Credit card holding:
A microeconomic perspective for the case of Italian households

Angel Garcia*
University of Siena
PhD Programme in Economics
Microeconometric Applications

Abstract

This paper provides a simple microeconomic evaluation of the determinants of credit card holding in Italy. Using a Probit model, the analysis mostly concentrates on the demand side of the credit card market. Thus, the focus has been on identifying specific individual characteristics of Italian households, which show to be statistically significant for determining the probability of possessing a credit card. The data has been entirely collected from the *Survey of Italian households' Income and Wealth 2002*. Relevant expected results are derived from this study. In the first place, the probability of holding a credit card is shown to move up with increases in average family income perceptions, although further increases to higher levels of income show weak diminishing returns captured by a negative quadratic association included in the estimation. Secondly, the age of the head of household is also shown to be a positive determinant even though decreasing returns are as well significant when the age squared value is considered. Additionally, discrete variables such as geographic location, precisely, not living in the south or islands of Italy, basic and university-level education, owning a vehicle, being married and formally employed are positively related to a higher probability of possessing a credit card. Unexpectedly, having a full-time job seems to be negatively related to the same probability. Regarding, gender not much can be formally stated since even though the coefficient shows a negative relation, it is statistically insignificant. Particularly, at mean values of the sample distribution, the probability of holding a credit card mainly increases with basic education in 17%, university level education in 38%, and ownership of a vehicle in 11%. Equivalently, decreases associated to discrete variables are mainly driven by southern household location in around <14>%, and, unexpectedly by, fulltime working in <5>%.

* email: garcia@unisi.it

TABLE OF CONTENTS

1. INTRODUCTION

Money and means of exchange have always evolved over time. Starting from the most primitive forms of money like pearls, salt, cattle, grain, precious metals and others to the most sophisticated and modern forms such like checks, credit and debit cards, e-chips, electronic payments, and others, the payment system has always been facing a continuous process of transformations which have mainly been culturally, governmentally, and technologically-driven.

Regardless of the interests of the national states in the use of a legal tender, or national currency subject to seignorage, the private banking industry worldwide has been increasingly proficient in offering alternative means of payment, although still denominated in national currencies. Thus, a great number of modern instruments of payment have increasingly been associated with private credit instruments, that is, with financial instruments that not only serve as a means of payment, but also represent a form of credit or "in-advance" expenditure.

Precisely, two of the most popular instruments of payment nowadays are credit and debit cards. First credit cards were introduced in 1951 by Diners Club, but were only widely spread until the standards for magnetic strips were established around year 1970. Simultaneously, during the same period, the coincidence with the end of the Bretton Woods system, the liberalisation of capital accounts, the development of off-shore bank businesses, the deregulation of banking systems, and the new generation of technology which allowed for the storage of monetary value on silicon chips, explain, to a great extent, the dissemination of credit and debit cards during the last decades of the past millennium.

However, abstracting from macroeconomic and technological aspects, some of which have been previously mentioned, national and international credit card systems have been widely growing also due to a variety of microeconomic reasons. From the viewpoint of the banking industry (supplier), it represents a profitable business provided that banks obtain net revenues from both, issuing funds, charging merchant discount fees, annual fees to cardholders, and in the case of revolving credit, by imposing an interest rate on the monthly due amount[1]. From the point of view of cardholders (consumers), a credit card allows for the purchase of all kinds of goods in a growing number of establishments, without having to immediately debit bank accounts through the use of

[1] Revolving credit represents the case of cardholders who usually roll-over credit card balances over month to month without ever paying in full, or at least, during a relatively long period of time.

checks or cash withdrawals. In the case of *revolving credit*, credit cards also allow consumers to finance their expenditures over a medium-term horizon. In short, even though credit cards involve the addition of an intermediary, they undoubtedly increase the efficiency of exchange.

This paper provides a simple microeconomic evaluation of the determinants of credit card holding in Italy. Using a Probit model, the analysis mostly concentrates on the demand side of the credit card market. Thus, the focus has been on identifying specific individual characteristics of Italian households, which show to be statistically significant for determining the probability of possessing a credit card.

The data has been entirely collected from the Survey of Italian households' Income and Wealth 2002. Relevant expected results are derived from this study. First of all, the probability of holding a credit card is shown to move up with increases above average family income, although further increases to higher levels of income show weak diminishing returns captured by a negative quadratic association included in the estimation. Secondly, the age of the head of household is also shown to be a positive determinant even though decreasing returns are as well significant when the age squared value is considered. Additionally, variables such as geographic location, precisely not living in the south or islands of Italy, basic and university-level education, owning a vehicle, being married and formally employed are positively related to a higher probability of possessing a credit card. Unexpectedly, having a full-time job seems to be negatively related to the previously mentioned probability. Regarding, gender not much can be formally stated since even though the coefficient shows a negative relation for the case of women such coefficient is statistically insignificant.

The paper is structured as follows. Next section briefly describes the profile of the credit card business in Italy. The third section comments, in brief, on the literature review regarding credit and behavioural scoring. The fourth section points out certain aspects about the management of the data. The fifth introduces the Probit model. The following section presents the results, and the final offers some conclusions.

2. CREDIT CARDS IN ITALY

Ardizzi (2003) indicates that at least 590 million card payment operations took place during year 2000 in Italy, from which 46% were made by credit cards. Card transactions average around 10 per capita in a year, which is indeed low in comparison to many other developed countries.

Table Nro 1 summarises the market power distribution in the credit card business in Italy at the beginning of the new millennium. It shows that CartaSì is the leading credit card company in both the issuing market and the acquiring market[2]. The table also shows that BankAmericard represents the second most spread credit card in both the issuing and acquiring businesses, while Amex, Topcard, Moneta, Diners and others control only a minor part of both markets. In short, two credit card companies control over half of both the issuing and the acquiring market.

Table Nro 1: Credit Card Market Share in Italy as of year 2000

CREDIT CARD Issuer	ISSUING MARKET % of value transacted	ACQUIRING MARKET % transactions at Point of Sale terminals
CartaSì	57	46
BankAmericard	18	15
Amex	9	13
TopCard	5	2
Moneta	6	9
Diners	3	5
Other cards	2	10
	100	**100**

Source: Bank of Italy.

One major evident observation by Ardizzi (2003) is the fact that the majority of the credit cards issued in Italy work as charge cards. That is, most of the credit card contracts in Italy are established under conditions which allow, at most, for a one-month payment delay before the bank proceeds to debit the credit cardholder's bank account. This implies that most credit card agreements in Italy do not actually involve consumer credit operations, at least for over 60-day periods. Indeed, most credit card contracts in Italy include a direct debit pre-authorization, and therefore, involve no interest rate payment by the cardholder. Thus, the Italian credit card business

[2] A bank or a credit card company acts as an acquirer when it accepts and receives electronic funds from a different credit card company (issuer) through its own terminals or "Point of Sale" (POS) network available at different commercial establishments.

seems to be concentrated in the profitability from imposing merchant discount fees, rather than in the expansion of credit, consumer lending, or revolving credit *per se*[3].

3. ON CREDIT AND BEHAVIOURAL SCORING

Durand (1941) is the first to implement statistical study techniques to discriminate among good and bad loans. His original research worked as a spark light for the development of future private credit analysis in both, the area of financial behavioural and credit scoring. Precisely, regarding the notions of credit and behavioural scoring, Thomas (2000) refers to it as an “application of financial risk forecasting to consumer lending”. He points out that adults in the UK or US are continuously being credit scored or behaviour scored at least once a week as the annual reports of the credit bureaux of both countries reveal. Thomas indicates that the fact that most people are unaware of this does not diminish the relevance and implications of theses practices[4].

Precisely, credit scoring and behaviour scoring are methods which allow organisations decide whether or not to grant a credit to consumers who ask for it. Specifically, while credit scoring refers to a technique which allows lending firms to decide whether or not to grant a credit to a new applicant, behaviour scoring is a method which allows organisations to take decisions on how to deal with existing customers from the viewpoint of credit limit extensions, marketing, payment collection, and others.

In general, as Thomas (2000) points out, credit scoring is a way of discriminating among different groups in a given population when it is not simple to see the characteristics that separate groups but only the related ones.

The Probit model estimation carried out throughout this paper attempts to contribute within this framework as it searches for statistically significant associations of individual characteristics of Italian households with the probability of possessing a credit card. The following section briefly describes the data used for the estimation.

[3] Thus, contrarily to the experience of other developed countries, the fact that most credit card agreements in Italy do not imply medium-term consumer lending restricts the profits from the issuing business to the benefits from charging merchant discount fees to commercial establishments.

[4] Those readers interested in the literature on credit scoring and behaviour scoring may consult Rosenberg & Gleit (1994); Hand & Henley (1997); Thomas, 1992, 1998, 2000.

4. DESCRIPTION OF SAMPLE DATA

The data, which, as previously mentioned, has been entirely obtained from the *Survey of Italian households' Income and Wealth 2002* (SHIW) has been transformed to generate the desired variables for the Probit estimation. The survey is electronically available at the Bank of Italy's web page[5] and collects 8,011 households involving 22,148 individuals from whom 13,536 are income-earners[6].

Specifically, the variables used in this paper are the following: CARTA, employed to generate a dummy variable renamed as CARD, taking the value of 1 for those households from which at least one member possesses a credit card and 0 for others; Y, renamed as YFAMILY, standing for family income; AREA3, corresponding to the geographical area and transformed in order to differentiate among those households which belong to the SOUTH of Italy (value of 1) and those which do not (value of 0); ANASC, which is related to the year of birth of the family members, and has been used to compute the AGE of the head of household[7]; SEX, which is self-explained and has been renamed as SEXFEM taking the value of 1 for women and 0 for men.

Additionally the variable STUDIO, which in the original SHIW takes different values according to the schooling level of the head of household, has been used to generate two dummy variables: BASICSECEDU and UNIVEDU. The first variable takes the value of 1 when the head of household has reached up to basic or high-school education, and the second one takes the value of 1 when undergraduate or postgraduate level-education has been completed. Finally, both variables simultaneously take the value of 0 when the head of household has not completed even a basic schooling level.

Furthermore, the variable APQUAL, which has been used as a reference for the work status of the head of household, and takes a variety of values for employees, self-employed and not employed individuals, has been compacted into one dummy variable in order to account for being EMPLOYED (value of 1) or not (value of 0).

The variable PARTIME has also been used and renamed as FULLTIME evidently in order to capture when the head of household has a fulltime job (value of 1) and when not (value of 0).

---

[5] http://www.bancaditalia.it/.

[6] It is important to keep in mind that provided the sampling structure is composed by different stratum divisions, the SHIW incorporates a weighting at household level in order to obtain unbiased estimates.

[7] In the SHIW, the head of household is defined as "the major income earner".

Additionally, the variable STACIV which originally considers 4 different civil status, 1 for married, 2 for single, 3 for separated/divorced, and 4 widow/widower, has been compacted into a single dummy, namely MARRIED, which takes the value of 1 when the civil status corresponds to married, and 0 when not. Finally, the variable JWDURAT1 which represents an estimated monetary value of the means of transport possessed by the household, was used in order to generate a dummy variable, named VEHICLE, taking the value of 1 when JWDURAT1 is found to be positive (assumed to be when the household owns a means of transport), and 0 when not.

As previously mentioned in the Introduction, the squared values of the family income and the age of the head of household have been computed (YFAMILYSQ and AGESQ) in order to account for probably significant diminishing returns. Finally, the justification for working at a household level, instead of at the individual level, is that the most relevant data, precisely that regarding the possession of a credit card (CARTA), is associated with the household unit, instead of with a specific member of it[8].

Table Nro 2: Main Descriptive Statistics

Variable	Number of Obs.	Mean Value (% Yes)	Std. Dev.	Min Value	Max Value	Answers		
						Yes	No	Did not answer
CARD	6,853	28%	0.45	0	1	1,911	4,942	1,158
YFAMILY	8,011	28,229	22,225	0	461,248	n/a	n/a	n/a
YFAMILYSQ	8,011	uninteresting	uninteresting	0	uninteresting	n/a	n/a	n/a
AGE	8,011	55	17	6	102	n/a	n/a	n/a
AGESQ	8,011	uninteresting	uninteresting	36	uninteresting	n/a	n/a	n/a
SOUTH	8,011	33%	0.47	0	1	2,665	5,346	0
BASICSECEDU	8,011	56%	0.50	0	1	4,511	3,500	0
UNIVEDU	8,011	9%	0.29	0	1	734	7,277	0
EMPLOYED	8,011	54%	0.50	0	1	4,362	3,649	0
FULLTIME	8,011	41%	0.49	0	1	3,249	4,762	0
VEHICLE	8,011	32%	0.47	0	1	2,558	5,453	0
MARRIED	8,011	62%	0.48	0	1	4,989	3,022	0
SEXFEM	8,011	30%	0.46	0	1	2,411	5,600	0

Source: SHIW 2002

[8] Specifically, the question from the SHIW 2002 was as follows: "In 2002 did you or another member of your household possess at least one credit card for household expenditure (which can be used to make payments in hotels, restaurants and shops, etc.)?"

Table Nro 2 summarises the main descriptive statistics of the variables used for the estimation. The total number of observations is confined to the effective number of affirmative and negative answers to the question of possessing or not a credit card. Thus, the final effective number of observations, which is subsequently referred to as the reduced sample, is 6,853.

Dummy variables have been precisely defined to take the value of 1 when an event occurs and 0 when it does not. This allows for interpreting their mean values as the percentage of all households in the whole sample sharing in common a particular characteristic. Thus, for instance, Table Nro 2 shows that the percentage of cardholders in the reduced sample is 28%. Equivalently, but precisely, by sampling construction, the percentage of households belonging to the South (and islands) of Italy is exactly 33%.

Regarding the level of education, while the percentage of households whose head has achieved at least basic or secondary-level education is 56%, the percentage of households whose head has reached up to university level, including both undergraduate and graduate degrees, is only 9%. Additionally, while employed head of households account for 54%, ¾ of them, that is 41% of household heads work fulltime. Only 62% of households are married, 32% own a vehicle, and just 30% of them are lead by a woman.

With respect to the non-dummy variables, the average household income per year is €28,229, and the average age of the household head is 55 years old. Precisely, Table Nro 3 reflects the cumulative distribution of Italian households' income. It shows that for year 2002, a bit more than 50% of the households earned less than €24,000 in year 2002. Equivalently, Table Nro 4 shows that only 42% of household heads are younger than 50 years old.

Table Nro 3: Household Income Distribution

Variable	Obs.	Cum %	Mean	Std. Dev.	Min	Max	Limit
YFAMILY	1,315	16%	8,269	2,822	0	12,000	<=12,000
	4,154	52%	14,688	5,460	0	24,000	<=24,000
	6,038	75%	19,301	8,434	0	35,990	<=36,000
	7,052	88%	22,448	11,027	0	47,994	<=48,000
	7,517	94%	24,348	13,021	0	59,990	<=60,000
	8,011	100%	28,229	22,225	0	461,248	

Table Nro 4: Head of household's age

Variable	Obs	Cum %	Mean	Std. Dev.	Min	Max	Limit
AGE	500	6%	27	3	6	30	<=30
	1,785	22%	33	5	6	40	<=40
	3,333	42%	39	7	6	50	<=50
	4,850	61%	44	10	6	60	<=60
	6,268	78%	49	13	6	70	<=70
	8,011	100%	55	17	6	102	

5. THE PROBIT MODEL

Probit models are meant to model the choice between two discrete alternatives. Generally, as Verbeek (2001) indicates, this type of models describes a binary dependent variable which takes the value of:

$$y_i = \begin{cases} 1 & \text{if certain event or characteristic is present.} \\ 0 & \text{if not.} \end{cases}$$

The probability of choosing an option is taken to be a function of explanatory variables:

$$p_i = P[y_i = 1 / x_i] = F(x_i'\beta) \qquad i = 1,\ldots,n$$

As $F(\bullet)$ equals a probability it should lie in the [0,1] interval, so it is sensible to let F be some distribution function. Thus, in the case of the Probit model the standard normal distribution is assumed. That is:

$$F(w) = \Phi(w) = \int_0^{x_i'\beta} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{1}{2} x_i'\beta\right\} dx$$

Thus, the marginal effect of a change in a continuous independent variable is given by the derivative of the probability that $y_i = 1$ with respect to the k^{th} element of x_i. That is by:

$$\frac{\partial \Phi(x_i'\beta)}{\partial x_{ik}} = \phi(x_i'\beta)\beta_k$$

This is precisely the main difference with respect to linear models, from which a *constant marginal effect* is obtained. One reason why linearity has been discarded is because linear models do not guarantee probability estimates lying in the [0,1] interval. Additionally, there are reasons mostly related to the fact that the error term from linear probability models tends to be highly non-normally distributed and heteroskedastic, implying a violation of two of the fundamental Gaussian assumptions of classical linear econometrics.

However, in the particular case of a Probit model, the likelihood contribution of observation i associated to $y_i = 1$ is precisely the probability $P\{y_i = 1/x_i\}$ which depends on the unknown parameter β, and equivalently for $y_i = 0$. Thus, the likelihood function is given by:

$$L(\beta) = \prod_{i=1}^{N} P\{y_i = 1/x_i;\beta\}^{y_i} P\{y_i = 0/x_i;\beta\}^{1-y_i}$$

Substituting $P\{y_i = 1/x_i;\beta\} = F(x_i'\beta)$, and for simplicity, taking logs, the expression is reduced to:

$$\log L(\beta) = \sum_{i=1}^{N} y_i \log F(x_i'\beta\} + \sum_{i=1}^{N} (1-y_i)\log(1-F(x_i'\beta)) \qquad (*)$$

Maximization with respect to β yields orthogonality of FOC's as follows:

$$\frac{\partial \log L}{\partial \beta} = \sum_{i=1}^{N} \frac{y_i - \Phi_i}{\Phi_i(1-\Phi_i)}\phi_i x_i = 0$$

where $\phi_i = \phi(x_i'\beta)$ is the derivative of the distribution function (or density function). The generalised residual of the model is given by the expression within the square brackets, taking the value of $f(x_i'\beta)/F(x_i'\beta)$ for $y_i = 1$ and $-f(x_i'\beta)/(1-F(x_i'\beta))$ for $y_i = 0$.

SOC's are guaranteed under non-collinearity of the independent variables, yielding a negative definite Hessian matrix of second order derivatives, and therefore, a globally concave loglikelihood function. Precisely the Hessian matrix is given by:

$$\frac{\partial^2 \log L(\beta)}{\partial \beta \partial \beta'} = -\sum_{i=1}^{N} \Lambda(x_i'\beta)(1-\Lambda(x_i'\beta)x_i x_i'$$

5.1 A PROBIT MODEL ON CREDIT CARD HOLDING

Once the fundamental theoretical issues regarding the use of Probit models have been reviewed, the definition of the specific Credit card holding Probit model for the case of Italian households is presented as follows:

$$CARD_i = \begin{cases} 1 & \text{if household possesses a credit card.} \\ 0 & \text{if not.} \end{cases}$$

DEPENDENT VARIABLE

$YFAMILY_i =$ Household's income.

$YFAMILYSQ_i =$ Household's income squared.

$$SOUTH_i = \begin{cases} 1 & \text{if the household belongs to the south or islands of Italy.} \\ 0 & \text{if not.} \end{cases}$$

$AGE_i =$ Head of household's age.

$AGESQ_i =$ Head of household's age squared.

$$SEXFEM_i = \begin{cases} 1 & \text{if the head of household is a woman.} \\ 0 & \text{if not.} \end{cases}$$

$$BASICSECEDU_i = \begin{cases} 1 & \text{If HH has reached up to basic or high-school education.} \\ 0 & \text{if not.} \end{cases}$$

$$UNIEDU_i = \begin{cases} 1 & \text{If HH has reached up to undergraduate or postgraduate level.} \\ 0 & \text{if not.} \end{cases}$$

$$MARRIED_i = \begin{cases} 1 & \text{If the household is married.} \\ 0 & \text{if not.} \end{cases}$$

$$EMPLOYED_i = \begin{cases} 1 & \text{If the head of household is employed.} \\ 0 & \text{if not.} \end{cases}$$

$$FULLTIME_i = \begin{cases} 1 & \text{If the head of household works fulltime.} \\ 0 & \text{if not.} \end{cases}$$

$$VEHICLE_i = \begin{cases} 1 & \text{If the household owns a vehicle.} \\ 0 & \text{if not.} \end{cases}$$

5. THE RESULTS

Table Nro 5 shows the results from the Probit model. It associates the probability of possessing a credit card to the individual characteristics of Italian households. *However, notice that, from Table Nro 5 only the sign and statistical significance of the coefficients is relevant, since as previously mentioned, such coefficients are not equivalent to the total marginal effect*[9].

Thus, the total marginal effect of a change in a continuous variable is computed as the value of the first derivative of the probability function with respect to the specific independent variable, when the dependent equals 1 (CARD=1) and all other independent variables, both discrete and continuous, are kept fixed at a given value (eg. at their mean values).

In the case of dummy variables, the discrete marginal effect is computed as the difference between the total probability when the specific independent variable takes the value of 1, and when it takes the value of 0, keeping as well as in the continuous case, all other independent variables (discrete and continuous) fixed at a given value (eg. at their mean values).

Despite of the previous observations, Table Nro 5 is still relevant as it indicates the presence of significant associations between the dependent variable, namely the households' probability of having a credit card, and all independent variables, but one. The unique statistically insignificant association refers to the specific gender of the head of household (SEXFEM) which, even though is of negative sign as might have been expected, seems not to be sufficiently relevant in statistical terms for the determination of household's credit card holding in Italy.

[9] Recall that in the Probit model, the total marginal effect of a change in a continuous variable is given by:

$$\frac{\partial \Phi(x_i' \beta)}{\partial x_{ik}} = \phi(x_i' \beta)\beta_k$$

Moreover, Table Nro 5 reflects a positive association between the households‘ probability of possessing a credit card and the level of income of the particular household (YFAMILY). Additionally, it shows a negative dependence upon the squared value of the household’s income (YFAMILYSQ), implying the presence of diminishing returns. That is, starting from an average household income, an increase in family income perceptions increases the probability, but further increases in family income weakens this effect. In relation to the contribution of the geographic location (SOUTH) to the probability of households’ credit card possession, the dependence is of negative sign, implying that being from the south or islands of Italy reduces the probability of holding a credit card.

Regarding the age of the head of household (AGE) there exists a positive dependence, even though diminishing returns are present and captured by the inverse contribution of the squared value of the head of household’s age (see Graph Nro. 1 in the Appendix). Additionally, in relation to the level of schooling both variables, basic and secondary level-education (BASICSECEDU), and undergraduate and graduate education (UNIVEDU), are positive contributors to a higher probability.

Table Nro 5: Probit Model

Number of obs	=	6,853
LR chi2(12)	=	2,046
Prob > chi2	=	0.000
Pseudo R2	=	0.2522
Log likelihood	=	-3,033

CARD	COEF.	STD. ERR.	Z	P>Z	[95% CONF. INTERVAL]	
YFAMILY	0.0000210	1.50E-06	14.02	0.000	0.0000181	0.0000240
YFAMILYSQ	-4.57E-11	6.07E-12	-7.53	0.000	0.0000000	-3.38E-11
SOUTH	-0.5341891	0.0465274	-11.48	0.000	-0.6253811	-0.4429970
AGE	0.0450803	0.0091779	4.91	0.000	0.0270919	0.0630688
AGESQ	-0.0005505	0.0000909	-6.05	0.000	-0.0007287	-0.0003722
SEXFEM	-0.0306565	0.0477553	-0.64	0.521	-0.1242552	0.0629421
BASICSECEDU	0.6373802	0.0594790	10.72	0.000	0.5208036	0.7539568
UNIVEDU	1.0752700	0.0775431	13.87	0.000	0.9232885	1.2272520
MARRIED	0.1241594	0.0473210	2.62	0.009	0.0314119	0.2169068
EMPLOYED	0.2017699	0.0722654	2.79	0.005	0.0601324	0.3434075
FULLTIME	-0.1796757	0.0494957	-3.63	0.000	-0.2766854	-0.0826659
VEHICLE	0.3755495	0.0400133	9.39	0.000	0.2971249	0.4539742
CONSTANT	-2.6863010	0.2308170	-11.64	0.000	-3.1386940	-2.2339080

Unexpectedly, having a full-time job is associated with a lower probability of holding a credit card; however, being employed (EMPLOYED), married (MARRIED), and owning a vehicle (VEHICLE), are positive contributors.

In relation to the goodness of fit of the Probit model, the pseudo R^2 shows only a 25% of accuracy[10]. However, contrarily to the case of linear models, judgements about the goodness of fit of categorical models might as well be considered by examining the ability to predict observed responses. The trace of the 2x2 (YES, NO; YES, NO) matrix from Table Nro 6 shows that the model correctly classifies 78.48% of the actual observations (880+ 4,498)/ 6,853. However, it also shows that the model is more efficient at targeting NO answers (91.02%) than at targeting YES answers (46.05%) – Error Type I -. Equivalently, Table Nro 6 indicates that the model wrongly predicted YES answers in 33.53% and NO answers in18.65% – Error Type II -.

Table Nro 6: Classification of predicted values

Credit card holding	Observed		
Classified	YES	NO	Total
Classified as YES if predicted Pr(YES) >=50%			
YES	880	444	1,324
NO	1,031	4,498	5,529
Total	1,911	4,942	6,853
Sensitivity	Pr(YES/ YES)		46.05%
Specificity	Pr(NO/NO)		91.02%
Positive predictive value	Pr(YES)		66.47%
Negative predictive value	Pr(NO)		81.35%
False YES rate for true NO	Pr(YES/NO)		8.98%
False NO rate for true YES	Pr(NO/YES)		53.95%
False YES rate for classified YES	1-Pr(YES)		33.53%
False NO rate for classified NO	1-Pr(NO)		18.65%
Correctly classified			78.48%

[10] The pseudo R^2 is given by:

$pseudoR^2 = 1 - \dfrac{1}{1 + 2(\log L_1 - \log L_0)/N}$ where $\log L_1$ is the maximum loglikelihood of the model, and $\log L_0$ is the maximum loglikelihood when all variables, but the intercept are set to 0. An alternative measure is the Mc Fadden R^2 which is given by:

$McFaddenR^2 = 1 - \dfrac{\log L_1}{\log L_0}$ with $\log L_0 \leq \log L_1 \prec 1$.

If one judges the Probit model as a non-discretionary rule for the issuance of credit cards in accordance to certain specific characteristics of an individual applicant (or household), it would be completely sensible from the point of view of credit card issuers, to expect credit card holders and non-holders to be concentrated in high and low levels of qualification. Once this is accepted, then the discrepancies among actual card holdings and predicted card holdings for every specific observation might as well be seen as an error committed by the credit card issuer. That is, for instance, issuers might grant credit cards to low-qualified individuals (households) – Error Type I -, or as well, might not offer them to highly-qualified individuals (households) – Error Type II.

CARD = Pr(card) (predict) 0.20456132

Table Nro 7: Marginal Effects (at mean values)

VARIABLE	dCARD/dX	STD. ERR.	Z	P>Z	P>Z	[95% C.I.]	X (**)
YFAMILY	5.97E-06	0.0000000	13.87	0.000	5.10E-06	6.80E-06	30,761.6
YFAMILYSQ	-1.30E-11	0.0000000	-7.53	0.000	-1.60E-11	-9.60E-12	1.5E+09
SOUTH*	-0.1355342	0.0103800	-13.05	0.000	-0.155887	-0.115181	27%
AGE	0.0127922	0.0025700	4.97	0.000	0.007750	0.017835	54.3431
AGESQ	-0.0001562	0.0000300	-6.16	0.000	-0.000206	-0.000107	3,212.30
SEXFEM*	-0.0086516	0.0134000	-0.65	0.518	-0.034907	0.017604	28%
BASICS~U*	0.1706355	0.0143900	11.85	0.000	0.142423	0.198848	60%
UNIVEDU*	0.3804558	0.0289700	13.13	0.000	0.323672	0.437240	10%
MARRIED*	0.0347061	0.0130200	2.67	0.008	0.009196	0.060217	64%
EMPLOYED*	0.0564517	0.0200000	2.82	0.005	0.017259	0.095645	58%
FULLTIME*	-0.0504448	0.0137700	-3.66	0.000	-0.077425	-0.023464	43%
VEHICLE*	0.1108682	0.0122600	9.04	0.000	0.086839	0.134898	36%

(*) dCARD/dx is for discrete change of dummy variable from 0 to 1
(*) the mean value of the independent variable its computed for the reduced sample data of 6,853 obs.

Table Nro 7 corroborates the previously obtained results regarding the sign and significance of the coefficients associated to the independent variables. However, contrarily to Table Nro 5, the information displayed on Table Nro 7 is not misleading in the sense that it allows for a clearer interpretation of the coefficients.

For instance, in a locus close to the mean values of all independent variables, the coefficient accompanying the variable YFAMILY indicates that every €10,000 of additional annual household income increases the probability of possessing a credit card in 6%. However, the coefficient associated to the variable YFAMILYSQ also indicates that every €10,000 of additional annual household income has also the negative effect of decreasing the probability of possessing a credit card in <0.000013>%.

Regarding the age of the head of the household, while the variable AGE indicates a positive marginal effect of 1.28% from being one year older, the variable AGESQ reports a decreasing return on age of <0.02>%.

Additionally, in relation to discrete variables, and precisely in the case of geographic location, being from the south or the islands of Italy implies a <13.55>% lower probability of possessing a credit card. With respect to the level of schooling both variables, basic and secondary level-education (BASICSECEDU), and undergraduate and graduate education (UNIVEDU), contribute by increasing the probability of holding a credit card in 17.06% and 38.05% respectively. Being married, employed, and owning a vehicle have both a positive marginal effect of 3.47%, 5.65% and 11.09% respectively. As previously stressed, unexpectedly, having a full-time job marginally contributes in a negative way by reducing the probability in <5.04>%.

8. CONCLUSION

This paper provided a simple microeconomic evaluation of the determinants of credit card holding in Italy. Using a Probit model, the analysis focused on the demand side of the credit card market. Thus, the attention was placed on identifying specific individual characteristics of Italian households, which showed to be statistically significant for determining the probability of possessing a credit card.

Relevant expected results were derived from this paper. Firstly, credit card holding is shown to be highly-positively related with family income, although, modest diminishing returns are also present when a quadratic form is allowed. Secondly, the age of the household's head is also shown to be a positive determinant even though decreasing returns exist when its squared value is present in the estimation.

Additionally, discrete variables such as geographic location, precisely not living in the south or islands of Italy, basic and university-level education, owning a vehicle, being married and formally employed are positively related to a higher probability of possessing a credit card.

Unexpectedly, having a full-time job seems to be negatively related to the same probability. Regarding, gender not much can be formally stated since even though the coefficient shows a negative relation for the case of women such coefficient is statistically insignificant.

Particularly, at mean values of the sample distribution, the probability of holding a credit card mainly increases with basic education in 17%, university level education in 38%, and ownership of a vehicle in 11%. Equivalently, decreases associated to discrete variables are mainly driven by southern household location in around <14>%, and fulltime working in <5>%

With respect to the goodness of fit, the model correctly classifies 78.48% of the actual observations (880+ 4,498)/ 6,853. However, it is also shown that the model is more efficient at targeting NO answers (91.02%) than at targeting YES answers (46.05%) – Error Type I -. Equivalently, the model wrongly predicts YES answers in 33.53% and NO answers in18.65% – Error Type II -.

A possible explanation to the abovementioned results suggests that, If one judges the Probit model as a non-discretionary rule for the issuance of credit cards in accordance to certain specific characteristics of an individual applicant (or household), it would be completely sensible to associate the discrepancies among actual card holdings and predicted card holdings for every specific observation as errors committed by the credit card issuer. That is, for instance, issuers might grant credit cards to low-qualified individuals (households) – Error Type I -, or as well, might not offer them to highly-qualified individuals (households) – Error Type II.

Many of the variables under consideration were expected to have an influence in both the demand side and the supply side for the credit card market in Italy. However, further research, should explore the inclusion of additional variables which might still be playing a relevant simultaneous role in both sides of the market. Panel data analysis might allow for the study of the implications of credit cycles, and financial distresses for the restructuring and modernization of the credit card market in Italy.

REFERENCES

Ardizzi, Guerino (2003). Cost efficiency in the retail payment networks: first evidence from the Italian credit card system. *Temi di discussione del Servizio Studi, Banca D'Italia*, Number 480 - June 2003.

Durand, D. (1941). Risk elements in consumer installment financing. *NBER*, New York.

Hand, D. J., & Henley,W. E. (1997). Statistical classification in consumer credit. *Journal of the Royal Statistical Society Series A 160*, 523-541.

Rosenberg, E., & Gleit, A. (1994). Quantitative methods in credit management: a survey. *Operations research 42*, 589-613.

Thomas Lyn (1992). Financial risk management models. In: Ansell, J., & Wharton, F. (Eds.), *Risk analysis, assessment and management*, Wiley, Chichester.

Thomas Lyn (1998). Methodologies for classifying applicants for credit. In: Hand, D. J., & Jacka. S.D. (Eds.), *Statistics in finance*, Arnold, London, 83-103.

Thomas Lyn (2000). A survey of credit and behavioural scoring: forecasting financial risk of lending to consumers. *International Journal of Forecasting 16*, 149–172.

Verbeek, Marno (2001). "*A guide to Modern Econometrics*", 234-236.

APPENDIX

Table Nro 8: Credit Card holding and the continuous variables

Reduced Sample N= 6,853					Credit card holding	
Variable	Range	Obs.	Mean	Std. Dev.	holders	non-holders
YFAMILY	0<=YFAMILY<12,000	692	8,835	2,417	6%	94%
	12,000<=YFAMILY<24,000	2,409	17,900	3,447	14%	86%
	24,000<=YFAMILY<36,000	1,808	29,469	3,432	27%	73%
	36,000<=YFAMILY<48,000	994	41,225	3,433	45%	55%
	48,000<=YFAMILY<60,000	459	53,177	3,409	57%	43%
	60,000<=YFAMILY	491	87,395	41,525	71%	29%

Reduced Sample N= 6,853					Credit card holding	
Variable	Range	Obs.	Mean	Std. Dev.	holders	non-holders
AGE	0<=AGE<=20	1	18	0	0%	100%
	20<=AGE<=30	340	26	2	28%	72%
	30<=AGE<=40	1,105	35	3	39%	61%
	40<=AGE<=50	1,406	45	3	43%	57%
	50<=AGE<=60	1,351	54	3	34%	66%
	60<=AGE	2,650	71	8	12%	88%

Graph Nro. 1. Age of head of household and the Percentage of Credit card holders in Italy

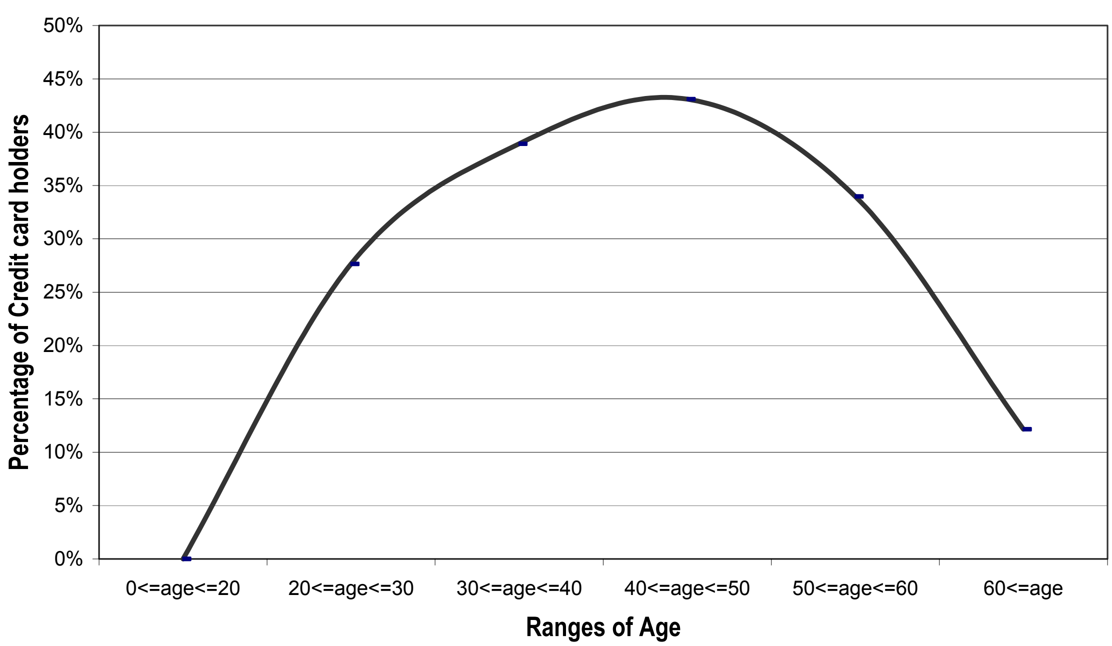
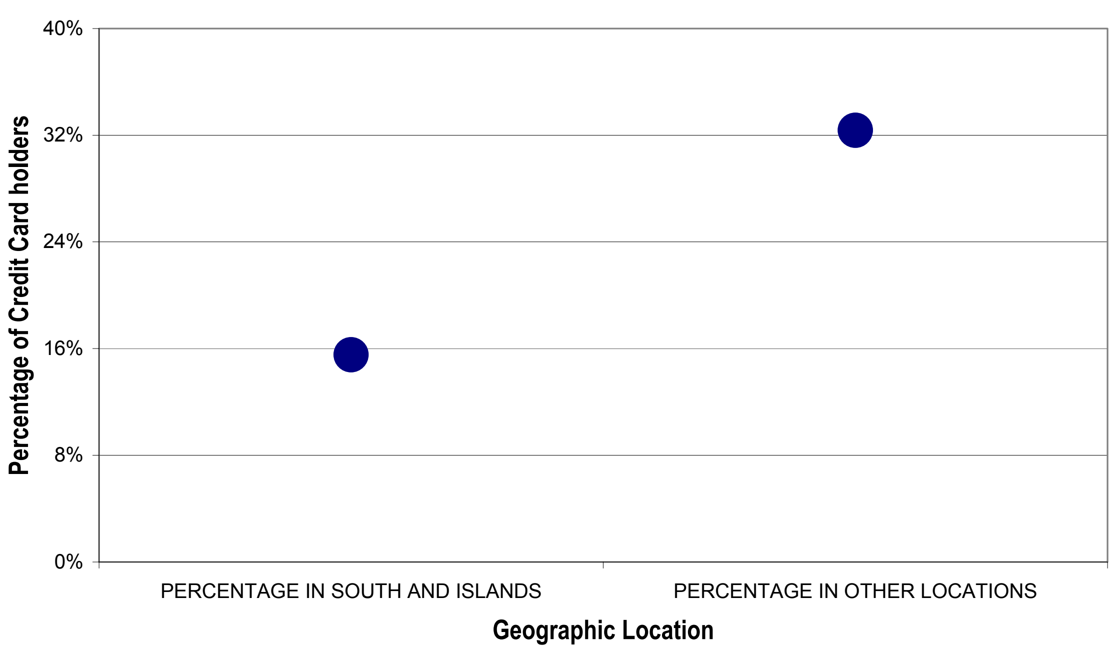


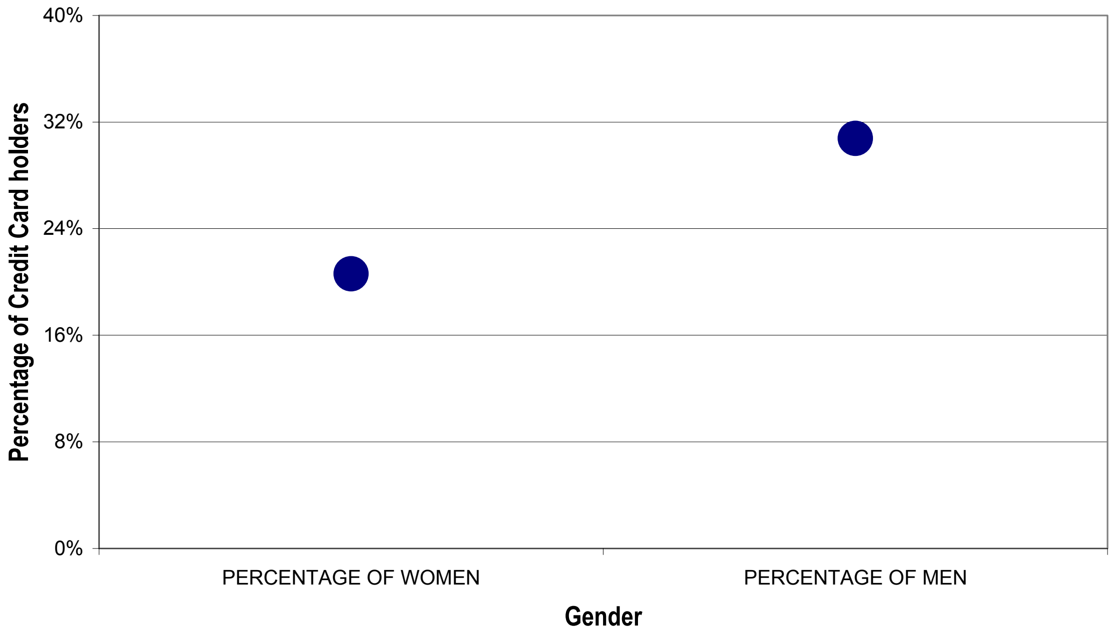
Table Nro 9: Credit Card holding and the discrete variables

Reduced Sample N= 6,853			Percentage of those who hold a credit card	
Variable	**Characteristic**	**Obs. in reduced sample**	**holders**	**non-holders**
SOUTH	From south and islands	1,827	**16%**	84%
	From other locations	5,026	**32%**	68%
SEXFEM	Women	1,950	**21%**	79%
	Men	4,903	**31%**	69%
	Without basic education	2,024	**6%**	94%
BASICSECEDU	With secondary or basic education	4,111	**34%**	66%
UNIVEDU	With postgrad. or undergrad. education	718	**57%**	43%
MARRIED	Married	4,409	**32%**	68%
	Not married	2,444	**20%**	80%
EMPLOYED	Employed	3,982	**39%**	61%
	Not employed	2,871	**13%**	87%
FULLTIME	With fulltime job	2,956	**36%**	64%
	Without fulltime job	3,897	**22%**	78%
VEHICLE	With vehicle	2,469	**48%**	52%
	Without vehicle	4,384	**17%**	83%

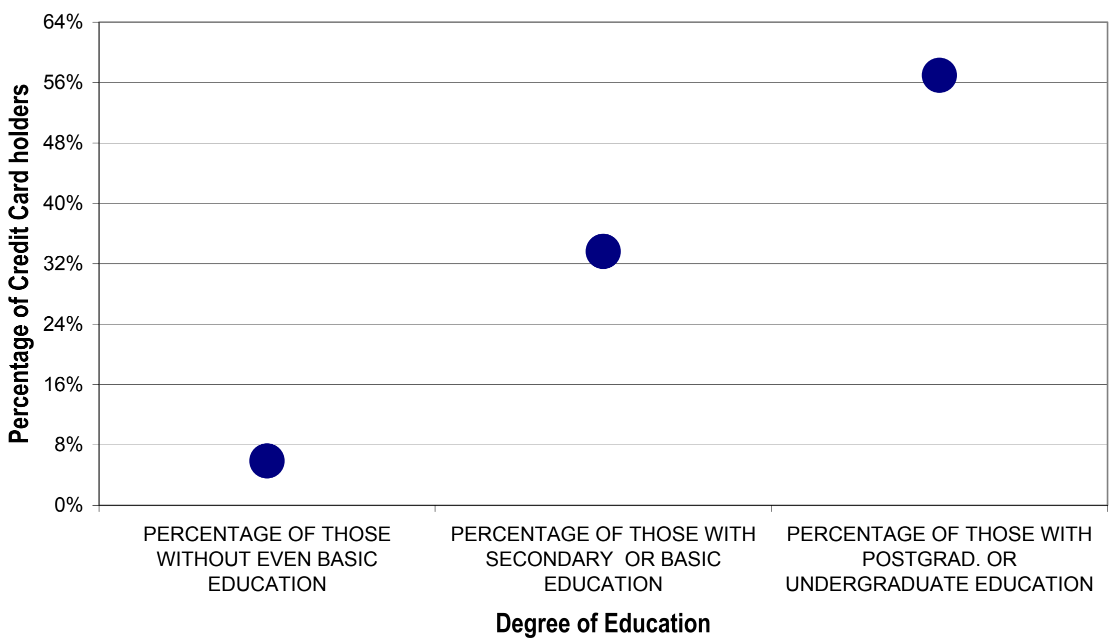
Graph Nro. 2: Percentage of Credit card holders in the different geographic locations of Italy



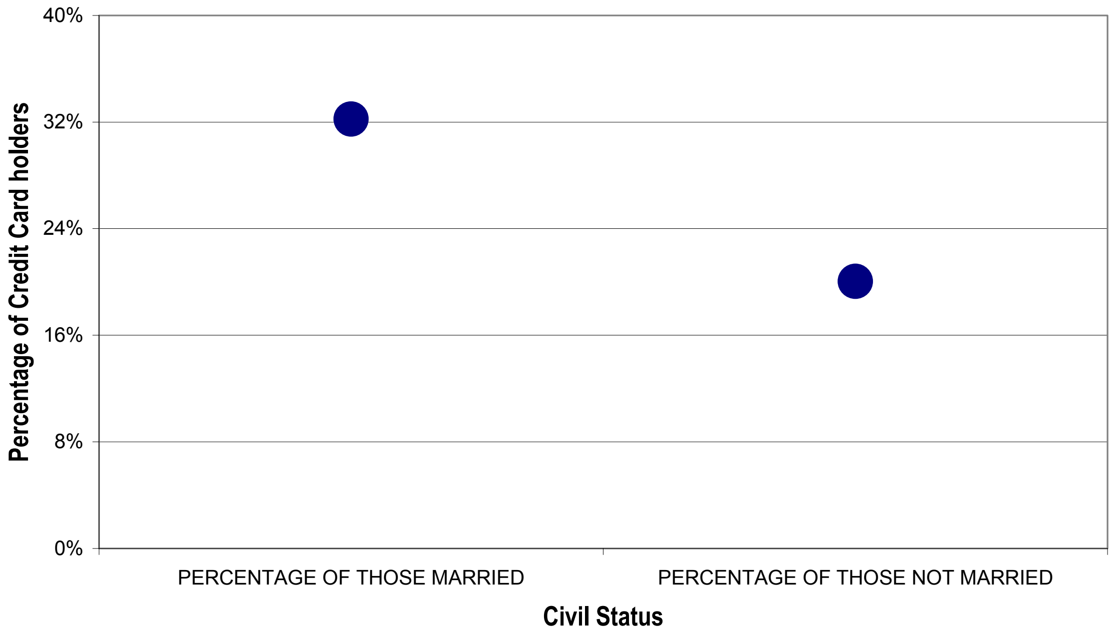
Graph Nro. 3: Gender and
the Percentage of Credit card holders in Italy



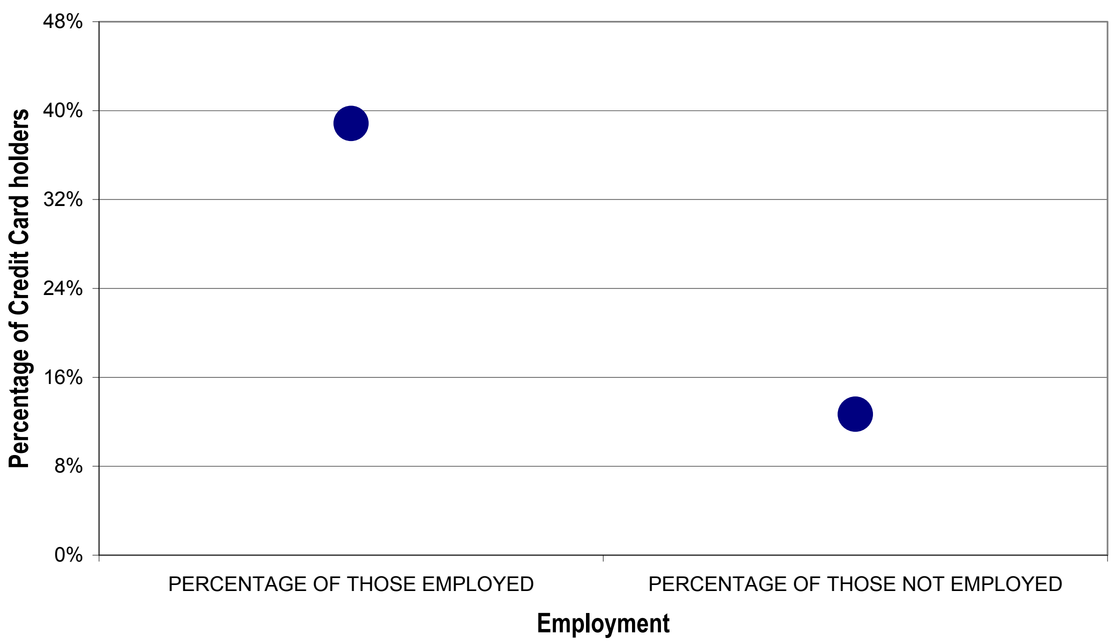
Graph Nro. 4: Education and
the Percentage of Credit card holders in Italy



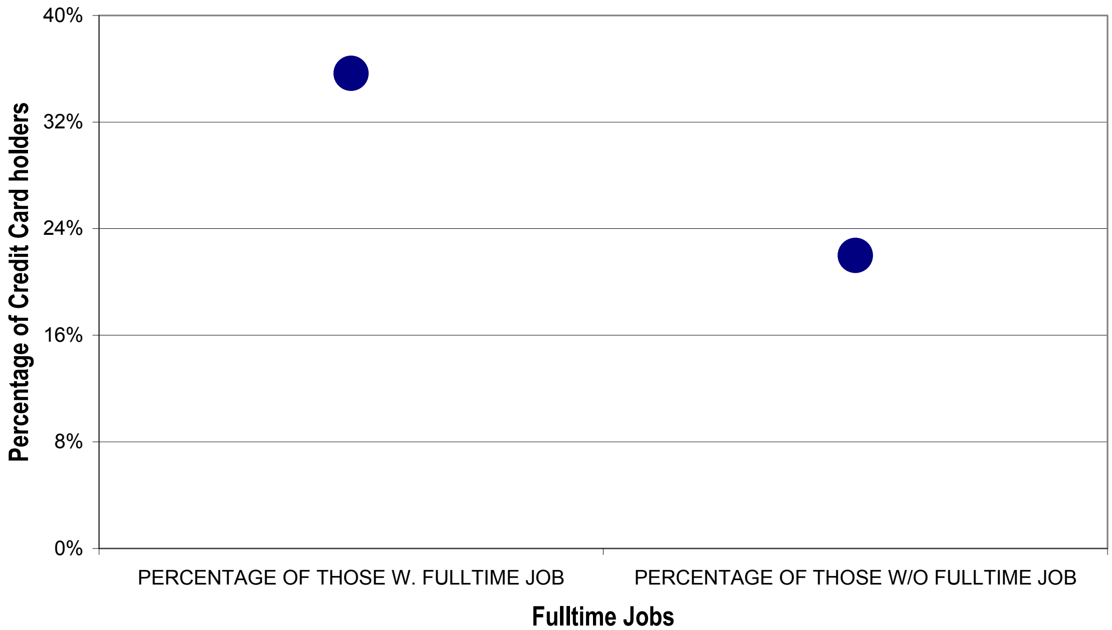
Graph Nro. 5: Civil Status and the Percentage of Credit card holders in Italy



Graph Nro. 6: Employment and the Percentage of Credit card holders in Italy



Graph Nro. 7: Fulltime Jobs and the Percentage of Credit card holders in Italy



Graph Nro. 8: Vehicle ownership and the Percentage of Credit card holders in Italy

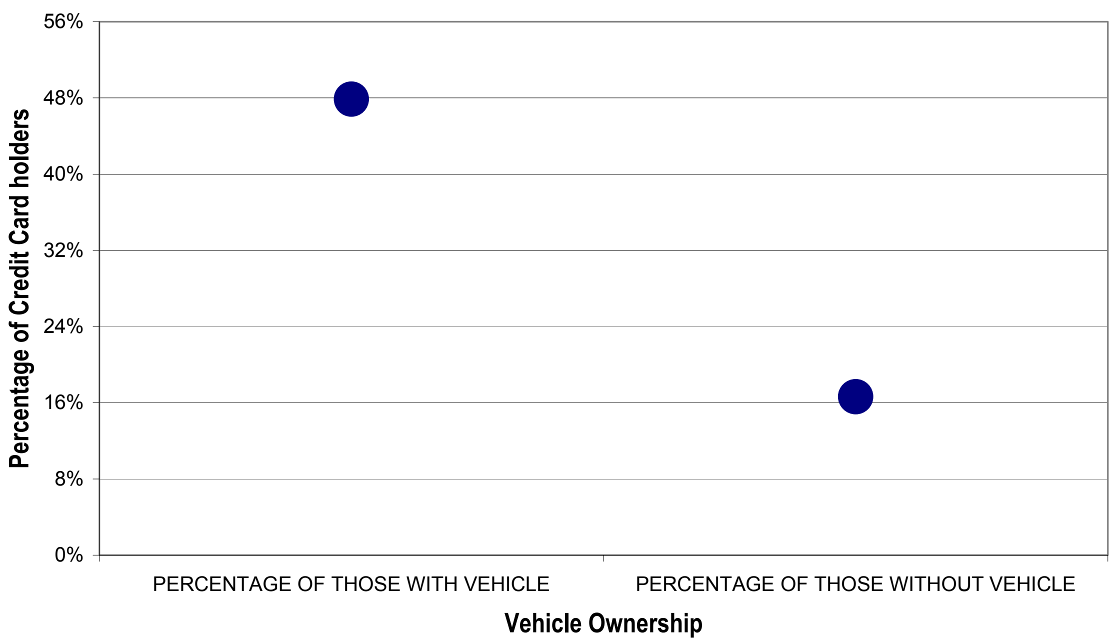


Table Nro 10: Variance-Covariance Matrix

	YFAMILY	YFAMILSQ	SOUTH	AGE	AGESQ	SEXFEM	BASICSECEDU	UNIVEDU	MARRIED	EMPLOYED	FULLTIME	VEHICLE	CONS
YFAMILY	0.0000												
YFAMILYSQ	0.0000	0.0000											
SOUTH	0.0000	0.0000	0.0022										
AGE	0.0000	0.0000	0.0000	0.0001									
AGESQ	0.0000	0.0000	0.0000	0.0000	0.0000								
SEXFEM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0023							
BASICEDU	0.0000	0.0000	-0.0001	0.0000	0.0000	0.0000	0.0035						
GRADUATEDU	0.0000	0.0000	-0.0005	0.0000	0.0000	-0.0002	0.0031	0.0060					
MARRIED	0.0000	0.0000	-0.0002	-0.0001	0.0000	0.0008	0.0000	0.0002	0.0022				
EMPLOYED	0.0000	0.0000	-0.0002	-0.0001	0.0000	0.0001	-0.0001	-0.0003	-0.0001	0.0052			
FULLTIME	0.0000	0.0000	0.0001	0.0000	0.0000	-0.0001	-0.0002	-0.0002	0.0000	-0.0016	0.0025		
VEHICLE	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	-0.0001	-0.0001	0.0001	0.0016	
CONS	0.0000	0.0000	-0.0001	-0.0018	0.0000	-0.0006	-0.0032	-0.0026	0.0021	-0.0024	-0.0004	-0.0001	0.0533