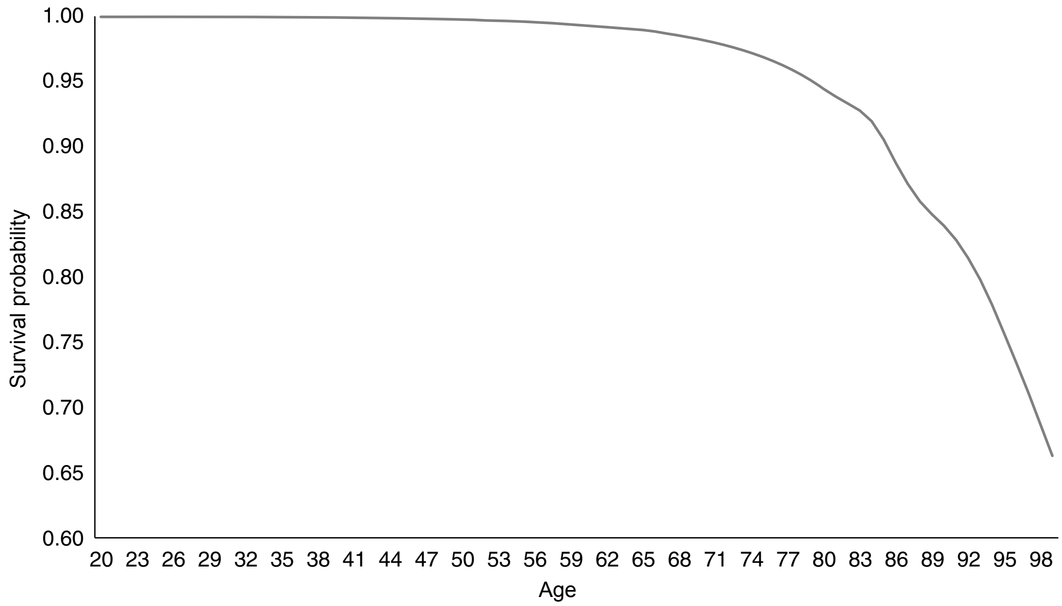
$$\Delta TC = TC_0^* - TC_1^* = (\sqrt{2T_0 \cdot c_0} - \sqrt{2T_1 \cdot c_1}) \cdot \sqrt{w \cdot R}. \tag{4}$$

Section 6.2 discusses how we use household income and consumption of nondurables to approximate w and c_j.

[14] This model is also called the money demand model in the monetary economics literature.

[15] Alvarez and Lippi (2009) extend the basic Baumol–Tobin model to a dynamic environment that focuses on precautionary motives. However, they do *not* model adoption decisions of ATM cards. Instead, they study the impact of ATMs on the money demand and welfare costs of inflation, taking ATM card adoption decisions as exogenously given.

Figure 1 **Age-Specific Survival Probability in Italy**



5.2. ATM Card Adoption: An Optimal Stopping Problem

Following the previous literature of new technology adoption, we model consumer ATM card adoption decisions as an optimal stopping problem. Let a_{it} be the adoption status in period t, where $a_{it} = 1$ if the head of household i chooses to adopt ATM cards; $a_{it} = 0$ otherwise. Note that a_{it} is a choice variable at time t, but it becomes one of the state variables at time $t+1$.

Let $S_{it} = (a_{it-1}, \bar{S}_{it})$ be the vector of state variables for household i at time t. In addition to a_{it-1}, the set of state variables, $\bar{S}_{it}$, includes year (t), age (age_{it}), number of ATMs per 1,000 population (n_{it}), income (y_{it}), consumption of nondurables (c_{it}), interest rate (R_{it}), age-specific survival probability (z_{it}),[16] and other household demographic characteristic (X_{it}). The utility function of a potential adopter i (with $a_{it-1} = 0$) is assumed to be

$$U_{it}(a_{it}; a_{it-1} = 0, \bar{S}_{it}) = \begin{cases} B(\Delta TC_{it}(\bar{S}_{it}), n_{it}) + \psi(t) - F_{it} + e_{i1t} & \text{if } a_{it} = 1, \\ e_{i0t} & \text{if } a_{it} = 0, \end{cases} \tag{5a}$$

where ΔTC_{it} is the cost saving from adoption defined in the previous subsection; n_{it} is the number of ATMs per 1,000 population; $\psi(t)$ captures the ATM technological progress over time;[17] F_{it} is the one-time lump sum adoption cost; and e_{i0t} and e_{i1t} are unobserved independent and identically distributed (i.i.d.) taste shocks. Because only utility difference matters, we normalize the mean utility of waiting (i.e., $a_{it} = 0$) to zero. The utility function of a consumer who has already adopted ATM cards (i.e., $a_{it-1} = 1$) is assumed to be

$$U_{it}(a_{it} = 1; a_{it-1} = 1, \bar{S}_{it}) = B(\Delta TC_{it}(\bar{S}_{it}), n_{it}) + \psi(t). \tag{5b}$$

Note that there is no taste shock associated with $U_{it}(1; 1, \bar{S}_{it})$ because we assume that this is an optimal stopping problem (i.e., once someone adopts, he or she will always keep the ATM card). Also, $U(0; 1, \bar{S}_{it})$ does not exist because we assume that adoption is an absorbing state.

Let z_{it} be the survival probability of the head of household i at age_{it}, and β be the discount factor. We assume that in each period, nonadopters choose a_{it} to maximize their total expected discounted utility. This dynamic adoption decision problem can be formulated using dynamic programming. The value function for a potential adopter i (i.e., $a_{it-1} = 0$) can then be written as

$$V(a_{it-1} = 0, \bar{S}_{it}) = E_e \max\{V_0(a_{it-1} = 0, \bar{S}_{it}), V_1(a_{it-1} = 0, \bar{S}_{it})\}, \tag{6}$$

where E_e is the expectation with respect to the error terms, e_{ijt}'s.

A potential adopter i's alternative-specific value of waiting in time t (i.e., $a_{it} = 0$) is

$$\begin{aligned} V_0(a_{it-1} = 0, \bar{S}_{it}) &= U(0; 0, \bar{S}_{it}) + z_{it+1}\beta \int V(a_{it} = 0, \bar{S}_{it+1})\, dF(\bar{S}_{it+1} \mid \bar{S}_{it}) \\ &= z_{it+1}\beta \int V(a_{it} = 0, \bar{S}_{it+1})\, dF(\bar{S}_{it+1} \mid \bar{S}_{it}) + e_{i0t}, \end{aligned} \tag{7}$$

[16] Note that we treat the survival probability as a function of age only. Therefore, once we include age_{it}, adding z_{it} to the problem does not increase the size of the state space.

[17] For example, $\partial\psi(t)/\partial t > 0$ means the ATM technology has improved over time; it might become more reliable, secure, or versatile (with more functions).

and his alternative-specific value of adopting an ATM card in time t $(a_{it}=1)$ is

$$\begin{aligned} &V_1(a_{it-1}=0,\bar{S}_{it})\\ &\quad=U(1;0,\bar{S}_{it})+z_{it+1}\beta\int V_1(a_{it}=1,\bar{S}_{it+1})\,dF(\bar{S}_{it+1}\mid\bar{S}_{it})\\ &\quad=B(\Delta TC_{it}(\bar{S}_{it}),n_{it})+\psi(t)-F_{it}\\ &\qquad+z_{it+1}\beta\int V_1(a_{it}=1,\bar{S}_{it+1})\,dF(\bar{S}_{it+1}\mid\bar{S}_{it})+e_{i1t}. \end{aligned} \tag{8}$$

For a household that has already adopted in previous periods, the alternative-specific value of holding an ATM card in time t $(a_{it}=1)$ is

$$\begin{aligned} &V_1(a_{it-1}=1,\bar{S}_{it})\\ &\quad=U(1;1,\bar{S}_{it})+z_{it+1}\beta\int V_1(a_{it}=1,\bar{S}_{it+1})\,dF(\bar{S}_{it+1}\mid\bar{S}_{it})\\ &\quad=B(\Delta TC_{it}(\bar{S}_{it}),n_{it})+\psi(t)\\ &\qquad+z_{it+1}\beta\int V_1(a_{it}=1,\bar{S}_{it+1})\,dF(\bar{S}_{it+1}\mid\bar{S}_{it}). \end{aligned} \tag{9}$$

Since we do not allow households to abandon ATM cards, there is no expression for $V_0(a_{it-1}=1,\bar{S}_{it})$.

6. Estimation

We use the nested fixed point algorithm to estimate the structural parameters of the model (Rust 1987). We assume that if $age_{it}>\overline{age}$, then $z_{it}=0$. This allows us to use the backward induction approach to solve for the value function.[18] Following Rust and Phelan (1997), we set $\overline{age}=102$. Note that the oldest observed age in our sample is 97.

6.1. Econometric Specification

6.1.1. Adoption Benefits and Adoption Costs. We now explain in detail how to measure adoption benefits per period in monetary values. To continue from §5.1, we assume that the opportunity cost of time, w_{it}, is a function of household income, y_{it}, and that the amount of consumption financed by cash, $c_{j,it}$, is a function of consumption of nondurables, c_{it}; the cash withdrawal technology is captured by μ_j. In our econometric specification, we use $w_{it}=\lambda\cdot y_{it}$, and $c_{j,it}=\mu_j\cdot c_{it}$, where λ and μ_j are constants and $0<\mu_j\le 1$. ATM card holders might make purchases through POS transactions, so a smaller proportion of their consumption is paid by cash. Therefore, we allow $\mu_0\neq\mu_1$, which indicates that the proportion of consumption of nondurables financed by cash is conditional on the ATM card adoption status. With these specifications, we define $\rho_j=\sqrt{2\lambda\mu_j T_j}$. It then follows that

$$m^*_{jit}=\rho_j\cdot\sqrt{y_{it}c_{it}/R_{it}}, \tag{10}$$

$$\Delta TC_{it}=(\rho_0-\rho_1)\cdot\sqrt{y_{it}c_{it}R_{it}}. \tag{11}$$

We assume that $c_{j,it}$ is a function of c_{it} for four reasons. First, as discussed in §3, during the period studied in this paper, ATM cards in Italy were mainly used for cash withdrawals. Second, consumption of durables is less than 10% of consumption of nondurables for the households in our sample. Third, around 70% of the observations have zero consumption of durables. Fourth, people might use credits to purchase more expensive durable goods. So we believe that (a certain proportion, μ_j, of) consumption of nondurables is a reasonable approximation of consumption financed by cash.

However, we cannot directly apply the above equations to the data. One complication is that ATM adopters can withdraw cash from both bank counters and ATMs while nonadopters can only do bank counter withdrawals. Table 4 shows that ATM adopters still use bank counters to withdraw cash for around 25% of total withdrawals. To accommodate this feature, we need to modify our cash demand model as follows. Define the share of consumption financed by ATM withdrawals as

$$\begin{aligned} s_{it}&=\text{value of ATM withdrawals}\\ &\quad/(\text{value of ATM withdrawals}\\ &\qquad+\text{value of bank withdrawals}). \end{aligned}$$

We can then rewrite the expression for ΔTC as

$$\Delta TC_{it}=s_{it}\cdot(\rho_0-\rho_1)\cdot\sqrt{y_{it}c_{it}R_{it}}.\text{[19]} \tag{12}$$

We further assume that

$$s_{it}=s+\nu_{it}, \tag{13}$$

where ν_{it} is an i.i.d. error term with mean zero.

To measure ΔTC_{it}, we also need to know ρ_0 and ρ_1. To estimate them, we add an error term to Equation (10),

$$m^*_{jit}=\rho_j\cdot\sqrt{y_{it}c_{it}/R_{it}}+\varepsilon_{jit}. \tag{10'}$$

[18] Aguirregabiria and Mira (2010) and Keane et al. (2011) provide excellent recent surveys of the nested fixed point algorithm and other alternative methods to estimate dynamic programming models.

[19] An intuitive way to interpret this new equation is to divide total cash spent in each time period into two parts: (i) cash withdrawn from ATMs, and (ii) cash withdrawn from bank counters. ATM adopters have efficiency advantages over nonadopters only for the first part, which takes up s share of the total cash spent. Equation (1) then becomes $\min_m TC_j=w\cdot T_j\cdot((s\cdot c_j)/m)+s\cdot R\cdot(m/2)$. We can easily derive Equation (12) from the optimality condition.

For the expected benefit function, $B(\Delta TC_{it}, n_{it})$, we assume that

$$\begin{aligned} B(\Delta TC_{it}, n_{it}) &= E[\alpha_{TC} \cdot \Delta TC_{it}] + \alpha_n \cdot n_{it} \\ &= E[\alpha_{TC} \cdot s_{it} \cdot (\rho_0 - \rho_1) \cdot \sqrt{y_{it} c_{it} R_{it}}] + \alpha_n \cdot n_{it}, \quad (14) \end{aligned}$$

where α_{TC} can be interpreted as the marginal utility of income because ΔTC_{it} is expressed in monetary value.[20]

Before consumers adopt ATM cards, it is plausible that they know their own $(y_{it}, c_{it}, R_{it}, n_{it})$. Yet there could be many unforeseen factors that affect s_{it}. As a result, we assume that they do not observe s_{it} and hence the expectation above comes down to taking expectation with respect to s_{it}. Then Equation (14) becomes

$$B(\Delta TC_{it}, n_{it}) = \alpha_{TC} \cdot s \cdot (\rho_0 - \rho_1) \cdot \sqrt{y_{it} c_{it} R_{it}} + \alpha_n \cdot n_{it}. \quad (14')$$

To capture the technological progress of ATMs, we specify $\psi(t) = \psi * ((t-1)/t)$. We further specify the adoption cost as

$$\begin{aligned} F_{it} = F_0 &+ \alpha_{\text{old}} \cdot (age_{it} - 50 \mid age_{it} > 50) + \alpha_{\text{young}} \\ &\cdot (50 - \min\{age\} + 1 \mid age_{it} > 50) + \alpha_{\text{young}} \\ &\cdot (age_{it} - \min\{age\} + 1 \mid age_{it} \le 50), \quad (15) \end{aligned}$$

where $\min\{age\}$, the minimum observed age of the household head in our sample, is 20.

The above formulation allows the adoption costs to vary with age and the coefficients of age-specific adoption costs to be different in two age groups: α_{old} (α_{young}) is for the over (less than) 50 age group. We choose this functional form because it is relatively convenient to interpret the meanings of these two key coefficients in Equation (15). As for the choice of age = 50 as the cutoff, we also tried 60 and 65 as cutoff points in static model estimations. The qualitative results do not change and the goodness-of-fit of these two alternatives is inferior. This suggests that 50 may be a good choice. Note also that Italians usually retire in their fifties (e.g., see *BBC News* 2007) and people's cost structure might change (physiologically and psychologically) after retirement.

6.1.2. Evolution and Consumer Expectation About State Variables. We assume that n_{it}, y_{it} and c_{it} each follow an independent Markov process. Regarding consumer expectations about the evolution of the state variables, we believe that consumers are generally better at forecasting "internal" variables, such as y_{it} and c_{it}, than "external" variables, such as improvements of new technology and interest rates.[21] Yet one external variable, n_{it}, is likely an exception because it can be easily observed and is probably one of the key variables that consumers pay attention to. (This is why we allow n_{it} to enter the utility function directly.) We, therefore, assume that consumers have rational expectations about y_{it}, c_{it}, and n_{it}; i.e., they know the stochastic processes that govern the evolution of these variables. For simplicity, we assume consumers treat R_{it} and $\psi(t)$ as time invariant when solving their dynamic programming problem.[22] Finally, X_{it}, which includes gender, location, and education, is usually fixed over time, except when the household head changes. In the model, we therefore assume that changes of household head always come as a surprise. Hence, when solving the dynamic programming problem, consumers also treat X_{it} as time invariant.

We specify the stochastic processes of y_{it}, c_{it}, and n_{it} as follows:

$$n_{it+1} = \underset{(0.005)}{0.056} + \underset{(0.010)}{0.986} * n_{it} + \varepsilon_n, \quad R^2 = 0.957; \quad (16)$$

$$\begin{aligned} y_{it+1} = &\underset{(0.014)}{0.714} * y_{it} + \underset{(0.042)}{0.632} * age_{it+1} \\ &- \underset{(0.0005)}{0.0063} * age^2_{it+1} + \varepsilon_y, \quad R^2 = 0.895; \quad (17) \end{aligned}$$

$$\begin{aligned} c_{it+1} = &\underset{(0.015)}{0.693} * c_{it} + \underset{(0.028)}{0.468} * age_{it+1} \\ &- \underset{(0.0003)}{0.0045} * age^2_{it+1} + \varepsilon_c,^{23} \quad R^2 = 0.916. \quad (18) \end{aligned}$$

Note that the R^2's of these equations range from 0.895 to 0.957, indicating that they are reasonable approximations of the evolution processes.

[20] In the results section, we use α_{TC} to convert the estimated adoption costs to monetary value.

[21] By internal variables, we mean consumers have some control over them (even though we might not model those decisions explicitly). By external variables, we mean individual consumers do not have control (or have very little control) over them.

[22] 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 also could not 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). We view this as evidence that it may not be reasonable to assume that consumers can forecast interest rates well. Because it is not clear how consumers form expectations about future interest rates, we assume that they treat it as time invariant in our application for simplicity.

[23] It is possible that the adoption of ATM cards may increase consumption because adopters have easier access to cash. If this effect is important and consumers do anticipate it, one should include a_{it} in the consumption evolution process. In a robustness check (available upon request), we find that adopting ATM cards increases consumption by 4.66% on average. This would convert to a 2.30%

We discretize n_{it}, y_{it}, and c_{it} into separate grid points. The range of n_{it} is from 0 to 1.5. We evenly discretize it into 16 points $(0, 0.1, 0.2, \ldots, 1.5)$. The range of y_{it} (c_{it}) is from 0 to 150 (0 to 100). We evenly discretize y_{it} and c_{it} into 11 grid points; each unit corresponds to €500. In addition, we discretize R_{it} into 9 grid points. We also have a time trend $\psi(t)$, which takes 6 different values corresponding to 6 survey waves from 1993 to 2004. As a result, our state space has 104,544 $(= 16 * 11 * 11 * 9 * 6)$ grid points.

6.1.3. Likelihood with Unobserved Heterogeneity: A Concomitant Variable Latent Class Model. Let t_i^0 be the first observed time period of consumer i, t_i^T be the last observed time period of consumer i, and t_i^a be the time period that consumer i adopts. Again, $a_{i,t} = 0$ means consumer i chooses not to adopt at time t, and $a_{i,t} = 1$ means consumer i chooses to adopt at time t. We allow $(\rho_j, s, \alpha_n, F_0)$ to be heterogeneous, and use the latent class approach to capture it. In other words, we allow $(\rho_j^k, s^k, \alpha_n^k, F_0^k)$, for $k = 1, \ldots, K$. Let k be the index for the unobserved type of consumers. Each type has its own set of parameters for the cash demand model and dynamic adoption model. Let $L_{it}(k)$ be the individual likelihood for type k and π_i^k be the probability of being type k. Let $f(m_{jit}^* \mid S_{it}, k)$ be the density of observed m_{jit}^* (m_{1it}^* is average ATM withdrawal; m_{0it}^* is average bank withdrawal). We assume that the measurement errors in the cash demand model are i.i.d. across time and consumers. Let $g(s_{it} \mid s, k)$ be the density of observed s_{it} (share of ATM withdrawals).

For $t < t_i^a$,

$$L_{it}(k) = \Pr(a_{it} = 0 \mid \bar{S}_{it}, k) \cdot f(m_{0it}^* \mid S_{it}, k). \tag{19}$$

For $t = t_i^a$,

$$L_{it}(k) = \Pr(a_{it} = 1 \mid \bar{S}_{it}, k) \cdot f(m_{1it}^* \mid S_{it}, k) g(s_{it} \mid s, k). \tag{20}$$

For $t > t_i^a$,

$$L_{it}(k) = f(m_{1it}^* \mid S_{it}, k) \cdot g(s_{it} \mid s, k). \tag{21}$$

We adopt the concomitant variable latent class segmentation approach (Dayton and McReady 1988, Gupta and Chintagunta 1994) and specify the probability that household i belongs to segment k, π_i^k, as follows:[24]

$$\pi_i^k = \frac{\exp(\gamma_{0,k} + \gamma_{X,k} * X_{i,t})}{1 + \sum_{k=1}^{K} \exp(\gamma_{0,k} + \gamma_{X,k} * X_{i,t})}. \tag{22}$$

The demographic variables $(X_{i,t})$ include education, gender, and location. Yet on a few occasions, the household head probably changed because the original household head died. Consequently, X_i could change over time. If the change happened at time t'_i, we allow π_i^k to be different in the prechange and postchange stages, and the likelihood contribution of L_i becomes

$$\left[\sum_k \pi_i^k \cdot \prod_{t=t_i^0}^{t'_i} L_{it}(k)\right] * \left[\sum_k \pi_i'^k \cdot \prod_{t=t'_i+1}^{t_i^T} L_{it}(k)\right]. \tag{23}$$

For the error terms in the cash withdrawal equations, we assume that $\varepsilon_{ijt} \sim N(0, \sigma_{\varepsilon_j}^2)$. For the error term in the share of ATM transactions, we assume that $v_{it} \sim N(0, \sigma_v^2)$. Also, following Rust (1987), we assume that the unobserved taste shocks in the adoption equations, e_{i0t} and e_{i1t}, are i.i.d. extreme value distributed. Therefore,

$$\begin{aligned}
\Pr(a_{it} = 1 \mid \bar{S}_{it}, k) &= Pr(V_1^k(0, \bar{S}_{it}) > V_0^k(0, \bar{S}_{it})) \\
&= \frac{\exp(\bar{V}_1^k(0, \bar{S}_{it}))}{\exp(\bar{V}_0^k(0, \bar{S}_{it})) + \exp(\bar{V}_1^k(0, \bar{S}_{it}))}, \\
\Pr(a_{it} = 0 \mid \bar{S}_{it}, k) &= \Pr(V_1^k(0, \bar{S}_{it}) \le V_0^k(0, \bar{S}_{it})) \\
&= \frac{\exp(\bar{V}_0^k(0, \bar{S}_{it}))}{\exp(\bar{V}_0^k(0, \bar{S}_{it})) + \exp(\bar{V}_1^k(0, \bar{S}_{it}))},
\end{aligned}$$

where $\bar{V}_j^k(0, \bar{S}_{it}) = V_j^k(0, \bar{S}_{it}) - e_{ijt}$, $j = 0, 1$.

6.2. Identification (Intuitive Arguments)

Identification for the cash demand model is relatively straightforward. Our data set exhibits large variations in household income and consumption of nondurables as shown in Table 2. Our data also indicate significant differences between bank withdrawals and ATM withdrawals as shown in Tables 4 and 5. In addition, there is large time series and some cross-sectional (by region) variation in interest rates as shown in Table 6. These sources of data variation, together with the observed ATM card adoption status of each household and the corresponding withdrawal behavior, allow us to identify the parameters of the cash demand model.

Identification for the adoption costs is less obvious. Initially, it may seem difficult to disentangle the relative importance of the adoption benefits explanation and the traditional explanations that emphasize adoption costs. Our hypothesis implies that the total expected discounted benefits of adoption decrease with age; the traditional hypotheses imply that adoption costs increase with age. Both approaches can

increase in adoption benefits. Therefore, we do not expect that including a_{it} in the consumption process would have a significant impact on our results.

[24] An alternative and more flexible approach is to allow $X_{i,t}$ to enter the utility function directly, and treat π_i^k's as parameters to be estimated. The disadvantage is that it will dramatically increase the computational burden of the estimation algorithm because each value of $X_{i,t}$ requires us to solve a different dynamic programming problem. On the other hand, the concomitant latent class approach is not as restrictive as it may seem. Although there are only K latent classes in our model, our approach still allows us to capture the marginal impacts of $X_{i,t}$ on adoption decisions via its effects on π_i^k.

explain why consumers become more reluctant to adopt as they become older. If all we observe are consumer adoption decisions at different ages, it would be impossible to separately measure the relationship between costs and age versus the relationship between benefits and age. To uncover the relationship between adoption costs and age, we also need to (i) assume that the consumer discount factor and the survival probability (which depends deterministically on age) are known, so that we can calculate the total discounted benefits of adopting ATM cards;[25] and (ii) observe some factors that will shift the adoption benefits (i.e., benefit shifters) but not the adoption costs for any given age.[26] In general, the more data variation we have in benefit shifters, the more precisely we can estimate the adoption cost parameters.

In our application, the cash demand model generates the per period adoption benefits over time for each household, which depend on interest rates, household income, and consumption of nondurables. These three variables can be considered benefits shifters. Given our assumption about the discount factor and the age-specific survival probability, we can combine the per period adoption benefits and stochastic evolution processes of y_{it}, c_{it}, and n_{it} to compute the total discounted adoption benefits. If individual level data provide variation in benefit shifters R_{it}, y_{it}, and c_{it}, when we fix an age group, then we can identify the adoption costs for this age group. As shown in the data section, our data set indeed provides variations in these variables. However, to estimate adoption costs by age, we will certainly require a very large amount of data to get precise estimates. We therefore opt to use a parsimonious approach by specifying a functional form relationship, as shown in Equation (15). We present more formal identification arguments in Appendix A.[27]

6.3. Estimation Results

When estimating models with forward-looking agents, researchers typically fix the discount factor according to the interest rate because this parameter is usually difficult to identify (Keane et al. 2011). As with most previous work, we will not estimate the discount factor in our maximum likelihood procedure. Instead of calibrating it according to the interest rate, we use the responses to one question asked in SHIW, which aims at soliciting consumers' time preferences. In Appendix B, we show this survey question and the distribution of the responses. We set the annual discount factor at the average response to this question, which is 0.943. Note that the discount factor can be context specific. It is unclear whether the discount factor solicited by the survey question necessarily applies to ATM card adoption decisions. Therefore, readers should remain cautious when reading our results below.

6.3.1. Which Model Performs the Best? In total, we estimate three specifications based on models with one, two and three latent segments. According to both Akaike information criterion (AIC) and Bayesian information criterion (BIC), the model with two segments produces the best fit.[28] Figure 2 shows that the two-segment specification fits the adoption rates over time very well. In terms of goodness-of-fit for the cash demand model, the R-squares are 0.68 and 0.48 for the ATM (868 observations) and bank counter (1,870 observations) withdrawals, respectively. Given that our cash demand model relies only on four parameters to fit the withdrawal patterns, we find the R-squares reasonably satisfactory. Because the two-segment model produces better fit, we will focus our discussion on it and use it to conduct counterfactual experiments.

6.3.2. Parameter Estimates. Table 7 shows the estimation results for the two-segment model. Most of the parameters in the adoption model and cash demand model are statistically significant, except for α_n^1. The point estimate of ψ is positive, which suggests that consumers care about the technological improvement of ATMs. The point estimate of α_n^2 is positive, which implies that segment 2 consumers care about the density of ATMs. According to the point estimates, $(\rho_0^k - \rho_1^k) > 0$. It follows from Equation (11) that consumers can reduce total transaction costs of managing cash (i.e., $\Delta TC > 0$) if they adopt ATM cards. The point estimate of α_{TC} is positive, which suggests that ΔTC (generated from the cash demand model) is a good measure of adoption benefits. One advantage of having a cash demand model is that we can impute the potential adoption benefits for consumers who choose not to adopt ATM cards. Table 8 summarizes the monetary values of ΔTC over time for adopters and nonadopters, respectively. As expected, adopters generally save more than nonadopters by using ATM cards. Finally, because the interest rate starts to decrease after 1993, the average

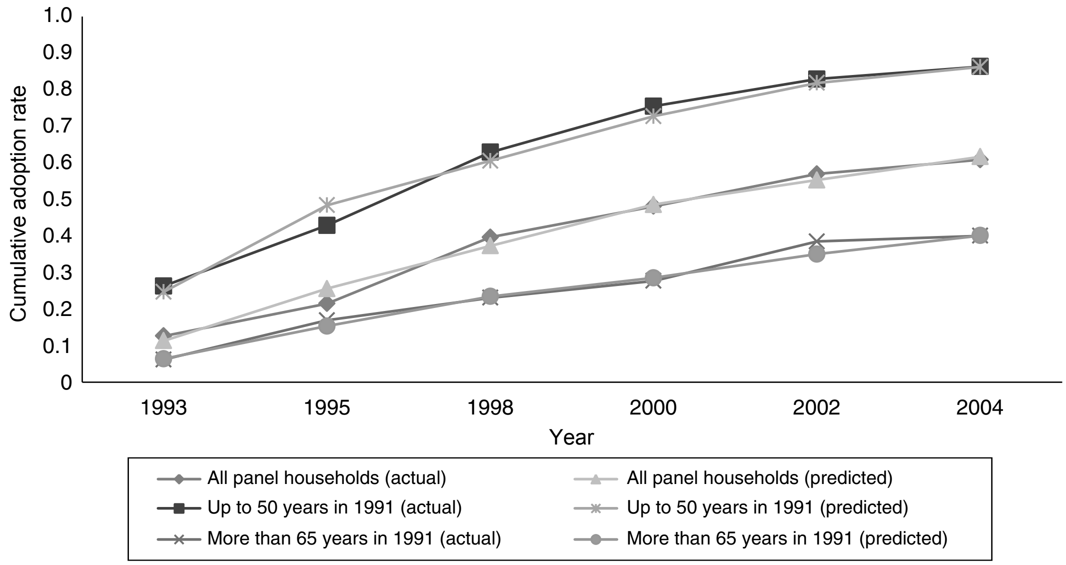
[25] Note that although the planning horizon is stochastic, it is not estimated. We assume that consumers use the observed survival probability by age (which is publicly available) to set up their planning horizon.

[26] Strictly speaking, to identify adoption costs, we need to observe mixed adoption decisions. If no one adopts for a given age, even if we observe a range of adoption benefits, we can only identify the lower bound of the adoption costs at that age.

[27] For a more general discussion about identification for this class of dynamic models, see Arcidiacono and Miller (2013).

[28] The results for one- and three-segment models are available upon request.

Figure 2 Cumulative Adoption Rate: Actual and Predicted



value of ΔTC gradually falls from €14.57 (€10.45) in 1993 to €4.18 (€3.00) in 2004 for segment 1 (segment 2) consumers.

Table 7 Main Estimation Results

	$\beta = 0.943$, average self-reported beta		Static model	
Parameter	Estimate	S.E.	Estimate	S.E.
ψ (time trend)	1.787**	0.260	6.173**	1.083
α_{TC} (adoption benefit)	0.032**	0.004	0.087**	0.011
s^k $(k = 1)$	0.877**	0.201	0.626	0.774
ρ_0^k $(k = 1)$	5.350**	1.382	11.020**	1.545
ρ_1^k $(k = 1)$	2.248**	0.235	5.591**	0.349
α_n^k (no. of ATMs, $k = 1$)	−0.050	0.544	−2.122	1.804
s^k $(k = 2)$	0.748**	0.039	0.754**	0.038
ρ_0^k $(k = 2)$	3.248**	0.143	3.193**	0.126
ρ_1^k $(k = 2)$	0.640**	0.023	0.661**	0.021
α_n^k (no. of ATMs, $k = 2$)	0.219*	0.093	0.725*	0.314
F_0^1 (adoption cost in segment 1)	15.551**	1.918	7.418**	0.964
$\log(F_0^2 - F_0^1)$ (log(adoption cost difference))	−1.881*	0.812	−3.251	3.579
$\log(\sigma_{\epsilon_0})$	6.975**	0.020	6.953**	0.022
$\log(\sigma_{\epsilon_1})$	5.663**	0.023	5.628**	0.024
$\log(\sigma_v)$	−1.233**	0.025	−1.230**	0.025
α_{old} (age-specific adoption cost, age > 50)	−0.012	0.010	0.065**	0.009
α_{young} (age-specific adoption cost, age < 50)	−0.175**	0.035	0.005	0.007
γ_0	−0.352**	0.087	−0.425**	0.104
γ_{sex}	−1.915	1.243	−0.663	0.793
γ_{north}	−2.505	5.204	−0.571	0.929
γ_{edu1} (none)	−2.382*	0.971	−2.444**	0.841
γ_{edu2} (elementary)	−0.791	2.883	1.053	1.142
γ_{edu3} (middle school)	1.666	1.162	1.133	1.132
−ll	16,268.4		16285.3	
N	5,489		5,489	
AIC	32,582.8		32,616.6	
BIC	32,734.84		32,768.64	

*Significant at 95% confidence level; **significant at 99% confidence level.

Consistent with common wisdom, education is an important predictor for which segment a household belongs to. Household heads with a lower level of education, namely, none or elementary school, are much more likely to belong to the segment with larger adoption costs and smaller adoption benefits. Residency in the north or south does not affect an individual's likelihood to fall into a given segment.

6.3.3. How Large Are the Adoption Costs? For identification reasons, we assume that the adoption costs for the second segment are higher than those for the first segment (i.e., $F_0^2 - F_0^1 > 0$). The estimated total adoption costs in monetary value when $age = 51$ are €166.06 and €168.52 (2002 base) for segment 1 and segment 2, respectively. (We obtain the monetary

Table 8 Consumers' Cost Savings per Year from Adopting ATM Cards (ΔTC)

	1991	1993	1995	1998	2000	2002	2004
Segment 1							
Mean cost savings for nonadopters	13.46	13.89	11.14	7.81	5.91	5.42	3.17
	(5.80)	(6.00)	(4.89)	(3.59)	(2.68)	(2.47)	(1.54)
Mean cost savings for adopters	n.a.	18.76	14.75	10.91	8.22	7.80	4.69
		(8.46)	(6.16)	(4.23)	(3.28)	(3.19)	(1.98)
Mean cost savings for both adopters and nonadopters	13.46	14.57	12.00	9.16	7.14	6.91	4.18
	(5.80)	(6.60)	(5.46)	(4.26)	(3.25)	(3.17)	(2.00)
Segment 2							
Mean cost savings for nonadopters	9.65	9.96	7.98	5.60	4.24	3.89	2.27
	(4.16)	(4.30)	(3.51)	(2.57)	(1.92)	(1.77)	(1.10)
Mean cost savings for adopters	n.a.	13.45	10.57	7.82	5.89	5.59	3.36
		(6.07)	(4.42)	(3.03)	(2.35)	(2.29)	(1.42)
Mean cost savings for both adopters and nonadopters	9.65	10.45	8.60	6.57	5.12	4.95	3.00
	(4.16)	(4.73)	(3.91)	(3.06)	(2.33)	(2.27)	(1.43)

Notes. Measured in 2002 euros. Numbers in parentheses are standard deviations.

value by using α_{TC}.) Note that Attanasio et al. (2002) estimate the upper bound of adoption costs to be €28.1, which is much lower than our estimates. This is because they assume households only care about the current period benefits of adopting the ATM card instead of its total discounted future benefits.

Our results also allow us to investigate how adoption costs vary with age. According to our estimates, elderly people might *not* have larger adoption costs. Note that the age-specific component of adoption costs for people over age 50, α_{old}, is not significantly different from zero. This indicates that adoption costs are fairly flat for people over age 50. This finding is very different from the estimates from a model of myopic consumers (static model) reported in columns 4 and 5 of Table 7, which imply that the age-specific component of adoption costs for household heads over age 50 is positive and significant. This indicates that in the static model the estimated adoption costs will have to increase over age when *age* > 50, to fit the observed adoption rates.

Our estimates of adoption costs may seem surprising because they appear to go against the common belief that the elderly have more difficulties learning or are reluctant to learn new technology, including the use of ATMs. A more careful examination of our results shows that our findings are consistent with previous research. Note that we estimate the total adoption costs, including both monetary and nonmonetary. The monetary costs are the total discounted annual fees, which *decrease* with age because the remaining life span becomes shorter. The nonmonetary adoption costs include learning costs, hassle costs, psychological costs, etc. Given that our estimated total adoption costs are fairly flat across age for people over age 50, this implies that the nonmonetary adoption costs increase with age for people over age 50. In Table 9, we show the breakdown of segment 1 consumers' total adoption costs into monetary and nonmonetary components. To calculate the monetary component, we set the average annual fee at €7.32.[29] Our results show that monetary adoption costs decrease with age, and nonmonetary costs generally increase with age. For example, a 50-, 64-, and 74-year-old person's nonmonetary adoption costs (measured in monetary terms) are €62.99, €81.83, and €100.91, respectively, if they belong to segment 1.

6.3.4. How Does the Estimate of Adoption Costs Vary with Discount Factor? As mentioned earlier, how consumers discount the future can be context specific. Hence, even though we fix the discount factor using a survey question that specifically solicits time preferences, consumers may consider future benefits differently in the case of ATM card adoption. Therefore, we re-estimate our model by fixing the discount factors at a range of additional values: 0.8, 0.6, 0.4, and 0.2. The results are reported in Table 10. As expected, as we decrease the discount factor the age-specific component of adoption costs for the elderly (α_{old}) becomes increasingly more positive and significant. The corresponding estimated adoption cost moves in the opposite direction; i.e., it increases with the discount factor. To illustrate this result, we report the adoption cost of segment 1 consumers at age = 51 in the last row of the table. It shows that the adoption cost increases from €28.85 ($\beta = 0$) to €166.06 ($\beta = 0.943$). This suggests that as long as consumers are forward-looking (i.e., $\beta > 0$), ignoring the heterogeneous life span could lead to biased estimates in adoption costs for different age groups and, possibly, misleading policy implications.

Table 9 **A Breakdown of Segment 1 Consumers' Total Discounted Adoption Costs**

Age	Total adoption costs	Monetary adoption costs[a]	Nonmonetary adoption costs
50	166.25	103.26	62.99
52	165.86	100.76	65.10
54	165.48	98.09	67.39
56	165.09	95.21	69.88
58	164.70	92.10	72.60
60	164.31	88.81	75.51
62	163.93	85.37	78.55
64	163.54	81.71	81.83
66	163.15	77.78	85.37
68	162.76	73.68	89.08
70	162.38	69.46	92.92
72	161.99	65.12	96.87
74	161.60	60.69	100.91

Note. Measured in 2002 euros.
[a]Monetary adoption costs: Discounted annual fees up to the terminal age based on annual fee = 7.32 euros, and $\beta = 0.943$.

6.4. Counterfactual Experiments

It has been argued that banks' adoption of financial innovations such as ATMs can improve their productivity in general. ATMs allow banks to process cash withdrawals and deposits at significantly lower marginal costs than tellers, and potentially better serve their customers' basic needs. (For example, a bank can install ATMs in different locations more cheaply than opening brick-and-mortar branches, and ATMs can operate 24 hours a day and seven days per week.) If most customers use ATMs to conduct withdrawal and deposit transactions, bank tellers can shift their focus to help customers with more complicated transactions, which could potentially be more profitable for banks. With more customers adopting

[29] Attanasio et al. (2002) report that the average annual fee is €6.2 (1995 base). Because all of our monetary variables are expressed in 2002 euros, we convert the annual fee to 2002 base when calculating monetary adoption costs.

Table 10 Estimation Results Fixing β at Different Values

	$\beta = 0.8$		$\beta = 0.6$		$\beta = 0.4$		$\beta = 0.2$	
Parameter	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
ψ (time trend)	3.908**	0.549	4.446**	0.773	5.374**	0.946	5.968**	1.049
α_{TC} (adoption benefit)	0.058**	0.007	0.066**	0.009	0.078**	0.010	0.085**	0.011
s^k ($k = 1$)	0.827^{+}	0.496	0.667	0.640	0.645	0.699	0.631	0.754
ρ_0^k ($k = 1$)	8.905**	0.651	10.843**	1.505	10.921**	1.521	10.997**	1.538
ρ_1^k ($k = 1$)	5.692**	0.335	5.593**	0.347	5.592**	0.348	5.591**	0.348
α_n^k (no. of ATMs, $k = 1$)	0.348	0.934	−1.777	1.321	−1.982	1.602	−2.092	1.757
s^k ($k = 2$)	0.754**	0.038	0.754**	0.038	0.754**	0.038	0.754**	0.038
ρ_0^k ($k = 2$)	3.217**	0.131	3.191**	0.126	3.192**	0.126	3.193**	0.126
ρ_1^k ($k = 2$)	0.660**	0.021	0.661**	0.021	0.661**	0.021	0.661**	0.021
α_n^k (no. of ATMs, $k = 2$)	0.385*	0.166	0.546*	0.231	0.650*	0.277	0.708*	0.304
F_0^1 (adoption cost in segment 1)	12.146**	1.414	8.192**	1.093	7.642**	1.008	7.462**	0.974
$\log(F_0^2 - F_0^1)$ (log(adoption cost difference))	−2.296	2.010	−2.986	3.743	−3.131	3.594	−3.224	3.593
$\log(\sigma_{\epsilon_0})$	6.958**	0.022	6.954**	0.022	6.953**	0.022	6.953**	0.022
$\log(\sigma_{\epsilon_1})$	5.627**	0.024	5.628**	0.024	5.628**	0.024	5.628**	0.024
$\log(\sigma_v)$	−1.231**	0.025	−1.230**	0.025	−1.230**	0.025	−1.230**	0.025
α_{old} (age-specific adoption cost, age > 50)	0.011	0.015	0.055**	0.011	0.062**	0.010	0.065**	0.009
α_{young} (age-specific adoption cost, age < 50)	−0.012	0.010	0.001	0.008	0.004	0.007	0.005	0.007
γ_0	−0.351**	0.079	−0.410**	0.099	−0.418**	0.102	−0.423**	0.103
γ_{sex}	−0.629	0.706	−0.650	0.791	−0.652	0.795	−0.663	0.793
γ_{north}	−1.479	1.111	−0.726	0.974	−0.640	0.952	−0.587	0.933
γ_{edu1} (none)	−2.398	6.525	−2.433	7.988	−2.438	8.234	−2.443	8.322
γ_{edu2} (elementary)	0.529	0.948	0.906	1.098	0.969	1.123	1.037	1.136
γ_{edu3} (middle school)	0.742	0.886	0.994	1.082	1.069	1.108	1.116	1.126

Beta	0.943	0.8	0.6	0.4	0.2	0.0
Adoption costs in 2002 euros when age $= 51$ (segment 1)	166.06	71.54	42.39	33.52	29.88	28.85

$^{+}$Significant at 90% confidence level; *significant at 95% confidence level; **significant at 99% confidence level.

ATM cards, customers' waiting time at bank counters is also likely to drop, which should improve customer satisfaction. In addition, banks may be able to open more branches quicker without hiring as many human tellers as before.

To encourage the elderly to use ATM cards, a direct marketing strategy is to give them monetary incentives. For instance, a bank can run a targeted promotion for their senior customers: e.g., apply for an ATM card today and receive a €50 sign-up bonus after first use. There are two ways to implement this targeted promotion strategy: (i) temporary promotion (e.g., limited-time offer, so act quickly!); or (ii) permanent promotion, i.e., a promotional offer without an expiration date. When consumers are forward-looking, these two policies can have very different outcomes. The temporary promotion often comes as a surprise to consumers. On the contrary, if the promotion is a "permanent" strategy, it may generate some unwanted effects because forward-looking consumers may strategically take it into consideration and delay their adoption. For instance, if the sign-up bonus is for anyone who is at least 50 years old, consumers who are close to this cutoff (e.g., age 49) may decide to wait until they reach age 50 to adopt the ATM card. Our structural model provides us with a formal way to account for such strategic delay behavior.

We use our model to analyze the impacts of these two sign-up bonus strategies. In both cases, we consider banks giving a sign-up bonus to consumers who are age 50 and older (note that Italians retire in their fifties). We use the percentage of predicted new adopters in each period over the previous period nonadopters to measure the adoption rate in the experiments. For the limited-time offer, we will treat this temporary promotion as a surprise to consumers, and it will only last for a year. Therefore, we assume that consumers will not change their expectations about the adoption costs in the future.[30] Yet

[30] More specifically, for consumers who are age 50 or above, they see that their current adoption costs are reduced by the amount of the sign-up bonus, but expect that future adoption costs will return to a normal level; for consumers who are younger than age 50, their expectations about current and future adoption costs remain the same as those in the benchmark model.

Table 11 Effects of Limited-Time vs. Permanent Sign-Up Bonus for Consumers Older Than Age 50

Year	1993 (%)	1995 (%)	1998 (%)	2000 (%)	2002 (%)	2004 (%)
Benchmark model predictions: No bonus						
% of new adopters	17.75	22.00	22.69	18.18	17.33	11.13
% of new adopters age < 40	23.56	31.63	34.13	31.02	31.69	26.94
% of new adopters 40 ≤ age < 50	27.77	32.61	33.37	31.08	33.22	25.44
% of new adopters 50 ≤ age < 65	16.28	21.43	25.13	20.99	22.94	16.45
% of new adopters age ≥ 65	6.89	11.93	12.26	10.85	10.11	6.87
Model predictions based on limited-time sign-up bonus offer (€50) to people over age 50						
% of new adopters	47.37	58.28	62.23	61.68	62.53	56.57
% of new adopters age < 40	23.56	31.63	34.13	31.02	31.69	26.94
% of new adopters 40 ≤ age < 50	27.77	32.61	33.37	31.08	33.22	25.44
% of new adopters 50 ≤ age < 65	66.24	65.84	78.76	76.13	78.48	74.69
% of new adopters age ≥ 65	51.60	63.10	67.79	65.80	64.25	55.48
Model predictions based on permanent sign-up bonus offer (€50) to people over age 50						
% of new adopters (predicted)	26.45	33.74	36.19	35.51	37.03	33.37
% of new adopters age < 40 (predicted)	20.66	29.09	31.87	27.70	29.22	23.17
% of new adopters 40 ≤ age < 50 (predicted)	15.01	17.02	16.28	14.19	18.83	11.34
% of new adopters 50 ≤ age < 65 (predicted)	32.41	39.46	41.62	38.72	40.20	36.69
% of new adopters age ≥ 65 (predicted)	31.25	40.03	41.59	40.38	40.07	34.89

when the sign-up bonus is a permanent policy, we assume that consumers take this policy into account when they form expectations about future adoption costs. We consider a sign-up bonus of €50. Table 11 shows the results broken down by age groups based on our sample of nonadopters in each year. The top panel is the predictions based on the estimated model; we treat it as the benchmark for predictions. The rest of the panels are the results of counterfactual experiments. We show three interesting findings.

First, a permanent sign-up bonus offer to people over age 50 would increase adoption rates for consumers who are at least 50 years old, but not as much as the limited-time offer. For example, a €50 bonus under a permanent offer only increased the adoption rate of consumers aged between 50 and 65 to 32.41% in 1993, which is much lower than the results from the limited-time offer—66.24% in 1993. The logic behind this result is that the sign-up bonus is a permanent policy, and hence it is not urgent for consumers to take the sign-up bonus since it is always there once the consumer is qualified. This procrastination idea is captured by the option value of waiting in the alternative specific value function. The permanent sign-up bonus not only reduces the current adoption costs for consumers who are at least 50 years old, but it also increases their option value of waiting. For the limited-time offer, the option value of waiting remains unchanged.

Second, adoption rates for consumers under age 50 are negatively affected by the permanent sign-up bonus policy; i.e., their adoption rates decrease relative to the benchmark case without a sign-up bonus. For instance, a €50 bonus lowered the adoption rate for the 40–50 age group from 27.77% to 15.01% in 1993. This is because forward-looking consumers under age 50 can foresee this monetary incentive, and are willing to postpone adoption until they reach age 50 to receive this bonus. While the sign-up bonus encourages seniors to adopt, it generates a *disincentive* effect on adoption among younger customers.

Third, for consumers under age 50, the closer they are to 50, the more incentives they have to postpone adoption. Consumers in the 40–50 age group are more negatively affected by the sign-up bonus than consumers in the under age 40 group. For example, consider the sample in 1993, where a €50 sign-up bonus decreases the adoption rate by 12.76% (= 27.77% − 15.01%) for customers in the 40–50 age group, while the adoption rate only drops by 2.90% (= 23.56% − 20.66%) for customers under age 40. This is because the farther a consumer is below age 50, the more he or she discounts the sign-up bonus.

Overall, our counterfactual exercises suggest that sign-up bonus offers targeted at a particular age group should be more effective if they are implemented as a limited-time offer rather than a permanent offer. The permanent sign-up bonus could also lead to surprising negative impacts on consumers younger than the age group targeted by the promotion. Note that these types of outcomes would be hard to quantify without a dynamic structural life-cycle model, such as the one we propose here.

7. Conclusion

To the best of our knowledge, this is the first paper that uses a forward-looking consumer life-cycle model to empirically study consumers' adoption decisions of a new technology. We apply our framework to ATM card adoption decisions in Italy. A unique feature of our model is that it incorporates both technology adoption decisions and usage decisions (by using the cash demand model). If consumers understand how age affects longevity and their discount factor is known, one can apply our framework to control for the heterogeneous life span (which leads to heterogeneous total discounted adoption benefits) faced by consumers of different ages, and recover adoption costs in monetary terms more accurately. Our results provide evidence that one can significantly overestimate adoption costs for the elderly when ignoring their shorter remaining life span.

We also conduct counterfactual experiments to study two different ways (limited-time offer versus permanent offer) to offer a sign-up bonus to consumers who are age 50 or older. We show that if consumers are forward-looking, the limited-time offer could be much more effective than the permanent offer. This is because the permanent offer gives consumers an incentive to procrastinate. The permanent sign-up bonus offer could also cause some consumers to postpone their adoption decisions until they are qualified for the bonus.

Note that we did not attempt to compute the optimal sign-up bonus for banks. Although this is an important issue, such an exercise is beyond the scope of this paper. To address this, we will need to estimate the marginal benefits to banks of having additional consumers adopt ATM cards. Such benefits are difficult to quantify because they involve positive externalities. Suppose we want to estimate/calibrate the benefits of shortening the waiting time to speak with bank tellers when an additional customer adopts ATM cards. We will need to estimate not only the time saved but also how other customers (those who have to see bank tellers for more complicated transactions that cannot be carried out at an ATM) value time. This would require us to obtain data to calibrate customers' opportunity cost of time, which are likely heterogeneous in the population. We would also need to estimate how shortening waiting time would improve customer satisfaction and loyalty, which in turn may lead to improved market shares (this would require us to model how banks compete). Another important benefit is to estimate the improved productivity of tellers (presumably, they can now spend more time helping other customers to complete more complicated transactions). This would probably involve obtaining access to proprietary company internal data.[31]

Our view is that this paper provides a partial framework that could ultimately help develop the optimal sign-up bonus. Our hope is that future research will teach us how to quantify banks' benefits of having additional customers adopt ATM cards. By combining this with our framework, which focuses on quantifying how consumers react to different sign-up bonus levels, we could help banks set the most profitable level of a sign-up bonus.[32]

One limitation of our research is that the estimation results depend on consumers' discount factor, which needs to be assumed a priori. Hence, to apply our framework, additional research is needed to measure the discount factor first. To measure consumers' time preferences, some recent research has used laboratory experiments or stated preference data (e.g., Houser and Winter 2004, Viscusi et al. 2008, Dubé et al. 2012). By combining our framework with these methodologies, we should be able to improve the accuracy of adoption cost estimates for new technologies during the consumer life cycle.

In the future, it may also be possible to design a survey to elicit information on consumers' subjective expected survival probabilities along with their adoption decisions for new technologies. This information, together with the methods of measuring discount factors, may permit testing to determine whether longevity is relevant for understanding how age moderates the adoption decision of a new technology. In fact, the Health and Retirement Survey and the Asset and Health Dynamics (AHEAD) Study have already collected such information. Some researchers (e.g., Hurd and McGarry 1995, 2002) have also argued that such measures of subjective survival probabilities have strong potential use in models of intertemporal decision making under uncertainty. The focus of the existing literature is mainly labor and health economics. Using such data to study consumer technology adoption decisions should be an important future research topic.

Acknowledgments

This paper significantly extends the first chapter of Botao Yang's Ph.D. dissertation at the Rotman School of Management, University of Toronto. The authors thank three anonymous reviewers, the area editor, and Pradeep Chintagunta for their valuable and detailed suggestions, which significantly improved this paper. The authors benefited from discussions with Avi Goldfarb, Sridhar Moorthy, Victor Aguirregabiria, Robert Clark, Ken Corts, Kim Hyunh, Ig Horstmann, Susumu Imai, Ahmed Khwaja, Nitin Mehta, Andy Mitchell, Marc Rysman, Mengze Shi, K. Sudhir, and Debabrata Talukdar. The authors also thank seminar participants at the University of Toronto, University of

[31] In a standard environment, the benefits of having more consumers adopt would be easier to quantify. For example, in Nair (2007) and Ishihara and Ching (2012), the benefit of having an extra consumer adopt is simply the markup (i.e., price minus marginal costs). These authors further assume that the supply side is characterized by a monopoly, which makes it feasible for them to compute the optimal pricing policy after estimating dynamic consumer adoption models.

[32] Recently, several papers have taken this approach of building a complicated supply side model and combining it with a demand side model developed and estimated from another paper, and then solving for firms' optimal policy (e.g., Ching 2010b, Dubé et al. 2010).

Chicago, University of Southern California, Cheung Kong Graduate School of Business, National University of Singapore, Hong Kong University of Science and Technology, Tsinghua University, McMaster University, Federal Reserve Bank at Boston, 2009 University of Texas-Dallas Marketing Conference, and 2009 Marketing Dynamics Conference for their helpful comments. The authors thank Luigi Guiso for generously sharing data on the number of ATMs. The authors acknowledge the financial support of the Michael Lee-Chin Family Institute for Corporate Citizenship at Rotman School of Management, University of Toronto. All remaining errors are the authors' responsibility.

Appendix A

In this appendix, we present a more formal identification argument. Our identification assumptions are (I1) survival probability z_{age} is a deterministic function of age, and is given by national level mortality statistics; (I2) the discount factor is known; and (I3) the transition of the state variables, $F(\bar{S}_{it+1} \mid \bar{S}_{it})$, are given by Equations (16)–(18).

We will explain that if, for each age group, we observe consumers making mixed adoption decisions (some choose to adopt; others choose to wait), one can identify adoption costs for all age groups. Let a_{it} be the adoption status of consumer i at time t. We assume that the adoption costs are a function of age, but we do not impose any functional form restrictions. If consumer i is a potential adopter at time t and $age_{it} = \tau$, his adoption costs, $F_{it} = F_\tau$. For simplicity, we assume the following: (1) the number of ATMs, n_{it}, and the time trend, $\psi(t)$, do not enter the utility function; (2) the benefit function, $\Delta TC(\bar{S}_{it})$, the stochastic processes of $\bar{S}_{it}$, and the discount factor, β, are known; and (3) e_{ijt}'s are i.i.d. extreme value distributed. We will first show that the adoption costs at the maximum age, $F_{\overline{age}}$, can be identified. Because we assume everyone dies after $\overline{age}$, the decision of whether to adopt at $\overline{age}$ is a static choice problem. Suppose we focus on a sample of observations with $age_{it} = \overline{age}$. It is easy to show that two first-order conditions of the log-likelihood for this subsample of observations (with respect to (w.r.t.) α_{TC} and $F_{\overline{age}}$) will give us the following two equations:

$$\alpha_{TC}\colon \sum_i (a_{it} - \Pr(a_{it} \mid \bar{S}_{it}; \alpha_{TC}, F_{\overline{age}})) \cdot \Delta TC(\bar{S}_{it}) = 0, \qquad \text{(A1)}$$

$$F_{\overline{age}}\colon \sum_i (a_{it} - \Pr(a_{it} \mid \bar{S}_{it}; \alpha_{TC}, F_{\overline{age}})) = 0. \qquad \text{(A2)}$$

These two equations allow us to identify $(\alpha_{TC}, F_{\overline{age}})$, as long as there is some variation in $\bar{S}_{it}$.

Now we focus on another sample of observations with $age_{it} = \overline{age} - 1$. Note that the expected future value for consumers who are at $\overline{age} - 1$ is $z_{\overline{age}}\beta \int V(a_{it}, \bar{S}_{it+1}; \alpha_{TC}, F_{\overline{age}})\, dF(\bar{S}_{it+1} \mid \bar{S}_{it})$. Since $z_{\overline{age}}$ is directly observed from the data, and $(\alpha_{TC}, F_{\overline{age}})$ are identified from Equations (A1) and (A2), it follows from our identification assumptions I1–I3 that we can identify the expected future value for consumers who are at $\overline{age} - 1$. Once we are able to control for the expected future value, setting up the choice probabilities for consumers at $\overline{age} - 1$ is straightforward. Now using the log-likelihood of this subsample, we can set up the first-order condition w.r.t. $F_{\overline{age}-1}$:

$$\sum_i (a_{it} - \Pr(a_{it} \mid \bar{S}_{it}; \alpha_{TC}, F_{\overline{age}}, F_{\overline{age}-1})) = 0. \qquad \text{(A3)}$$

Table B.1 Distribution of Stated Time Preferences

Answer	Annual discount factor	Bi-annual discount factor	Freq.	Percent
0	1	1	151	25.42
2	0.98	0.96	31	5.22
3	0.97	0.94	49	8.25
5	0.95	0.90	189	31.82
10	0.90	0.81	113	19.02
20	0.80	0.64	61	10.27
Total			594	100

Since Equations (A1) and (A2) have already identified $(\alpha_{TC}, F_{\overline{age}})$, we can use Equation (A3) to identify $F_{\overline{age}-1}$, as long as there is some variation in $\bar{S}_{it}$. It is straightforward to extend this backward induction argument to show that $F_{\overline{age}-2}, F_{\overline{age}-3}, \ldots, F_{initial\_age}$ are all identified provided that we observe consumers with different $\bar{S}_{it}$ making different adoption decisions at each age.

Appendix B

In the 2004 survey, respondents were asked about their time preferences:

"Imagine you were told you had won in the lottery the equivalent of your household's net annual income. The sum will be paid to you in a year's time.

However, if you give up part of the sum you can have the rest immediately."

a. To get the money right away would you give up 5 percent of this sum?
b. Or 10 percent?
c. Or 20 percent?
d. Or 3 percent?
e. Or 2 percent?
f. No, I'd wait a year to collect the whole amount.

The distribution of stated time preferences is summarized by Table B.1.

References

Ackerberg D, Gowrisankaran G (2006) Quantifying equilibrium network externalities in the ACH banking industry. *RAND J. Econom.* 37(3):738–761.

Adams AS, Thieben KA (1991) Automatic teller machines and the older population. *Appl. Ergonomics* 22(2):85–90.

Aguirregabiria V, Mira P (2010) Dynamic discrete choice structural models: A survey. *J. Econometrics* 156(1):38–67.

Alvarez F, Lippi F (2009) Financial innovation and the transactions demand for cash. *Econometrica* 77(2):363–402.

Arcidiacono P, Miller RA (2013) Identifying dynamic discrete choice models off short panels. Working paper, Carnegie Mellon University, Pittsburgh.

Attanasio OR, Guiso L, Jappelli T (2002) The demand for money, financial innovation, and the welfare cost of inflation: An analysis with household data. *J. Political Econom.* 110(2):317–351.

Bauer K, Hein SE (2006) The effect of heterogeneous risk on the early adoption of Internet banking technologies. *J. Banking Finance* 30(6):1713–1725.

Baumol WJ (1952) The transactions demand for cash: An inventory-theoretic approach. *Quart. J. Econom.* 66:545–556.

Borzekowski R, Elizabeth KK, Shaista A (2008) Consumers' use of debit cards: Patterns, preferences, and price response. *J. Money, Credit and Banking* 44(1):149–172.

BBC News (2007) Italy retirement age 'to go up.' (July 20), http://news.bbc.co.uk/2/hi/business/6908231.stm.

Canato A, Corrocher N (2004) Information and communication technology: Organizational challenges for Italian banks. *Accounting, Bus. Financial Hist.* 14(3):355–370.

Chen X, Chen Y, Weinberg CB (2013) Learning about movies: The impact of movie release types on the nationwide box office. *J. Culture Econom.* 37(3):359–386.

Ching AT (2010a) Consumer learning and heterogeneity: Dynamics of demand for prescription drugs after patent expiration. *Internat. J. Indust. Organ.* 28(6):619–638.

Ching AT (2010b) A dynamic oligopoly structural model for the prescription drug market after patent expiration. *Internat. Econom. Rev.* 51(4):1175–1207.

Dayton CM, Macready GB (1988) Concomitant-variable latent-class models. *J. Amer. Statist. Assoc.* 83(401):173–178.

Dubé J-P, Hitsch GJ, Chintagunta PK (2010) Tipping and concentration in markets with indirect network effects. *Marketing Sci.* 29(2):216–249.

Dubé J-P, Hitsch GJ, Jindal P (2012) The joint identification of utility and discount functions from stated choice data: An application to durable goods adoption. NBER Working Paper 18393, National Bureau of Economic Research, Cambridge, MA.

Fang H, Keane M, Khwaja A, Salm M, Silverman D (2007) Testing the mechanisms of structural models: The case of the Mickey Mantle effect. *Amer. Econom. Rev.* 97(2):53–59.

Fang H, Wang Y (2012) Estimating dynamic discrete choice models with hyperbolic discounting, with an application to mammography decisions. Working paper, University of Pennsylvania, Philadelphia.

Ferrari S, Verboven F, Degryse H (2010) Investment and usage of new technologies: Evidence from a shared ATM network. *Amer. Econom. Rev.* 100(3):1046–1079.

Gilly MC, Zeithaml V (1985) The elderly consumer and adoption of technologies. *J. Consumer Res.* 12:353–357.

Gordon BR (2009) A dynamic model of consumer replacement cycles in the PC processor industry. *Marketing Sci.* 28(5):846–867.

Gowrisankaran G, Rysman M (2012) Dynamics of consumer demand for new durable goods. *J. Political Econom.* 120(6):1173–1219.

Gowrisankaran G, Stavins J (2004) Network externalities and technology adoption: Lessons from electronic payments. *RAND J. Econom.* 35(2):260–276.

Gupta S, Chintagunta PK (1994) On using demographic variables to determine segment membership in logit mixture models. *J. Marketing Res.* 31:128–136.

Hannan TH, McDowell JM (1984) The determinants of technology adoption: The case of the banking firm. *RAND J. Econom.* 15(3):328–335.

Hannan TH, McDowell JM (1987) Rival precedence and the dynamics of technology adoption: An empirical analysis. *Economica* 54(214):155–171.

Hatta K, Liyama Y (1991) Ergonomic study of automatic teller machine operability. *Internat. J. Human Comput. Interaction* 3(3):295–309.

Hester DD, Calcagnini G, de Bonis R (2001) Competition through Innovation: ATMs in Italian banks. *Rivista Italiana degli Economisti* 3:359–381.

Houser D, Winter J (2004) How do behavioral assumptions affect structural inference? Evidence from a laboratory experiment. *J. Bus. Econom. Statist.* 22(1):64–79.

Hurd MD, McGarry K (1995) Evaluation of the subjective probabilities of survival in the health and retirement study. *J. Human Resources* 30(Supplement):S268–S292.

Hurd MD, McGarry K (2002) The predictive validity of subjective probabilities of survival. *Econom. J.* 112(482):966–985.

Huynh KP (2007) Financial innovation and the persistence of the extensive margin. Working paper, Indiana University, Bloomington.

Ishihara M, Ching AT (2012) Dynamic demand for new and used durable goods without physical depreciation: The case of Japanese video games. Working paper, Stern School of Business, New York University, New York. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2189871,

Ishii J (2007) Compatibility, competition, and investment in network industries: ATM networks in the banking industry. Working paper, Stanford University, Stanford, CA.

Keane MP, Todd PE, Wolpin KI (2011) The structural estimation of behavioral models: Discrete choice dynamic programming methods and applications. Ashenfelter O, Card D, eds. *Handbook of Labor Economics*, Vol. 4A (North-Holland, Amsterdam), 331–461.

Kerschner PA, Chelsvig KH (1984) The aged user and technology, in Dunkle. Ruth E, Haug Marie R, Rosenberg M, eds. *Communications Technology and the Elderly: Issues and Forecasts* (Springer, New York), 135–144.

Khwaja A (2010) Estimating willingness to pay for Medicare using a dynamic life-cycle model of demand for health insurance. *J. Econometrics* 156(1):130–147.

Lyman E (2009) Italy not immune to crisis. ISN Security Watch, International Relations and Security Network. http://www.isn.ethz.ch/Digital-Library/Articles/Detail/?Ing=en&id=95328.

Magnac T, Thesmar D (2002) Identifying dynamic discrete decision processes. *Econometrica* 70(2):801–816.

Nair H (2007) Intertemporal price discrimination with forward-looking consumers: Application to the US market for console video-games. *Quant. Marketing Econom.* 5(3):239–292.

Orlandi E (1989) *Computer Security Economics* (ICCST, Zurich, Switzerland), 107–111.

Ratchford B (2001) The economics of consumer knowledge. *J. Consumer Res.* 27(4):397–411.

Rogers WA, Cabrera EF, Walker N, Gilbert DK, Fisk AD (1996) A survey of automatic teller machine usage across the adult life span. *Human Factors* 38(1):156–166.

Rolfe R (2005) *European Payment Cards Yearbook 2005–2006* (Payments CM LLP, Norfolk, UK).

Rust J (1987) Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica* 55(5):999–1033.

Rust J, Phelan C (1997) How Social Security and Medicare affect retirement behavior in a world of incomplete markets. *Econometrica* 65(4):781–832.

Ryan S, Tucker C (2012) Heterogeneity and the dynamics of technology adoption. *Quant. Marketing Econom.* 10(1):63–109.

Saloner G, Shepard A (1995) Adoption of technologies with network effects: An empirical examination of the adoption of automated teller machines. *RAND J. Econom.* 26(3):479–501.

Sjuggerud S (2005) Interest rate forecast... The world's best prediction for 2005 will surprise you. *The Investment U e-Letter* (January 10).

Song I, Chintagunta PK (2003) A micromodel of new product adoption with heterogeneous and forward-looking consumers: Application to the digital camera category. *Quant. Marketing Econom.* 1(4):371–407.

Sriram S, Chintagunta PK, Agarwal M (2010) Investigating consumer purchase behavior in related technology product categories. *Marketing Sci.* 29(2):291–314

Swanson CE, Kopecky KJ, Tucker A (1997) Technology adoption over the life cycle and aggregate technological progress. *Southern Econom. J.* 63(4):872–887.

Tobin J (1956) The interest elasticity of transactions demand for cash. *Rev. Econom. Statist.* 38(3):241–247.

Tufano P (2003) Financial innovation. Constantinides GM, Harris M, and Stulz RM, eds. *The Handbook of the Economics of Finance* (Elsevier, Amsterdam), 307–336.

Viscusi WK, Huber J, Bell J (2008) Estimating discount rates for environmental quality from utility-based choice experiment. *J. Risk Uncertainty* 37(2–3):199–220.

Wall Street Journal (2009) Paul Volcker: Think more boldly. (December 14), http://online.wsj.com/article/SB10001424052748704825504574586330960597134.html.