

Dynamic Discrete Choice in ATM Card Adoption*

Angelika Welte, Kim P. Huynh, Philipp Schmidt-Dengler, and Gregor W. Smith

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Abstract

The discrete choice to adopt a financial innovation affects a household's exposure to inflation and transactions costs. We model the benefits and costs of this decision using a conditional choice probability estimator and drawing on the finite dependence property of the problem. A novel feature is that preference parameters are estimated separately, from the Euler equations of a shopping-time model of consumption and money demand. We apply this method to study ATM card adoption in the Bank of Italy's *Survey of Household Income and Wealth*. There, the implicit adoption cost varies significantly by age, education, and region.

Keywords: dynamic discrete choice, money demand, financial innovation.

JEL codes: E41, D14, C35.

*Welte: Currency Department, Bank of Canada, awelte@bankofcanada.ca; Huynh: Currency Department, Bank of Canada, kim@huynh.tv; Schmidt-Dengler, Department of Economics, University of Vienna, philipp.schmidt-dengler@univie.ac.at; Smith, Department of Economics, Queen's University, Canada, gregor.smith@queensu.ca. Schmidt-Dengler acknowledges financial support from the German Science Foundation through Sonderforschungsbereich Transregio 15. Smith acknowledges the Social Sciences and Humanities Research Council of Canada and the Bank of Canada research fellowship programme for support of this research. Dörte Heger provided excellent research assistance. This paper supersedes "Adoption Costs of Financial Innovation: Evidence from Italian ATM Cards" which was issued as Bank of Canada Staff Working Paper 2017-8. For constructive comments, we thank Victor Aguirregabiria, Jason Allen, Robert Clark, Yiran Gong, Thomas Lemieux, Héctor Pérez Saiz, Ben Tomlin, and seminar and conference participants. The views in this paper represent those of the authors alone and are not those of the Bank of Canada.

1 Introduction

We study how households adopt a new financial product. We are motivated by the observation that new financial and payment technologies often are not universally adopted or are adopted slowly and unevenly despite their apparent benefits. While we study the adoption of automated teller machine (ATM) cards, our findings may apply to innovations such as contactless payments, online banking, and mobile payments, and so may inform the inclusive introduction of new payment and financial technologies. Thus our research is relevant in the context of financial inclusion and financial literacy initiatives that have been launched in many countries, such as the in EU by the [Directorate-General for Financial Stability, Financial Services and Capital Markets Union](#), in the US by [U.S. Department of the Treasury \(2016\)](#), in Canada by [Financial Consumer Agency of Canada \(2021\)](#), Mexico ([Cassimon et al. \(2022\)](#)), or in India by [Department of Financial Services](#).

We study the adoption of ATM cards in Italy between 1989 and 2004, as tracked in the Bank of Italy’s *Survey of Household Income and Wealth*, a rich survey on household financial decisions. Specifically, we provide a measure of households’ perceived adoption costs and benefits. Consumers gain ongoing benefits after adopting an ATM card, which may, for example, help them use cash efficiently. These efficiency gains should be substantial for the households in our data set for two reasons. First, Italian households are among the most cash-intensive payers in the EU and among comparable economies worldwide. Second, consumers who withdraw cash from a bank teller are limited to branch hours, typically on weekday mornings and, sometimes, for an hour in the afternoon.

Yet, in the data set, Italian households’ uptake of ATM cards was slow and incomplete. Possible explanations include high adoption costs or barriers relative to the benefits from adopting the technology. In this paper, we estimate the implicit adoption costs and we also provide a framework in which counterfactual scenarios can be simulated. For example, we consider the scenario where all households adopt the financial innovation and estimate what compensation would achieve this universal adoption.

Households’ adoption patterns have two features that we strive to incorporate into the modelling and estimation strategy. First, financial technology adoption is a dynamic, discrete choice (DDC) where the household weighs the future benefits of the new technology against a one-time adoption cost. Second, households are heterogeneous in how they use the new technology and hence benefit from it.

There are three key features of the estimator. First, we combine a simulation estimator with the estimation of preference parameters via Euler equations for households with or without ATM cards. The Euler equations come from a shopping-time model that describes both the intensive margin of money-holding and the additional gains from holding an ATM card. Time effects in the implied money-demand function also allow for the diffusion of

ATM machines and bank branches over the historical sample. It is important to control for this diffusion in banking services in estimating the adoption cost. Second, we allow for both observed and unobserved heterogeneity among households, in their cash-holding behavior. Tracking their decisions over time allows us to control for this heterogeneity, which we find to be substantial. Third, we assume that adoption is irreversible in that a household cannot ‘un-adopt’ the new technology.

Our main finding is that, on the one hand, adopting an ATM card has non-trivial adoption costs for households. On the other hand, the card also generates efficiencies for households. Consistent with the literature on financial inclusion, we find that older, less educated individuals and those residing in economically less prosperous regions face higher barriers to adopting the ATM card. We compute the proportion of new adopters when counterfactual financial incentives are offered. While moderate financial incentives are effective for younger and well-educated consumers, older households or those with less formal education require larger incentives.

Related Literature The study contributes to the literature on adoption of financial innovation by proposing a conditional choice probability estimator for the parameters of these benefits and costs. It also showcases recent advances in the estimation of structural dynamic discrete choice models.

We build on several studies on household and consumer adoption of transaction technology. In studying cash holding using the data set collected from Italian households, we follow in the footsteps of [Attanasio et al. \(2002\)](#), [Lippi and Secchi \(2009\)](#), and [Alvarez and Lippi \(2009\)](#). [Attanasio et al. \(2002\)](#) study the demand for money using a generalized inventory model, and note the effects of ATM card usage. They then calculate the welfare cost of inflation. [Lippi and Secchi \(2009\)](#) show how to account for trends in the availability of banking services in order to estimate money-demand parameters. [Alvarez and Lippi \(2009\)](#) use an inventory-theoretic framework. They model the household’s cash withdrawal conditional on the adoption of an ATM card. Their framework also measures changes over time in withdrawal costs. They find a relatively small benefit to adopting an ATM card, although they note that it is based only on a reduction in withdrawal costs and not on the card’s use as a debit card. [Yang and Ching \(2014\)](#) model both the extensive and intensive margins, using the Baumol-Tobin model to describe the latter. They estimate a significantly larger cost of ATM card adoption than previous papers although they focus mainly on older consumers. Investigating the adoption of automated clearing house (ACH) payments by US consumers and banks, [Akerberg and Gowrisankaran \(2006\)](#) find that the large adoption cost borne by consumers hindered the replacement of paper checks.

We adopt a general, shopping-time model of money holding that is also widely used in

macroeconomic theory and allows for the trend and elasticity findings of [Attanasio et al. \(2002\)](#) and [Lippi and Secchi \(2009\)](#). This shopping-time model is derived from the money-in-the-utility model in [Walsh \(2003\)](#) to which we add a technology parameter for ATM card adoption. A key feature is the inclusion of unobserved heterogeneity in the money-demand equation that follows from the shopping-time model. This feature is motivated by [Lippi and Secchi \(2009\)](#) and [Felt \(2020\)](#) who find that the impacts of payment innovations are overstated when unobserved heterogeneity is omitted. The shopping-time model is used to estimate a subset of the parameters of the utility function conditional on the discrete action using Euler equation methods, as suggested by [Pakes \(1994\)](#), albeit in a different context.

Finally, to estimate the cost of adoption we employ a conditional choice simulation estimator in the spirit of [Hotz et al. \(1994\)](#) and [Hotz and Miller \(1993\)](#). However, the computational burden is significantly reduced by exploiting the finite dependence nature of the adoption problem. Finite dependence is implied by the assumption that ATM card adoption is once and forever. Thus we estimate the dynamic model by simulating only one-period ahead as shown by [Arcidiacono and Miller \(2011\)](#) and illustrated in [Arcidiacono and Ellickson \(2011\)](#). A particular feature of our setting with finite dependence is that we can identify the household discount factor as shown in [Abbring and Daljord \(2020\)](#). The DDC presented in this paper falls into the class of Euler Equations in Conditional Choice Probabilities (ECCP) estimators defined in [Kalouptsi et al. \(2021\)](#). We use the Euler equations in [Aguirregabiria and Magesan \(2013\)](#) and [Aguirregabiria and Magesan \(2023\)](#) for the ATM card adoption decision problem. We also use a parametric bootstrap procedure ([Kasahara and Shimotsu \(2008\)](#)) to compute confidence intervals for our two-step estimator where the first step is the partial estimation of the shopping time model and the transition functions, and the second step is e.g. the ECCP estimator.

Section 2 describes the data sources. Section 3 outlines the household decision problem. Section 4 describes the intratemporal Euler equations while Section 5 deals with the state variables and transition functions. Section 6 then discusses the dynamic discrete choice process and Section 7 presents the results. Section 8 concludes.

2 Data Sources

2.1 Survey of Household Income and Wealth

Our study relies on household-level data from the Bank of Italy’s *Survey of Household Income and Wealth (SHIW)*, which is the gold standard for panel surveys involving wealth and savings. It has detailed information on account status, wealth, and consumption, and the largest and longest coverage of any such panel. The *SHIW* is the main data source for studies

on money demand and financial innovation by [Attanasio et al. \(2002\)](#), [Alvarez and Lippi \(2009\)](#), and [Lippi and Secchi \(2009\)](#), among others.

The *SHIW* is a biennial survey run by the Banca d'Italia. We use the 1991, 1993, 1995, 1998, and 2000, 2002, and 2004 waves. We stop at 2004 as one of our main variables—average currency holdings—is discontinued from 2006 onwards with the exception of 2008. The three year spacing from 1995 to 1998 was a result of the Banca d'Italia switching survey providers. The Banca d'Italia spends considerable resources to ensure that the data is nationally representative, as outlined by ([Brandolini and Cannari, 1994](#)). The *SHIW* is a rotating panel with about 8,000 households per wave. The rotating panel design is incorporated because there is an attrition rate of roughly 50%. ([Jappelli and Pistaferri, 2000](#)) provide an extensive discussion of the quality of the *SHIW* data and also provide a comparison with Italian National Accounts data to address issues of sample representativeness, attrition, and measurement.

ATM cards involve a small annual fee, but no additional charges for withdrawals at machines owned by the issuing bank. Their first benefit is that they allow card-holders to withdraw cash rapidly and when banks are closed. Checking accounts bear interest, so the ability to make withdrawals at lower cost can reduce foregone interest earnings from holding cash. A second benefit is that they can be used as point-of-sale debit cards for retail transactions. Despite these benefits, though, the use of cash remained very widespread in Italy throughout this period.

Table 1 reveals that the fraction of households with an ATM card in 1991 was 29% and that it steadily increased to 58% in 2004. Although the survey has a high attrition rate, many actual ATM card adoptions can be observed. On average, the share of households who did not have an ATM card in the previous wave of the survey, were in both the current and previous waves, and had a card in a given, current wave was 16.7%. Table 1 next focuses on average currency holdings, consumption, and wealth. All the nominal variables are expressed in 2004 equivalent euros. During this period the average currency holdings fell for both the households with and without an ATM card. However, with the exception of 1991 the average cash holdings of ATM holders were lower than those of non-ATM holders. Not surprisingly, those with ATM cards tended to have higher consumption and financial wealth than those without ATM cards. Notice that the difference in consumption and wealth increased over time as was detailed by [Jappelli and Pistaferri \(2000\)](#).

The data support the assumption that ATM card adoption is irreversible. Of the observed households who appear in the data more than once, only 920 or 11.6% appear to adopt the card in one period and then report not having it in a later period. For 662 of these 920 households, at least one of the following variables is not reported consistently across time periods: the age, gender or education level of the household head, the region where the

household resides or the number of adults living in the household. The inconsistent adoption pattern of these households may therefore be explained by their inconsistent overall reporting or a change in the reporting household member from one period to the next.

2.2 Inflation and Regional Interest Rates

We also use data on inflation and interest rates from a variety of sources. The inflation rate, measured as the per-annum change in consumer prices, is taken from the *International Financial Statistics* of the International Monetary Fund. The data are on an annual basis from 1989 to 2010. For regional nominal deposit interest rates we draw on the data assembled by [Lippi and Secchi \(2009\)](#) who aggregated a variety of historical tables at a quarterly frequency. The quarterly data are then aggregated to an annual frequency using simple sum averaging to derive annual data from 1989 to 2010. We refer to [Alvarez and Lippi \(2009\)](#) for more details on the data sources and institutional details.

3 Household choice problem

We propose to model a household’s decision to adopt a financial innovation, specifically an ATM card, as an optimal stopping process. A household will adopt the innovation when it expects the benefits of adoption to outweigh the opportunity costs of not adopting. The model is dynamic since expectations about adoption benefits are computed from summing up (discounted) future per-period utilities.

3.1 Optimal Stopping

A household in period t is described by:

1. ATM card adoption status from the previous period $I_{t-1} \in \{0, 1\}$, where 1 denotes adoption.
2. Choice-specific adoption shocks $\epsilon_t = (\epsilon_t^0, \epsilon_t^1) \in \mathbb{R}^2$ where ϵ_t^I is incurred for choosing $I \in 0, 1$ in period t . These shocks are known to the household before it makes its decision, but they are not observed by the econometrician. We assume that ϵ_t^I are independently and identically distributed across adoption choices, households, and over time.
3. A vector of state variables z_t that are exogenous, i.e. do not depend on I_{t-1} . These state variables are for example the size of the household, its wealth, education and age of its members.

A household's utility depends on the adoption status of financial innovation I_t , its real consumption expenditures c_t , and its real money holdings m_t , and is given by $u(I_t, c_t, m_t)$. It is increasing in consumption ($u_c > 0$). We consider a shopping-time model of money-holding, as outlined by [McCallum \(1989\)](#) (pp 35–41) and [Walsh \(2003\)](#) (pp 96–100). Holding money also adds to utility because it reduces the time spent shopping and so adds to leisure ($u_m > 0$). We also impose the usual concavity assumption ($u_{cc} < 0, u_{mm} < 0$). Using a financial innovation, or more specifically access to cash through an ATM card, increases the utility of consumption for a given real cash balance m_t because the household can shop more efficiently. In the shopping-time utility function, this benefit shows up as $u(1, c, m) > u(0, c, m)$. We specify the functional form of u in section 4.

Adopting an ATM card is costly. It involves a deterministic cost $\bar{\kappa}$ and the choice-specific cost shock ϵ_t^ℓ :

$$\kappa_t(I_t, I_{t-1}, \epsilon_t) = \mathbb{1}\{I_{t-1} = 0\}(I_t - I_{t-1})\bar{\kappa} + \sigma_\kappa \sum_{\ell=0,1} \epsilon_t^\ell \mathbb{1}\{I_t = \ell\}. \quad (1)$$

The household's per-period payoff is thus given by

$$u(I_t, c_t, m_t | z_t) - \kappa_t(I_t, I_{t-1}, \epsilon_t). \quad (2)$$

With the specification of the cost shock, the period utility can be written in terms of observed and unobserved components:

$$\underbrace{u(I_t, c_t, m_t | z_t) - \mathbb{1}\{I_{t-1} = 0\}(I_t - I_{t-1})\bar{\kappa}}_{\text{observed}} - \underbrace{\sigma_\kappa \sum_{\ell=0,1} \epsilon_t^\ell \mathbb{1}\{I_t = \ell\}}_{\text{unobserved}}. \quad (3)$$

In each period t the household decides on real consumption, c_t , and real cash holdings, m_t . These two choice variables are continuous and observed by the econometrician. If the household does not yet have an ATM card ($I_{t-1} = 0$), it decides whether to adopt or not, that is, chooses $I_t \in \{0, 1\}$.

Let A denote the end of household's planning horizon, that is the time period where the household decides for the last time. The household discounts future payoffs with discount factor $\beta \in [0, 1)$. A household's state is fully described by $(I_{t-1}, z_t, \epsilon_t)$. The household chooses the sequence of ATM adoption decision, consumption, and money holding $\{I_\tau, c_\tau, m_\tau\}$, $\tau = t, \dots, A$ to maximize the discounted sum of future payoffs or the value function:

$$W_t(I_{t-1}, z_t, \epsilon_t) = \max_{\{I_\tau, c_\tau, m_\tau\}} E_t \left(\sum_{\tau=t}^A \beta^{\theta-t} [u(I_\tau, c_\tau, m_\tau | z_\tau) - \kappa_t a u(I_\tau, I_{\tau-1}, \epsilon_\tau)] \right). \quad (4)$$

3.2 The adoption decision

To study the optimal dynamic decision of adopting an ATM card, it useful to define the conditional choice value function (see for example [Hotz and Miller \(1993\)](#)) as the value of choosing I_t net of the choice specific shock ε_t^ℓ :

$$v(I_t, z_t) = u(I_t, c_t, m_t|z_t) - \mathbb{1}\{I_{t-1} = 0\}(I_t - I_{t-1})\bar{\kappa} + \beta(E(W(I_t, \varepsilon_{t+1}, z_{t+1}|z_t))), \quad (5)$$

where the expectation is taken by integrating out the stochastic components of the state variable z_{t+1} and the future adoption shocks, conditional on the state variable z_t and the choice I_t .

Recall that after a household adopts the technology, it keeps it forever or until the end of the decision problem's time horizon. Let $p(I_t|I_{t-1}, z_t)$ denote the probability of adopting conditional on adoption status I_{t-1} and state z_t .

By irreversibility, the probability of unadopting is zero ($p(I_t = 0|I_{t-1} = 1, z_t) = 0$) and the probability of keeping the ATM card is one ($p(I_t = 1|I_{t-1} = 1, z_t) = 1$). For this reason, the probability of interest is $p(I_t = 1|I_{t-1} = 0, z_t)$, which corresponds to $1 - p(I_t = 0|I_{t-1} = 0, z_t)$. To economize on notation we will from now abbreviate $p_t = p(I_t = 1|I_{t-1} = 0, z_t)$. Assume that the household has not adopted the ATM card prior to time t , thus $I_{t-1} = 0$. At time t , the household makes the adoption decision based on maximizing $W(0, z_t, \varepsilon_0)$ for the revealed choice specific error terms ε_t^0 and ε_t^1 , that is by comparing:

$$V^1(\varepsilon_t, z_t) := v(1, z_t) - \bar{\kappa} - \sigma_\kappa \varepsilon_t^1 \quad (6)$$

$$V^0(\varepsilon_t, z_t) := v(0, z_t) - \sigma_\kappa \varepsilon_t^0 \quad (7)$$

The adoption rule $V^1(\varepsilon_t, z_t) > V^0(\varepsilon_t, z_t)$ can be re-written in terms of the adoption cost and the conditional value functions:

$$\begin{aligned} V^1(\varepsilon_t, z_t) &> V^0(\varepsilon_t, z_t) \\ \Leftrightarrow v(1, z_t) - \bar{\kappa} - v(0, z_t) &> \sigma_\kappa (\varepsilon_t^1 - \varepsilon_t^0). \end{aligned} \quad (8)$$

Keeping in mind that the right hand side of (8) is a random variable whose distribution is known up to its scale σ_κ , the probability of adoption is given by:

$$p_t = \text{prob} \left[\frac{v(1, z_t) - \bar{\kappa} - v(0, z_t)}{\sigma_\kappa} \geq \varepsilon_t^1 - \varepsilon_t^0 \right]. \quad (9)$$

After setting up the household’s decision problem, we will now work through the econometric building blocks and the estimation procedure.

4 Intratemporal Euler equations

We exploit the fact, that conditional adoption choice I_t , consumption choices c_t , and real cash holdings m_t have to satisfy the standard Euler equations. In particular, the opportunity cost of holding real cash balances is the interest that could be earned when holding the deposits on an interest-bearing checking account. Let r_t denote the nominal interest rate. The intratemporal Euler condition is given by:

$$u_m(I_t, c_t, m_t) = r_t u_c(I_t, c_t, m_t). \quad (10)$$

In this equation, u_c and u_m are the first derivatives of u with respect to consumption c and cash holdings m . Equation (10) can be derived following [Carlstrom and Fuerst \(2001\)](#). Through this intratemporal Euler condition, the dimension of the per-period decision problem condition on ATM adoption status has been reduced to one from two. Given c and I , we can solve for the optimal m using equation (10).

To motivate the per-period utility function, we provide evidence that adoption is directly associated with changes in money holding. [Figure 1](#) plots the money-consumption (mr/c) and wealth-consumption (w/c) ratios over sequences of three waves of the SHIW for the adopters, denoted by (0,0,1) and (0,1,1), the always adopters, denoted by (1,1,1), and the never-adopters, denoted by (0,0,0). The plots apply to three time windows: 1991–1993–1995 (denoted W1), 1998–2000–2002 (denoted W2), and 2000–2002–2004 (denoted W3). The upper panel shows the ratio mr/c . It illustrates that the never-adopters have the highest ratios, followed by adopters, and then the always-adopters. In sequence of three waves, the ratio mr/c is decreasing, consistent with the earlier observation (in [section 2.1](#)) that the overall mr/c ratio is falling over time. The lower panel shows the w/c ratio for the same households. Comparing the three groups in the upper panel suggests that adoption per se is associated with a fall in money holding relative to consumption (in time periods W1 and W2), and economizing on money balances, which will raise utility. In addition, future adopters already hold less money compared to consumption than those who will not adopt in the next period, as can be seen by comparing (0,1,1) to (0,0,0).

We specify the per-period utility function $u(c, m, I)$ of each household i in period t as follows:

$$u(I_{it}, c_{i,t}, m_{i,t}) = (1 + \gamma I_{it})^\omega \frac{c_{i,t}^{1-\alpha} - 1}{1 - \alpha} + e^{\omega \cdot (\eta_i + \delta_t)} \frac{m_{i,t}^{1-\omega} - 1}{1 - \omega}, \quad (11)$$

with parameters (γ, α, ω) , household-specific parameters η_i and period-specific parameters δ_t . As before, the variable I_{it} equals 1 if the household has adopted an ATM card and 0, if not.

One verifies immediately that for $\alpha \geq 1$ and $\omega \geq 1$, it is true that $u_c > 0, u_m > 0$ and $u_{cc} < 0, u_{mm} < 0$ which are the usual monotonicity and concavity conditions. With the specification in (11), u is additively separable in consumption c and cash holdings m since it consists of one summand that varies in c and one summand that varies in m . Each of those summands has the constant relative risk aversion (CRRA) shape with risk aversion parameter α for the consumption part and parameter ω for the cash holdings part.

In the utility function (11), we allow for household and time varying heterogeneity in the parameters. The inclusion of household fixed-effects η_i is motivated by the observation that future adoption is correlated with lower cash balances relative to consumption, as documented in Figure 1. Similarly, year-specific fixed effects reflect that cash balances relative to consumption fall over the sample period for adopters and non-adopters. This enhanced efficiency of money-holding may reflect the diffusion of bank branches and ATMs from 1989 to 2004, as documented by Lippi and Secchi (2009). ATM card adoption leads to increased utility from consumption due to the “technology parameter” $\gamma > 0$.

Estimation of the parameters of the utility function begins with the intratemporal Euler conditions that specialize (10):

$$r_{it} \cdot ((1 + \gamma_i I_{it})^\omega \cdot c_{it}^{-\alpha}) = e^{\omega(\eta_i + \delta_t)} m_{it}^{-\omega}.$$

Recall that the adoption costs do not interact with c and m in the per-period utility and hence would disappear in the partial derivatives u_c and u_m . Taking logarithms on both sides then gives

$$\ln(r_{it}) + \omega \cdot \ln(1 + \gamma_i I_{it}) - \alpha \ln(c_{it}) = \omega \cdot (\eta_i + \delta_t) - \omega \ln(m_{it}). \quad (12)$$

For general $\alpha, \omega \in (1, \infty]$, isolating $\ln(m)$ on the right hand side yields

$$\ln(m_{it}) = -\frac{\ln(r_{it})}{\omega} + \frac{\alpha \ln(c_{it})}{\omega} + \eta_i + \delta_t - \ln(1 + \gamma_i I_{it}). \quad (13)$$

In the limiting case $\alpha = \omega = 1$, the utility function is still well-defined since $\lim_{\alpha \rightarrow 1} \frac{x^{1-\alpha}-1}{1-\alpha} = \ln(x)$ for all positive values of x . Equation (12) then simplifies to:

$$\ln\left(\frac{m_{it} r_{it}}{c_{it}}\right) = \eta_i + \delta_t - \ln(1 + \gamma_i I_{it}). \quad (14)$$

Given consumption c and ATM card adoption I , equation (13) or (14) implicitly defines the optimal level of cash holdings m .

The parameters of interest are thus $\alpha, \omega, \eta_i, \delta_t$ and γ_i . In the data, c, m, r and I are observed. To estimate the parameters of interest, we attach an error term to the money demand equations (13) and (14). Since the money demand equation contains a household level fixed effect on the right hand side, a linear model with within-household fixed effects is appropriate. Since the same household is observed multiple times and some households are observed before and after adoption, the coefficient of I_{it} is identified. The results of the regressions for the intratemporal Euler equations (13) and (14) are summarized in Table 2.

The left panel of Table 2 presents estimates of (13). It shows that point estimates are $\hat{\alpha} = 1.52$ and $\hat{\omega} = 6.68$ so that the utility function has considerable curvature in both consumption and money balances. However, the standard errors on these parameters are large enough that the special case with $\alpha = \omega = 1$ (log utility) is also of interest. The standard errors are shown in the right panel of Table 2 and we present calculations using both utility functions as a point of comparison.

The first row and panel of Table 2 show that $\hat{\gamma} = 0.23$ with a standard error of 0.03. This value and its precision are largely unaffected if we switch to log utility. We also find that allowing γ to vary with observable household characteristics does not improve model fit as measured by R^2 . In what follows we will use the specifications with constant γ as reported in the first row of Table 2. The key finding, then, is that $\hat{\gamma}$ is positive and precisely estimated. Thus, ATM-card adoption raises utility by allowing households to use money more efficiently.

5 State variables and transition functions

The model includes three types of observable state variables that make up the vector (I_{t-1}, z_t) : static state variables, time-varying deterministic state variables, and time-varying stochastic state variables.

The first group includes time-invariant or static state variables which describe the household composition, education level, and place of residence and which do not change from period to period. We need to specify transition functions for the time-varying state variables. The second group are deterministic and time-varying state variables such as the age of the household head and their employment status. Age advances by the length of the time period between t and $t + 1$, in the case of the SHIW by 2 years. Employment status is maintained until age 65 when the household head retires. The third group are time-varying stochastic state variables, namely inflation π_t and interest rates r_t , wealth w_t and adoption status I_t . We discuss them in this order below.

5.1 Interest rate and inflation processes

The inflation rate π_t is the year-to-year growth rate of the consumer price index, from 1989 to 2010. Interest rates r_t are regional nominal deposit rates for each of the twenty administrative regions of Italy.

To parametrize the transition function for $\{\pi_t, r_t\}$ we use ordered VARs and test the lag length with standard information criteria. It makes sense to penalize models with large numbers of parameters given the short time-series sample. As in the rest of the paper, t advances in two-year intervals. We work with natural logarithms to guarantee positive, simulated interest rates and inflation rates.

We find that inflation can be described autonomously:

$$\ln \pi_t = a_0 + a_1 \ln \pi_{t-1} + \epsilon_{\pi t}, \quad (15)$$

with $\epsilon_{\pi t} \sim IID(0, \sigma_\pi^2)$. In each region the deposit rate is well-described by:

$$\ln r_t = b_0 + b_1 \ln r_{t-1} + b_2 \ln \pi_t + \epsilon_{rt}, \quad (16)$$

with $\epsilon_{rt} \sim IID(0, \sigma_r^2)$. This setup ensures that $cov(\epsilon_{\pi t}, \epsilon_{rt}) = 0$ (which simplifies simulations). We use this specific ordering because it fits with the difference in the time periods to which the inflation rate and interest rate in a given year apply.

We estimate the r -equation for each of the twenty regions and report the average estimates over this set (rather than averaging the interest rates, which would lead to an understatement of uncertainty in a typical region). In practice, though, the variation in estimates across regions is quite small.

Table 3 contains the estimates for the parameters, their standard errors, and the two residual variances. Later, we will assume that $\{\epsilon_{\pi t}, \epsilon_{rt}\}$ are jointly normal and, with this ordering, the two shocks are uncorrelated.

5.2 Wealth and the consumption decision

We also estimate reduced form equations for the wealth transition $w_{t+1} = f^w(w_t, z_t)$ and the consumption decision $c_t = f^c(I_t, z_t)$. In our model, wealth will depend on previous period wealth, but the consumption decision does not depend on lagged variables. Graphically, the lower panel of Figure 1 suggests that adoption is associated with a rise in financial wealth relative to consumption in W1 and W3 but not W2. We do observe less variation over time in financial wealth relative to consumption for non-adopters. We account for these observations in two ways: first, we include the fixed effects from equations (13) and (14) in the wealth

transition and in the consumption decision, and second, we assess whether the transitions for adopters and non-adopters are statistically different.

We use ordinary least squares (OLS) regression of the logarithm of current period wealth on the observable state variables z_t and previous period wealth. We find that the estimated transitions for adopters and non-adopters are not statistically different. We thus pool the sample to estimate the transition function f^w which does not depend on the ATM adoption status.¹

Using the same wealth transition for adopters and non-adopters ensures that the discrete choice process has the renewal property (see Rust (1987)). If the state variables evolve independently of the ATM card decision, then $E(u(I_t, c_t, m_t))$ depends on I_t , but not on the adoption history I_1, \dots, I_{t-1} . The renewal property could potentially be used to generalize to a setting where adoption is not a terminal state.

Given their state z_t , households decide how much to consume per period. In contrast to the wealth transition, we estimate separate decision functions for adopters ($I_t = 1$) and non-adopters ($I_t = 0$). The decision functions $f^c(I_t, z_t)$ are computed using OLS regression of the logarithm of consumption c_t on observable state variables z_t , including wealth w_t . Furthermore, the fixed effects η_i also enter the consumption equation as independent variables. These reduced form equations allow us to re-parametrize the utility function as $u(I_t, z_t)$ and also compute $u(0, z_t) - u(1, z_t)$ below.

6 The dynamic discrete choice process

The dynamic discrete choice (DDC) process optimal stopping problem is tractable under certain assumptions. This section states these assumptions and then specifies the functional form of the model components and the parameters to be estimated.

The first assumption is additive separability of the per-period utility in the observables and unobservables, see (2). The second assumption is that the random variables $\kappa(I_t|I_{t-1})$ are independently and identically distributed over time with probability density function g . The third assumption is condition independence which means that the state variables z_t follow a Markov process that is not affected by the unobservable adoption cost κ_t . To fulfill this assumption, it suffices that the probability density function of the state variable z_t has the property $f(z_{t+1}|I_t, \epsilon_{t+1}, z_t) = f(z_{t+1}|z_t)$.

Typically, κ is assumed to follow a parametric distribution and the structural parameters to be estimated are the parameters characterizing this distribution. Since adoption probabilities depend on the difference $\epsilon_t^1 - \epsilon_t^0$, but not on the individual error terms, there is no loss

¹Fractional polynomials did not yield a large improvement in fit relative to the added complexity. The results are available upon request.

of generality in normalizing $\epsilon_t^0 = 0$. This normalization means that only one choice-specific error term, namely ϵ_t^1 , is left. We will therefore denote this error by $\sigma_\kappa \epsilon$ where σ_κ is the variance of κ relative to a chosen distribution for ϵ .

In this paper, ϵ is a normal random variable. We conducted robustness checks for a standard logistic random variable and found that the results were quantitatively and qualitatively very similar.

If $v(1, z_t) - v(0, z_t)$ is known and adoption choices at t are observed then the structural parameters can be estimated from the condition (9). Note that $\kappa_\tau, \tau > t$ enters $v(z_t, 0)$ since the household may adopt later and then pay the adoption cost. In the following section, we show that the terminal choice assumption addresses this recursivity problem.

6.1 Derivation of linear and MLE specifications

We now describe how the conditional value functions $v(I, z)$ are estimated from the data. The key points are first, to exploit the assumption that ATM card adoption is a terminal choice and second, to show that the structural parameters are identified.

We use the Euler equations in [Aguirregabiria and Magesan \(2013\)](#) and [Aguirregabiria and Magesan \(2023\)](#) for the ATM card adoption decision problem. From these Euler equations we retrieve moment conditions and the likelihood. For the remainder of this section, we will re-parametrize the utility function in terms of the exogeneous state vector $u(I, c, m) = u(I, c(I, z), m(c(z))) = u(I, z)$. The functional forms of $c(I, z)$ and $m(c)$ will be derived further below.

As before ϵ follows a normal distribution with mean 0 and variance 1, corresponding to a dynamic probit model:

$$\begin{aligned} 0 = & \left(u(1, z_t) - (1 - \beta^2)\bar{\kappa} - u(0, z_t) \right) - \sigma_\kappa \Phi^{-1}(p_t) \\ & - \beta^2 \sigma_\kappa \int \left(\phi(\Phi^{-1}(p_{t+1})) - (1 - p_{t+1})\Phi^{-1}(p_{t+1}) \right) f(z_{t+1}|z_t) dz_{t+1}. \end{aligned} \quad (17)$$

From this Euler equation, $\Phi^{-1}(p_t)$ can be expressed as:

$$\Phi^{-1}(p_t) = \frac{u(1, z_{t+1}) - u(0, z_{t+1}) - (1 - \beta^2)\bar{\kappa}}{\sigma_\kappa} + \beta^2 E \left((1 - p_{t+1})\Phi^{-1}(p_{t+1}) - \phi(\Phi^{-1}(p_{t+1})) \right), \quad (18)$$

and if we apply the function $\Phi(\cdot)$ to both sides:

$$p_t = \Phi \left(\frac{u(1, z_t) - u(0, z_t) - (1 - \beta^2)\bar{\kappa}}{\sigma_\kappa} + \beta^2 E \left((1 - p_{t+1})\Phi^{-1}(p_{t+1}) - \phi(\Phi^{-1}(p_{t+1})) \right) \right). \quad (19)$$

We note that the Euler equation for a terminal choice in the dynamic logit case also follows

from [Arcidiacono and Miller \(2011\)](#). In what follows, we will refer to the equation (18) as the linear specification and the equation (19) as the MLE specification.

Now, if we are able to compute $u(1, z) - u(0, z)$, p_t , and $E((1 - p_{t+1})\Phi^{-1}(p_{t+1}) - \phi(\Phi^{-1}(p_{t+1})))$ we can fit a linear model or a fractional probit model to obtain estimates of the structural parameters κ, σ_κ and also the discount factor β^2 . Note that β^2 is the discount factor corresponding to t in 2-year units. Specifically, our estimation strategy will be as follows: First, we attach an econometric error term to the linear specification (18), as suggested by [Kalouptsi et al. \(2021\)](#).² We then use a least squares estimator. Second, we maximize the pseudolikelihood corresponding to equation (19), the MLE specification. This is the same maximization problem as for a fractional probit regression. The next subsection provides the algorithm for $u(1, z) - u(0, z)$, p_t , and $E((1 - p_{t+1})\Phi^{-1}(p_{t+1}) - \phi(\Phi^{-1}(p_{t+1})))$.³

6.2 Algorithm

Finally, the probability to adopt an ATM card in period t comes from a static binary probit model of the dichotomous variable I_t on the deterministic state variables and real regional interest rates. Thus we can compute p_t . Since the right hand side of the reduced form for p_t contains stochastic state variables (inflation and regional interest rates), we need to integrate them out to obtain the offset term $E((1 - p_{t+1})\Phi^{-1}(p_{t+1}) - \phi(\Phi^{-1}(p_{t+1})))$. We use the following Monte Carlo algorithm:

First, S denotes number of Monte Carlo draws, Second, N is the number of households in the sample for which $I_{t-1} = 0$ and I_t is observed, and L is the number of distinct regions that these households live in. To be clear on the timing, the households are observed at two time intervals $t - 1$ and t .

For the algorithm, the vector z of state variables is split into three vectors $z = (z_1, \pi, r, w)$ where z_1 consists of all deterministic and static state variables, and the remaining state variables are Markovian, in particular, π is the inflation rate, r the regional deposit rate and w is household wealth.

²We use the linear specification with the inverse cumulative normal of the adoption probability on the left hand side which becomes the dependent variable in the linear model. As discussed by [Aguirregabiria and Magesan \(2013\)](#), it is also possible to re-arrange this equation so that U appears on the left hand side. We conducted a detailed simulation study based in which the former specification converges faster. Details are available upon request.

³To highlight the computational gains, $\frac{u(z) - 1, u(0, z) - (1 - \beta^2)\bar{\kappa}}{\sigma_\kappa} + \beta^2 E(\cdot)$ is equal to $EV_{(\bar{\kappa}, \sigma_\kappa)}$. Thus, with the notation in [Rust \(2000\)](#), we can compute, up to simulating p' , $EV_{(\bar{\kappa}, \sigma_\kappa)}$. Indeed, the algorithm has been reduced to estimating the structural parameters only using the “outer” steps of the fixed point algorithm which maximizes the partial maximum likelihood for MLE in Table 4 (ie solving a fractional probit or logit model).

Algorithm The expected value $E((1 - p_{t+1})\Phi^{-1}(p_{t+1}) - \phi(\Phi^{-1}(p_{t+1})))$ is approximated in three steps:

1. Obtain S draws of the state variable z_{t+1} :
 - (a) Update the deterministic components of $(z_1)_{t+1}$ according to the rules for age and employment.
 - (b) Draw S shocks ϵ_π^s for the inflation process. Simulate S paths for inflation π_{t+1} as $(\ln \pi_{t+1})^s = a_0 + a_1 \pi + \sigma_\pi \epsilon_\pi^s$.
 - (c) Draw S shocks $\epsilon_{r,l}^s$ for each of the L regional deposit rates and simulate $\ln(r_{l,t+1})^s = b_0 + b_1 \ln r_{l,t} + b_2 \ln \pi_{t+1}^s + \sigma_r \epsilon_{r,l}^s$.
 - (d) Draw S shocks $\epsilon_{w,i}^s$ for each for the wealth processes of the N households. Simulate $S \times N$ paths of the wealth process $w_{i,t+1} = f^w(z_i) + \sigma_w \epsilon_{i,w}^s$.
 - (e) Define $(z_{t+1})^s = ((z_{t+1})_1, \pi_{t+1}^s, r_{t+1}^s, w_{t+1}^s)$.
2. Compute $p_{t+1}^s = p(z_{t+1}^s)$ using the coefficients of the static binary probit model.
3. Output:

$$E((1 - p_{t+1})\Phi^{-1}(p_t) - \phi(\Phi^{-1}(p_{t+1}))) \cong \frac{1}{S} \sum ((1 - p_{t+1}^s)\Phi^{-1}(p_{t+1}^s) - \phi(\Phi^{-1}(p_{t+1}^s))). \quad (20)$$

7 Results

In this section, we present the estimation result for the structural parameters and the two-period discount factor β^2 . We also provide an estimate of the monetary compensation that a household would require to adopt. We use the estimation strategy outlined in Section 6.1 and obtain four sets of results, corresponding to two different functional forms of the utility (log and CRRA) as well as two distinct estimators (linear and MLE specification).

7.1 Parameter estimates

Table 4 summarizes results for the linear and MLE specifications, and log and CRRA utilities, for a total of 4 different specifications. We first obtain the coefficient vector $(1/\sigma_\kappa, (1 - \beta^2)\kappa/\sigma_\kappa, \beta)$, subject to $\sigma_\kappa > 0$ and $\beta \in [0, 1)$. We transform these estimates into $\kappa, \sigma_\kappa, \beta$, provided $\beta^2 \neq 1$. Confidence intervals are obtained from a parametric bootstrap. Note that, in order to present confidence intervals, we include estimates of the discounted adoption cost $\bar{\kappa}(1 - \beta)$ instead of $\bar{\kappa}$ in the table. The reason is that the upper bound of the confidence

interval for $1 - \beta^2$ is close to 0 while the estimate $\bar{\kappa}(1 - \beta^2)$ is bounded away from 0.⁴ In addition to estimating $\bar{\kappa}, \sigma_\kappa$ and β^2 , we also estimate $\bar{\kappa}$ and σ_κ for fixed $\beta \in [0, 1)$. We find that the estimates in Table 4 differ somewhat across the specification choices for the estimators (linear or MLE), while different specifications of the per-period utility functions lead to even larger differences in estimated parameters.

For each parameter, we discuss log utilities, then the more general CRRA utilities, followed by a comparison between the two.

Starting with the point estimates for $(1 - \beta^2)\bar{\kappa}$, log utility estimates are around 2.9 for linear and MLE methods, and the 95% bootstrap confidence intervals have approximately the same width (around 1.35) and shape. In the CRRA case, linear and MLE estimates are very close (7.65) and differ only after the second decimal. The confidence intervals are very wide. They are also not symmetric, with the right end point being much further away from the point estimate than the left end point. Comparing the log and CRRA specifications, log utility gives lower estimates that also appear to be more precise. We observe that $(1 - \beta^2)\bar{\kappa}$ and $\bar{\kappa}$ are sensitive to assumptions about β^2 .

The parameter σ_κ is estimated at 0.82 (0.86) with the linear (MLE) method. For CRRA utility the estimates are similar, and only differ in the third decimal. The bootstrap confidence intervals for the estimate σ_κ are large compared to estimate itself. While they are bounded away from zero at the lower end, the width of the 95% bootstrap confidence interval is around 3.5 times the value of the parameter estimate for log utilities and 500 times the value of the parameter estimate for CRRA utilities. A likely explanation is that our estimators involve transforming an estimate by inversion of $(1/\sigma_\kappa)$. Thus, small ranges of the untransformed estimate can translate into large ranges when the untransformed estimates are close to zero.

With regards to β^2 , it appears that the households are less myopic (larger β^2) under log utility than under constant relative risk aversion (CRRA). Specifically, the squared annual discount factor β^2 is around 0.97 to 0.98 for log utility and around 0.78 to 0.80 in the CRRA case.

Since most previous literature has relied on calibrated values of β^2 or investigated a range of values for β^2 , it also is instructive to estimate the structural parameters for fixed β^2 . To study this issue we set β^2 equal to an arbitrary but fixed value b in the interval $[0, 1)$. We then estimate $\sigma_\kappa(b)$ and $\kappa(b)$ from the least-square criterion in (18) and the MLE specification in (19) where $\beta^2 = b$, respectively. We thus can express the constrained estimates as functions of the discount factor.⁵ The graphs of these functions are shown in Figure 2 for four different

⁴It is possible that $\hat{\kappa}$ does not have well-defined second order moment, similar to a Cauchy distribution or the certain ratios of two normally distributed random variables

⁵Similar to Yang and Ching (2014) we investigate a range of β^2 . However, Yang and Ching (2014) assume the cost of a cash withdrawal is proportional to consumption or income. They also use steady-state

cases defined by the two choices for the per-period utility (log or CRRA) and the estimator (linear or MLE). In all four cases the parameter estimates for σ_κ and κ are sensitive to specifying the discount factor. Using log per-period utilities, we find that linear and MLE specifications yield quite different shapes for $\sigma_\kappa(b)$. Where $\sigma_\kappa(b)$ is increasing in b when the MLE specification is used, a hump-shaped relationship emerges for the linear specification. Using CRRA per-period utility, both linear and MLE specifications yield monotonically increasing relationship between σ_κ and the discount factor. Despite these differences for $\sigma_\kappa(b)$, $\kappa(b)$ has a similar shape for all four specifications.

Overall, we note that the estimates for $\bar{\kappa}$ are large compared to the utility from consumption. For example, with log utility and a typical consumption of €20,000, the utility of a non-adopter is around 10 units while the estimate for $\bar{\kappa}$ is close to 100 units.

That $\bar{\kappa}$ increases with β^2 could be driven by the observation that $\bar{\kappa}$ enters as $(1 - \beta^2)\bar{\kappa}$. To illustrate this dependency, we plot $(1 - \beta^2)\bar{\kappa}$ in Figure 3. We see that this discounted value of $\bar{\kappa}$ decreases in β^2 for all model specifications. Furthermore, the rate of decrease is constant in β^2 for log utility, but accelerates in β^2 for CRRA utility.

Myopic consumers might perceive adoption as more costly. Adopting earlier would allow the household to reap greater benefits in the future which become more important the larger the discount factor β is. This is supported by the observation that the CRRA specifications show a stronger increase of the discounted adoption cost with respect to β^2 .

7.2 Compensating variation

This subsection uses the structural estimates to calculate the one-time, per-household subsidy that would lead to ATM card adoption. Our specific question is: How much do we have to compensate Italian households in consumption so that they are indifferent between adopting and not adopting an ATM card in the current period? We follow the approach of [Cooley and Hansen \(1989\)](#) and [Goolsbee and Klenow \(2006\)](#) in obtaining a measure in monetary units (here: euros).

The compensating consumption CV is defined implicitly as:

$$u(1, c^1 + CV, m^1(c)) - \bar{\kappa} + \beta EW(z_{t+1}|I_t = 1) = u(0, c^0, m^0(c)) + \beta EW(z_{t+1}|I_t = 0) \quad (21)$$

Here the left-hand side represents the expected future value of adopting if the household's consumption were increased by CV in the initial period and the right hand side represents the future value of not adopting. Note that right hand side is $v(0, z_t)$

optimization (with no discount factor) to find the Baumol-Tobin rule then a separate optimization into which they enter the steady-state costs.

From the definition of $v(z, 1)$ and $v(z, 0)$, the equation can be re-written as

$$\begin{aligned} u(1, c^1 + CV, m^1(c^1)) - \bar{\kappa} + \beta EW(z_{t+1}|I_t = 1) &= v(0, z_t) \\ u(1, c^1, m^1(c^1)) - \bar{\kappa} + \beta EW(z_{t+1}|I_t = 1) - (1, u(c^1, m^1) - u(1, c^1 + CV, m^1)) &= v(0, z_t) \\ v(1, z_t) - \bar{\kappa} - u(1, c^1, m^1) - u(1, c^1, m^1) &= v(0, z_t) \end{aligned}$$

or,

$$v(1, z_t) - \bar{\kappa} - v(0, z_t) = u(1, c^1, m^1) - u(1, c^1 + CV, m^1).$$

Here, $c^I = f^c(I, z_t)$ and $m^I = m(I, c^I)$ Recall that $I_t = 1$ is the optimal choice if and only if $v(1, z_t) - \kappa - \sigma_\kappa \epsilon^1 > v(0, z_t) - \sigma_\kappa \epsilon^0$; thus there exists a unique $\bar{\epsilon}_\kappa$ such that

$$\begin{aligned} v(1, z_t) - \bar{\kappa} - \sigma_\kappa \bar{\epsilon}_\kappa &= v(0, z_t) \\ \iff v(1, z_t) - \bar{\kappa} - v(0, z_t) &= \sigma_\kappa \bar{\epsilon}_\kappa \\ \iff v(1, z_t) - \bar{\kappa} - v(0, z_t) &= \sigma_\kappa F^{-1}(p_t) \end{aligned}$$

where F^{-1} is the mapping from probabilities to differences in expected future values, induced by (9) Thus CV is implicitly defined by

$$u(1, c^1 + CV, m^1) - u(1, c^1, m^1) = -\sigma_\kappa F^{-1}(p_t). \quad (22)$$

To be able to derive meaningful results for variety of functional forms of u , we linearize u and compute the compensating variation as

$$LCV = \frac{-\sigma_\kappa F^{-1}(p_t)}{u(1, c^1, 0)} c^1. \quad (23)$$

For CRRA utilities, we thus obtain

$$LCV = \frac{(1 - \alpha)\sigma_\kappa F^{-1}(p)}{(1 + \gamma)^\omega (c^{1-\alpha} - 1)} c. \quad (24)$$

Our choice of linearizing u in this fashion is motivated by [Goolsbee and Klenow \(2006\)](#) who show that logarithmic demand functions can lead to large estimates for the consumer surplus of technological adoption when compared to e.g. linear demand functions. The reason is that logarithmic demand functions are steep at small values and flat at large values.⁶

⁶This linearization strategy also overcomes the following challenge: Because u is monotonically increasing in c , there exists at most one solution for CV (22). However, since u is not surjective, the real solution set could be empty. For log utility, we can obtain exact real solutions of (22), that is a number in \mathbb{R} . For CRRA utilities, this inversion may lead to complex solutions. We thus rely on the first order approximation. To find CV for a variety of functional forms of u , we could use a first order Taylor approximation at c^1 to solve for CV .

Note that in the special case of a linear utility function, $u = \alpha c$, $CV = LCV = \alpha \sigma_\kappa F^{-1}(p)$. Figure 4 illustrates the compensating variation measure in both cases for a convex utility function.

We now provide numerical estimates of the compensating variation. First, the two lower panels of Table 4 show the average value of LCV for different age groups, educational attainment and regions. We also provide confidence intervals from a bootstrap procedure. For log utility, point estimates for LCV range from €789 (highly educated) to €1907 (basic education), when taken across all specifications. For CRRA utility, they range from €52 (highly educated) to €117 (basic education). In general, LCV increases with age, decreases with educational attainment and is lowest in the North of Italy and highest in the South. We also observe that confidence intervals are narrower for log utility than for CRRA utility.

In addition to these point estimates and their confidence intervals, we also illustrate how LCV varies within the population. Violin plots, which are an extension of boxplots, are a useful tool to visualize the distribution of LCV. The violinplots in Figures 5, 6 and 7 are computed from the point estimates in Table 4. They show that the distribution of LCV is qualitatively similar for all specifications. In particular, we observe that oldest age group has a bimodal distribution of LCV, hinting at heterogeneity within this group.

Finally, we use the estimates of LCV from the MLE specification to compute the counterfactual adoption rates in the case of subsidies of 10, 50, 100 and 200 Euros for CRRA preferences. We assume that the household will adopt when the subsidy exceeds LCV . As shown in Table 5, most households that are older, less educated and live in the South require subsidies exceeding €100 to adopt immediately. On the other hand, those with high education require lower incentives. Overall, incentives of around €100 would be required to get about half of the non-ATM card adopters to adopt the cards immediately.

8 Conclusion

This paper provides an application of discrete dynamic choice (DDC) models to the adoption of financial innovation, contributing insights both to the literature on the identification of DDC models and the technology adoption in the banking sector. Our method is applicable to a range of additional financial adoption decisions.

Our paper uses several recent advances to modify the conditional choice simulation estimator of Hotz et al. (1994). In addition of exploiting the finite dependence property of the technology adoption problem (Arcidiacono and Ellickson (2011)), we also implement the

That is we approximate $u(1, c^1 + CV, m^1) \equiv u(1, c^1, m^1) + (\partial u / \partial c)|_{c=c^1} CV$. Since the derivative of the utility function with respect to c is $\partial u / \partial c = (1 + \gamma)^\omega c^{-\alpha}$, approximately $u(1, c + CV, m) - u(c, m, 1) \equiv (1 + \gamma)^\omega c^{-\alpha} CV$, and thus $CV \cong \frac{-\sigma_\kappa F^{-1}(p) c^\alpha}{(1 + \gamma)^\omega}$.

Euler equations in [Arcidiacono and Miller \(2011\)](#) and estimation of the discount parameter from [Abbring and Daljord \(2020\)](#). In doing so, we reduce the computational complexity of the DDC model. As a byproduct, we provide a closed form for the dynamic probit model similar to the often-cited formula for the dynamic logit model.

A key feature of the economic environment is the return or utility function. That is based on a shopping-time model of money demand, with two distinctive features. First, it allows for a gradual diffusion of bank branches and ATM machines between 1989 and 2004, which enhanced the efficiency of money holding (and so reduced the ratio of money to consumption) for both card-holders and non-card-holders. Second, it includes a parameter (γ) that isolates the additional degree to which card-holders economized on money holding. We estimate these features of money demand via the Euler equations in a first step, using data from more than 52,000 household-year observations. We also estimate transitions for consumption and wealth for both groups. We can therefore compute per-period utilities up to adoption cost. The adoption cost is then estimated from the dynamic choice model.

While we find that the discounted adoption cost is larger for myopic households, we provide empirical evidence that households have discount factors between 0.88 and 0.99, hence are not myopic when deciding whether to adopt financial innovations. Furthermore, if households have constant relative risk aversion, the data suggest that they are also somewhat more myopic when compared to the case of log utility. This finding is important since many dynamic decision problems take the discount factor, a measure of myopia, as given. It is also consistent with the experimental finding of [Andersen et al. \(2008\)](#).

We compute the compensating variation, that is the amount of consumption that corresponds to the disutility of adopting an ATM card which balances adoption costs against the enhanced efficiency of money holding. In this context, the compensating variation could be interpreted as the size of financial incentive or subsidy to encourage adoption of the financial innovation. The average compensating variation is €90 (CRRA) respectively €1400 (log utility). Older, less educated households in less prosperous regions would need to receive larger financial incentives. These non-trivial costs could explain some of the slow uptake of financial innovations, especially among the elderly, rural or less educated.

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Tables

Table 1: Descriptive Statistics

	1989	1991	1993	1995	1998	2000	2002	2004
% with ATM card	15%	29%	34%	40%	49%	52%	56%	58%
Average:								
Currency holdings (m):								
with card	741	527	398	421	374	349	341	352
without card	696	607	457	498	438	443	458	468
Non-durable consumption (c):								
with card	28395	26517	26430	27242	24463	25796	24941	25343
without card	20585	17757	17237	17299	15341	15405	15138	15899
Financial wealth (w):								
with card	161293	190016	210880	203246	190581	194804	201501	208796
without card	115507	119261	126080	120216	111700	112830	110951	129692
Interest rate (r):								
with card	8.3%	8.7%	9.0%	7.1%	3.2%	2.2%	1.6%	0.4%
without card	8.2%	8.5%	8.9%	7.0%	3.2%	2.2%	1.6%	0.4%
mr/c ratio:								
with card	0.23	0.19	0.15	0.12	0.06	0.03	0.03	0.006
without card	0.32	0.33	0.26	0.22	0.10	0.07	0.05	0.013
Observations	8038	7951	7799	7844	6801	7641	7660	7639

Note: Currency holdings, consumption, and wealth are expressed in terms of 2004 euros. The source is the Bank of Italy's *Survey of Household Income and Wealth*.

Table 2: Intratemporal Euler equation for CRRA and log utilities

	CRRA (13)				log (14)	
	α	ω	$\bar{\gamma}$	R^2	$\bar{\gamma}$	R^2
γ constant	1.52(0.87)	6.68 (3.8)	0.23 (0.04)	0.35	0.27 (0.04)	0.78
γ varies across demographics	1.76(1.17)	7.70 (5.1)	0.23 (0.04)	0.35	0.27 (0.04)	0.78
			p = 0.3		p = 0.3	

Note: This table is derived from the fixed effects regression for the money demand equations (13) and (14). The p-value reports the test that the interaction effects of demographic variables and the ATM adoption status are significant. Standard errors in parentheses. The Stata module `-fese-` gives standard errors for the fixed effects. The reported standard errors are in parentheses and obtained from the delta method,

Table 3: Interest-Rate and Inflation Process

$$\begin{aligned} \ln \pi_t &= a_0 + a_1 \ln \pi_{t-1} + \epsilon_{\pi t} \\ \ln r_t &= b_0 + b_1 \ln r_{t-1} + b_2 \ln \pi_t + \epsilon_{rt} \\ \epsilon_{\pi t} &\sim IIN(0, \sigma_\pi^2) \\ \epsilon_{rt} &\sim IIN(0, \sigma_r^2) \end{aligned}$$

Parameter	Estimate	Standard Error
a_0	0.182	0.256
a_1	0.694	0.208
σ_π^2	0.162	0.054
b_0	-1.185	0.288
b_1	0.826	0.127
b_2	0.947	0.312
σ_r^2	0.314	[0.261, 0.372]

Notes: Estimation uses annual observations from 1989–2010 on CPI inflation and regional deposit rates. The interval in the standard error column for σ_r shows the second lowest and second highest value among the twenty per-region regressions. Time t is measured in 2-year steps.

Table 4: Estimators and results

	Linear specification		MLE specification	
	Estimate	95% CI	Estimate	95% CI
log				
$\kappa(1 - \beta^2)$	2.93	[2.12, 3.37]	2.88	[1.85, 3.35]
σ_κ	0.82	[0.62, 2.35]	0.86	[0.65, 2.54]
β^2	0.97	[0.58, 1)	0.98	[0.5, 1)
CRRA				
$\kappa(1 - \beta^2)$	7.65	[4.2, 175.18]	7.65	[3.41, 251.87]
σ_κ	0.03	[0.03, 12.15]	0.03	[0.03, 18.07]
β^2	0.78	[0.38, 1)	0.80	[0.34, 0.99]
LCV log				
Age cohort				
young	955	[598, 3003]	1003	[574, 3114]
middle	1243	[865, 4055]	1306	[878, 4272]
old	1741	[1208, 5337]	1828	[1243, 5714]
Education level				
basic	1816	[1275, 5520]	1907	[1374, 5986]
intermediate	1316	[810, 3988]	1383	[880, 4403]
high	789	[428, 2787]	829	[400, 3009]
Region				
North	1257	[810, 3918]	1320	[865, 4222]
Centre	1468	[955, 4989]	1542	[989, 5185]
South	1607	[1026, 4813]	1687	[1076, 5151]
LCV CRRA				
Age cohort				
young	62	[34, 2350]	63	[35, 2246]
middle	81	[40, 2592]	82	[41, 2477]
old	111	[58, 3593]	113	[61, 3434]
Education level				
basic	116	[60, 3786]	117	[63, 3618]
intermediate	86	[48, 2689]	87	[50, 2570]
high	52	[23, 1938]	53	[24, 1852]
Region				
North	82	[44, 2610]	83	[45, 2495]
Centre	96	[45, 2967]	97	[47, 2835]
South	102	[55, 3548]	103	[56, 3391]

Note: The linear and MLE specifications are found in equations (18) and (19), respectively. The 95% confidence intervals (CI) are obtained from a parametric bootstrap procedure suggested by [Kasahara and Shimotsu \(2008\)](#). We resample the covariance matrices of the coefficient estimates for money demand function, the interest rate and inflation process and the transition functions. LCV denotes the linearized compensating variation from equation (23) or (24).

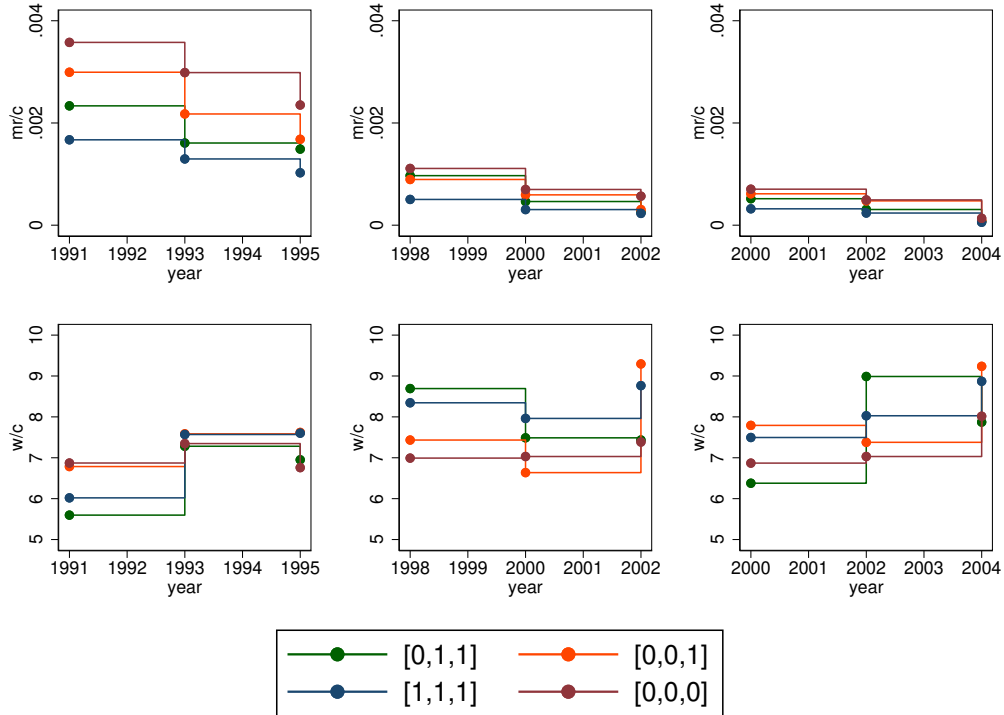
Table 5: Counterfactual adoption by cohort and subsidy amount

	€10	€20	€50	€100	€200
Age cohort					
young	0.12	0.17	0.37	0.79	1
middle	0.07	0.1	0.22	0.66	0.99
old	0.01	0.02	0.05	0.34	0.99
Education level					
basic	0.01	0.05	0.03	0.3	0.98
intermediate	0.03	0.23	0.17	0.63	1
high	0.17		0.45	0.86	1
Region					
North	0.09	0.11	0.22	0.61	1
Centre	0.06	0.08	0.17	0.49	0.99
South	0.01	0.02	0.1	0.45	0.99

Note: LCV denotes the linearized compensating variation from equation (23) or (24) in the text. Entries show the proportion of the sample for which the subsidy exceeds the linearized compensating variation (LCV), so that adoption will occur. The values for LCV are computed from the MLE estimator with CRRA utility.

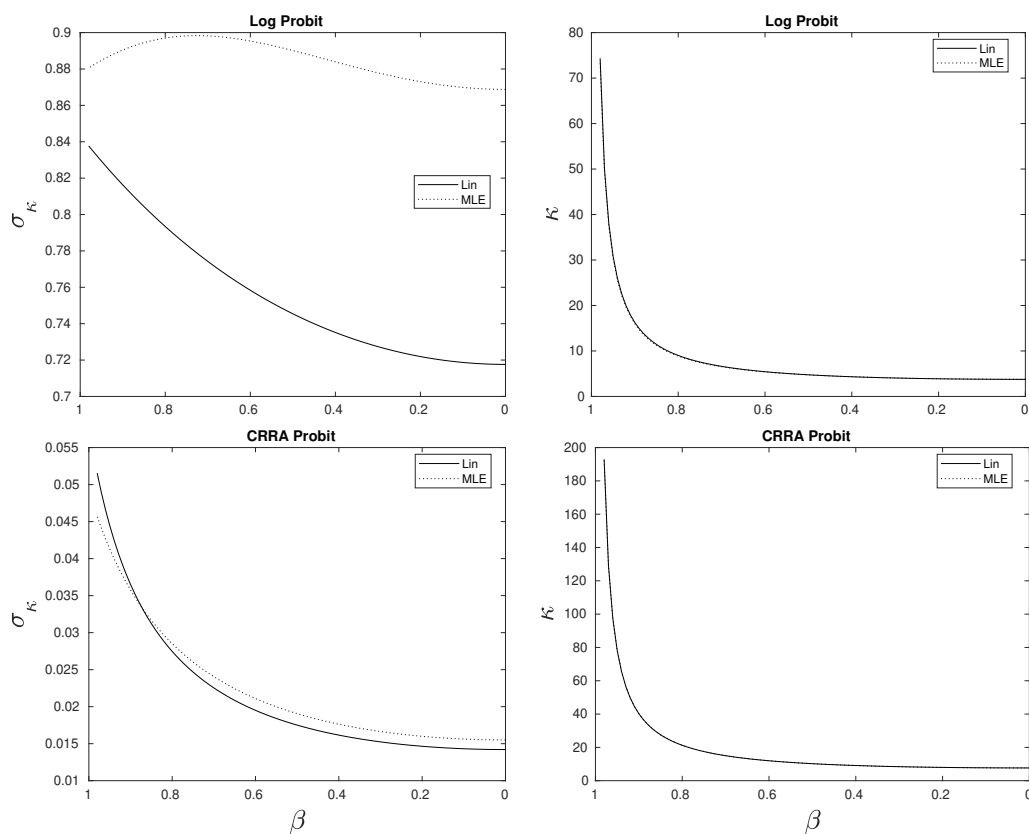
Figures

Figure 1: ATM Card Adoption, Money-Consumption and Wealth-Consumption Ratio



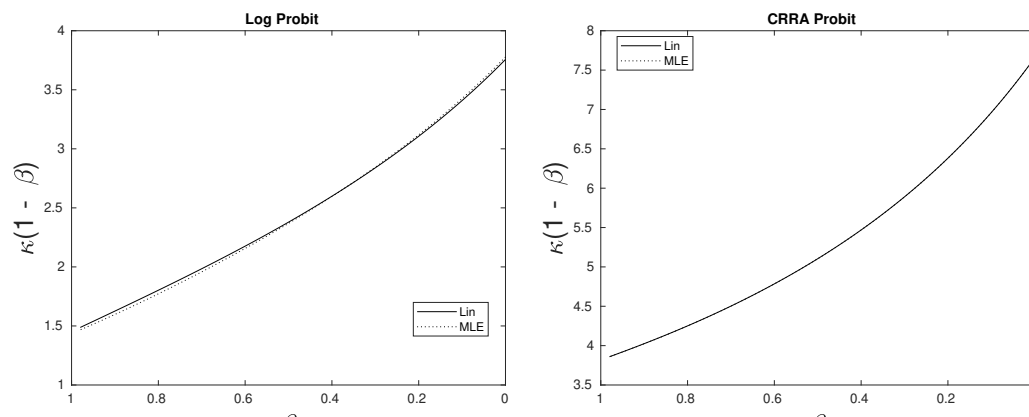
Note: The Figure plots the money-consumption (mr/c) and wealth-consumption (w/c) ratios over sequences of three waves of the SHIW for the adopters, denoted by (0,0,1) and (0,1,1), the always adopters, denoted by (1,1,1), and the never-adopters, denoted by (0,0,0). The plots apply to three time windows: 1991–1993–1995 (denoted W1), 1998–2000–2002 (denoted W2), and 2000–2002–2004 (denoted W3). The upper panel shows the ratio mr/c . The lower panel shows the w/c ratio for the same households.

Figure 2: Estimates of structural parameters



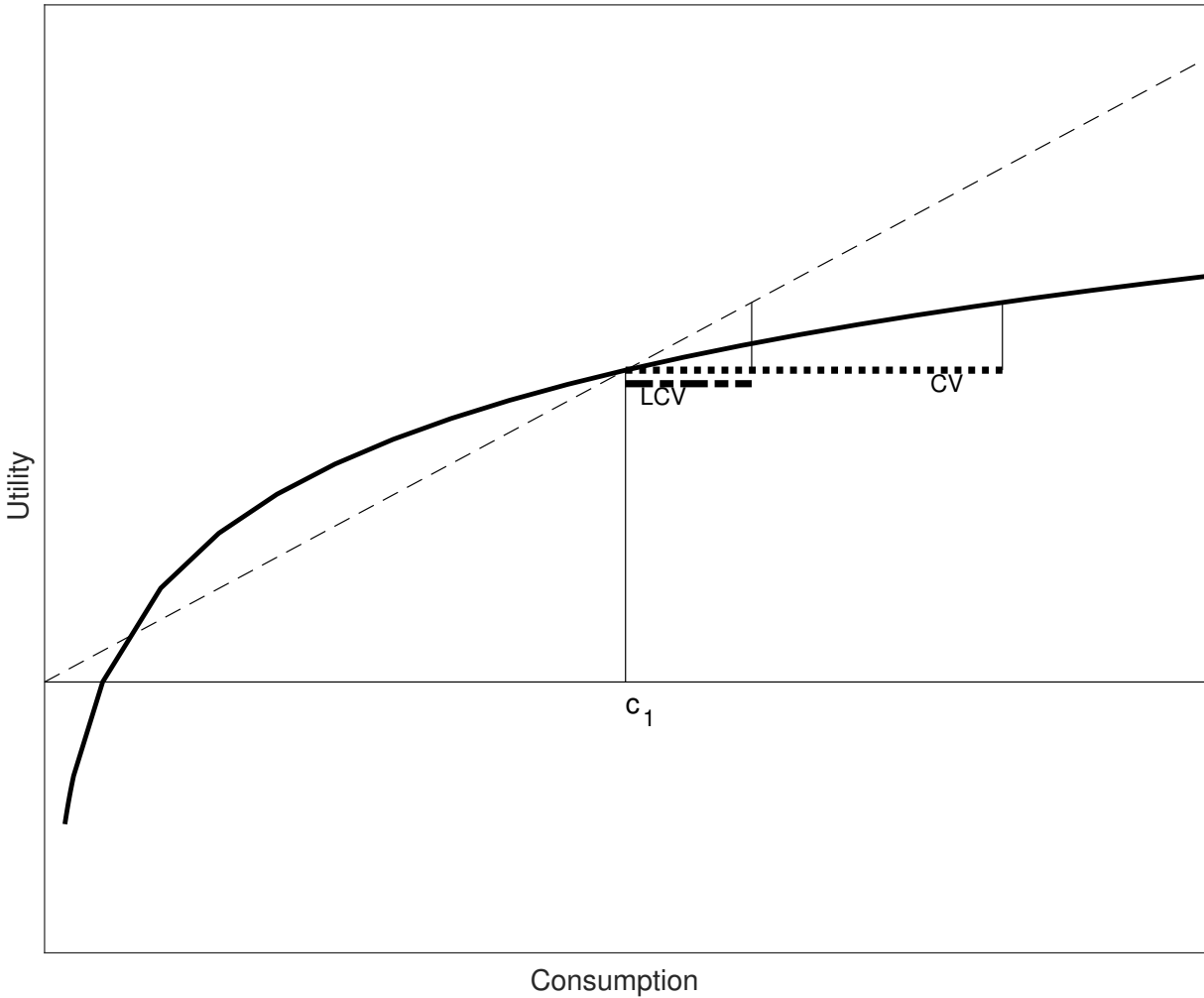
Note: The charts show the estimates of the parameters σ_κ and κ obtained from minimizing the linear least squares conditions (18) or the maximizing the likelihood functions (19) when β is fixed at the value on the horizontal axis. Log and CRRA indicate the functional form of the per-period utility function.

Figure 3: Estimates of discounted adoption cost



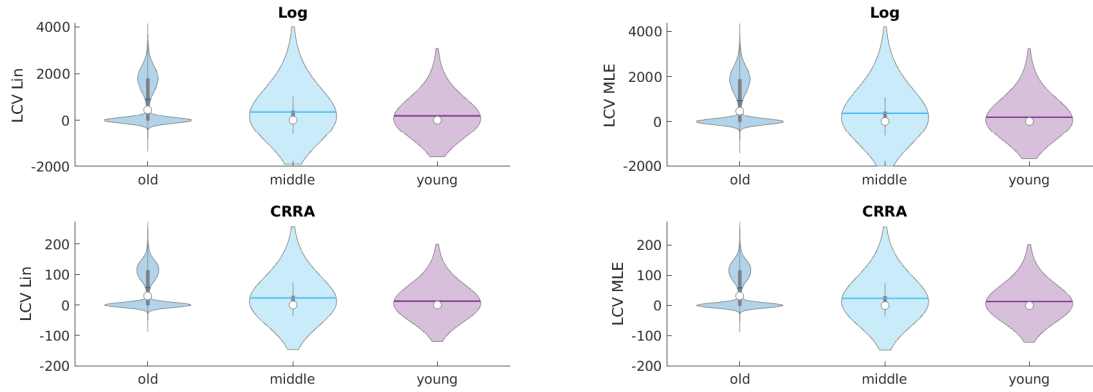
Note: The charts show the estimates of $\kappa(1 - \beta)$ obtained from minimizing the linear least squares conditions (18) or the maximizing the likelihood functions (19) when β is fixed. Log and CRRA indicate the functional form of the per-period utility function.

Figure 4: Consumption, utility and compensating variation



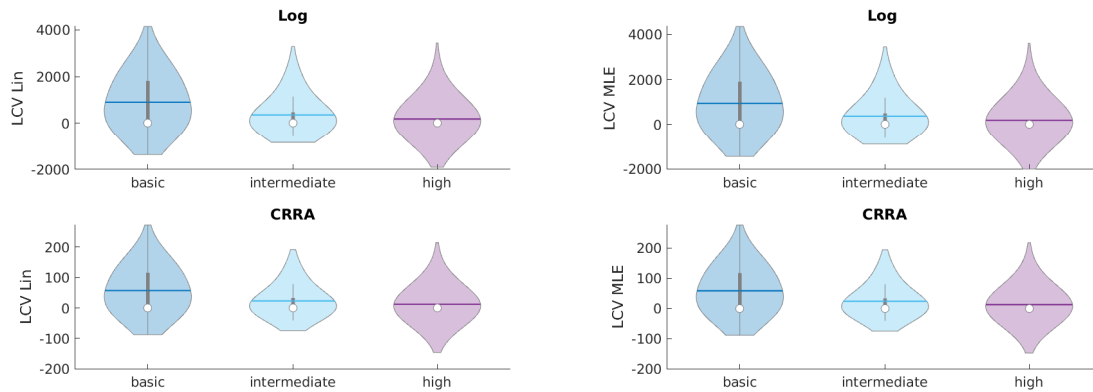
Note: The chart shows how to graphically obtain CV and LCV for a utility shock at a level of consumption c_1 , see [Goolsbee and Klenow \(2006\)](#) for further details. Consumption is plotted on the x-axis and the y-axis shows the level of utility corresponding to a certain level of consumption. If utility changes by the amount x represented by the short vertical line, CV represents the solution to $u(c_1 + CV) = u(c_1) + x$ and $LCV = \frac{x}{u'(c_1)}c_1$ is the proportional, or linear, compensation.

Figure 5: Estimates of LCV by age cohort



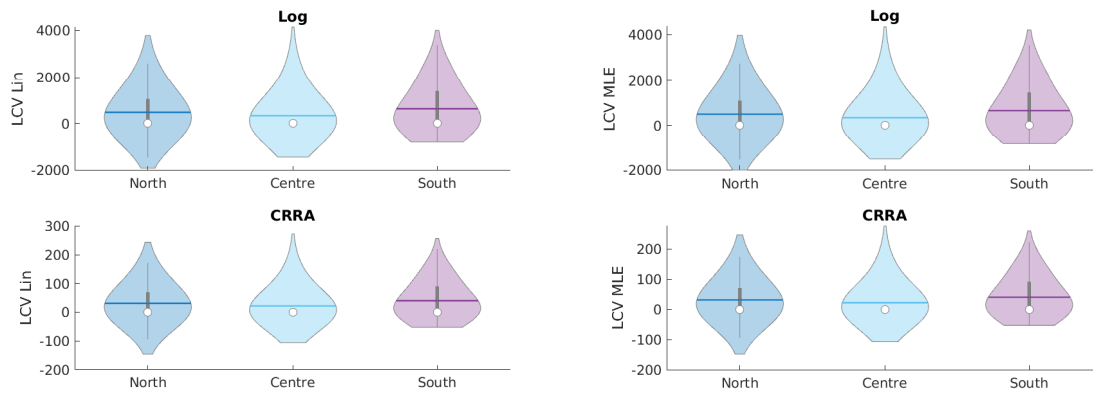
Note: The charts show the distribution of LCV by age cohort, using the parameters obtained from minimizing the linear least squares conditions (18) or the maximizing the likelihood functions (19). Log and CRRA indicate the functional form of the per-period utility function.

Figure 6: Estimates of LCV by education



Note: The charts show the distribution of LCV by education level, using the parameters obtained from minimizing the linear least squares conditions (18) or the maximizing the likelihood functions (19). Log and CRRA indicate the functional form of the per-period utility function.

Figure 7: Estimates of LCV by region



Note: The charts show the distribution of LCV by region, using the parameters obtained from minimizing the linear least squares conditions corresponding to (18) or the maximizing the likelihood functions corresponding to (19). Log and CRRA indicate the functional form of the per-period utility function.

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