International Business Research; Vol. 9, No. 6; 2016
ISSN 1913-9004 E-ISSN 1913-9012
Published by Canadian Center of Science and Education

Factors Driving the Credit Card Ownership in Italy

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Received: March 10, 2016 Accepted: March 24, 2016 Online Published: April 18, 2016

doi:10.5539/ibr.v9n6p131 URL: http://dx.doi.org/10.5539/ibr.v9n6p131

Abstract

The aim of this paper is to explore the main determinants of credit card ownership by analyzing the variables that may affect the decision to hold a credit card. Using the 2012 Survey on Household Income and Wealth provided by the Bank of Italy as main source, we estimated count data models in order to identify the socio-economic, demographic and territorial variables affecting the credit card accounts held by households. Our estimates give evidence of the significance of the considered factors. In particular, we find that geographical location is an important determinant of families behavior in line with the socio-economic gap between the North and the South of Italy. Other relevant variables acting on the number of credit cards held are age, income, municipality size, gender, education and marital status. The reached results are interesting in depicting the main characteristics of cardholders and in helping the implementation of a segment-specific marketing program in the banking services industry.

Keywords: count-data models, credit card ownership, variable selection

1. Introduction

The use of credit cards has increased substantially in recent decades becoming an essential bank service in consumer lifestyle management. Using a credit card as an alternative payment device in place of cash, checks and other forms of payment is an advantage in different situations and it is also an essential component of electronic commerce and internet commerce (Bernthal, Crockett & Rose, 2005). However, despite the benefit given by this form of payment, credit card ownership and usage have been associated with increased consumer debt and unplanned spending (Thomas, Maloles & Swoboda, 2010; Norum, 2008).

The characteristics of the credit card market involve many economic issues. First of all the credit card industry can be seen as a multi-side platform where the participation of a new agent determines a positive network externality. In particular, the credit cards network is a two-sided market (Rochet & Tirole, 2003; Rysman, 2009) where two sets of agents, sellers and users, share a common technical platform. The benefit of both sides depends upon the number of agents in the network (Chakravorti, 2003) implying competition policy effects (Carlton & Frankel, 1995; Lemley & McGowan, 1998).

The proliferation of credit card associations and the ease of access to a credit card have given consumers increased opportunities for making credit purchases. A consumer may hold a credit card from different agents in the network and use them for payment and credit functions. When a consumer only uses one credit card he is said to be "singlehome" otherwise, if he is in possession of credit cards from more than one provider he is said to be multi-homing (Guthrie & Wright, 2007).

One of the reasons that lead a card holder to own more than one credit card is due to the credit function. Since credit cards allow to borrow without applying for personal loans it can be seen as a short cut to have access to more financing (Castronova & Hagstrom, 2004). However, this can stimulate the increase of the long debts level (Loke, Yen & Tan, 2011) despite the high interest rates charged (Ausubel, 1991).

Even if this is not in line with the economic theory (Zywicki, 2000), the consumer might prefer to pay high interest on credit card debts instead of opening a negotiation with a financial institution (Brito & Hartley,1995) or may be driven to self-control failure and compulsive buying (Gathergood & Weber 2012).

In investigating the payment card platforms as two-sided markets the analysis of consumer homing can be of great interest as well as the identification of the determinants affecting the choice to hold a single credit card or a large number of cards. Understanding which factors may influence the number of credit cards held by an individual may help to explain the costumer behaviours and prevent negative effects (i.e debt exposure and family bankruptcy). This evidence may also be useful for the credit card industry in implement market development policies.

Extensive research has been conducted on credit card ownership and usage behaviour in recent years. This field of research also reflects similarities and differences in credit card ownership and usage among nations (e.g. Sharpe, Yao, & Liao, 2012).

Our interest is to explore the main determinants of credit card ownership and usage in Italy. Following a previous study (Amendola, Pellecchia & Sensini, 2014; 2015) conducted on a panel data set we have extended our results focusing in particular on the selection of the variables to be included in the model and on the effectiveness of socio-economic and demographic characteristics of credit card users in determining the number of credit cards held by each family in Italy. By means of a count data regression model, estimated on a data set provided by the Bank of Italy, we give evidence of the role of each variable depicting the status of the credit card holders in Italy.

The paper is organized as follows. Section 2 briefly surveys the previous studies on the determinants of credit card ownership. Section 3 highlights the main features and some trends of the Italian credit card markets. The econometric model is described in Section 4 while in Section 5 the description of data and variables is reported. Session 6 presents and discusses the reached results. The last section gives some concluding remarks.

2. Credit card Ownership: A Brief Review of the Literature

The Credit Card Industry has been largely analyzed in recent literature from a theoretical point of view and few empirical evidence have been addressed by implementing different statistic techniques driven by the nature of the data and the focus of the analysis. When the focus is on the dichotomy between using credit cards or not using them a promising choice is to use the logistic regression model. Abdul-Muhmin and Umar (2007) perform a stepwise binary logistic regression using a survey from 774 respondents living in Saudi Arabia. They found that credit card ownership is positively related to income, education, age, and attitude towards debt. Besides, their results showed that women are more likely to hold a credit card than men.

Yayar and Karaca (2012) use a logit model applied to a Turkey data set. According to their results, the probability of holding a credit card is larger for married and educated middle-aged man. This probability also increases with the number of family members earning an income and for people who recognize the usefulness of a credit card.

A different approach was followed by Kaynak and Harcar (2001) that, on a data-set collected from 673 Turkish respondents, use Chi-square analysis to test the association between the ownership rate and the demographic characteristics of the respondents. They discover that the former was positively linked to education and income, while gender and age were not statistically significant.

Other studies, such as Pulina (2011), used the multinomial logit model to investigate the factors affecting the type of credit card accounts. Using data from a set of Italian banking customers, she found that women, older people, residing in the centre of Italy and holding more than one credit card are more likely to acquire a classic card. Older customers prefer Gold cards, while younger people and the residents in the North-east choose a revolving card.

When information on the number of credit cards held is available, several authors (Kinsey, 1981; Tan, Yen, & Loke, 2011) used the tobit model. Kinsey (1981) found that income positively affects the number of credit card accounts held, whereas living in a small town or rural area has a negative impact. Moreover, the probability of having credit cards and the number of cards held is highly correlated to age and occupation, but the place of residence, the use of checking and savings accounts, and the attitude towards credit exert an even stronger effect.

Tan et al. (2011) developed a tobit model with binary selection. An ordinal treatment was developed to take into account the fact that debts are incurred only among card holders and the endogeneity of card holding in card debt. Results from a sample of Malaysian cardholders show that age, household size, income, education, loan commitments, and current-account ownership affect card holding. Age, loan commitments, previous card holdings, current-account ownership, and bad debt history impact the card debt. Finally, the probability to be credit revolvers is higher for multi-card holders than for convenience users.

Analysing the number of credit cards, held given the nature of the data expressed as non-negative integer, a good alternative can be the count data model as, for example, in Loke et al. (2011). Indeed, empirical count data sets typically exhibit over-dispersion and/or an excess number of zeros and small values that can affect the OLS regression results (Greene, 2012). The former issue can be addressed by extending the plain count regression model in various directions.

In their analysis Loke et al. (2011) estimated the effect of various socio-demographic characteristics on the number of credit cards held by customers based in Malaysia. By means of a hurdle-count data model, the decision on card ownership is separated into two stages: whether to hold or not a credit card, and if this is the case, how many cards to hold. They find that age, race, education, income, number of loan commitments, household size and current account ownership have affected the probability of ownership and the number of credit cards held. On the other hand, easy access to credit has not a role in determining the credit card ownership.

3. Some Trends in the Italian Payment Cards Markets

Credit cards belong to the broader category of payment cards which also include debit cards and prepaid cards. Debit cards are generally issued by banks to account holders. They can be used to withdraw from ATMs or instead of cash when purchasing good and services. Withdrawals and payments are debited to the cardholder almost in real time. Basically, the cardholder is not allowed to pay the money back at a later time as for credit cards, so that enough funds must be available on the bank account when the debit card is used.

A prepaid card can be used only after it has been recharged with funds by the holder. Like a debit card, it allows to withdraw or to pay for goods and services but without necessarily holding a bank account. Basically, it works in the opposite way of a credit card, because instead of buying something to pay for later, the holder pays in advance what will be bought afterwards.

Table 1 reports some trends in the number of payment cards issued in Italy in the years 2003-2012. The number of credit cards remained fairly constant during the period reaching a total of about 12,000 units in 2012. Debit cards, instead, followed an increasing trend and experienced a negative growth rate only in 2009. Currently, they amount to almost 40,000 units, that is 56% of the payment cards circulating in Italy. As regards to prepaid cards, their growth has been impressive. They increased from 677 in 2003 to 18,804 in 2012, which is to say a compound growth rate of 44% per year. In 2011, the number of prepaid cards passed that of credit cards (14,203 and 12,189, respectively).

Table 1. Number and Percentage Growth Rate of Payment Cards, Italy, 2003-2012

Year	**Credit cards**		**Debit cards**		**Prepaid cards**	
	Num.	**Growth**	**Num.**	**Growth**	**Num.**	**Growth**
2003	11,681	-	28,163	-	677	-
2004	11,607	-0.63	29,493	4.72	789	16.54
2005	13,379	15.27	30,744	4.24	3,288	316.73
2006	13,677	2.23	32,611	6.07	4,461	35.68
2007	14,486	5.92	33,097	1.49	5,805	30.13
2008	14,385	-0.7	35,527	7.34	8,208	41.4
2009	13,921	-3.23	33,185	-6.59	10,627	29.47
2010	13,022	-6.46	36,174	9.01	12,362	16.33
2011	12,189	-6.4	37,550	3.8	14,203	14.89
2012	12,102	-0.71	39,707	5.74	18,804	32.39

Source: Our elaboration on Bank of Italy data.

The per capita number and value of transactions realized by credit cards has increased over the years. In 1992, on average, Italian people aged 18 and over used their credit card 4 times spending 395 euros.[1] Thirteen years later, these figures were 10 and 737, respectively.[2]

Like in other countries (Chakravorti 2003), also in Italy the credit card industry has been under the scrutiny of antitrust authorities, even in recent years.[3] This is not surprising, since, as it is evident from Tables 2-3, both the issuing and the acquiring[4] credit card markets are highly concentrated, with CartaS ìas a leader. The CR4 concentration ratio is 66.1 in the former market and 85.9 in the latter.

[1] In constant 2000 euros.

[2] Bank of Italy data.

[3] See Italian Competition Authority (2010).

[4] Acquiring is the process that enables merchants to accept the credit cards issued to consumer by bank and other financial institutions.

Table 2. Market shares in the credit card issuing market (percentages), Italy, 2008

Issuer	**Market share**
CartaS ì	43.4
Unicredit	10.2
Intesa Sanpaolo	7.8
Deutsche Bank	4.7
BNL Paribas	3.8
ICCREA	2.6
UBI	2.2
Key Client	1.9
Antonveneta	1.9
BPER	1.7
CREDEM	1.2
Others	18.6

Source: Italian Competition Authority.

Table 3. Market shares in the credit card acquiring market (percentages), Italy, 2008

Acquirer	**Market share**
CartaS ì	39.7
Key Client	21.7
Setefi	16
Antonveneta	8.5
Banca Sella	6.8
Deutsche Bank	2.8
Unicredit	2.5
BNL Paribas	1.1
Others	0.9

Source: Italian Competition Authority.

4. Empirical Approach

Modelling count variables is a classic task in economics and the social sciences. A largely used technique for modelling count data is the Poisson regression. Given a set of N independent observations (y_i, x_i) where y_i is a count and x_i is a vector of covariates, assume that y_i given x_i is distributed as a Poisson, that is

$$f(y_i|x_i) = \frac{e^{-\mu}\mu^{y_i}}{y_i!} \quad (y_i = 0, 1, 2, \dots) \tag{1}$$

The conditional mean is parametrized as

$$E(y_i|x_i) = \mu_i = \exp(x_i{}'\beta), \tag{2}$$

where β is a vector of parameters to be estimated.[5] Since $Var(y_i|x_i) = E(y_i|x_i) = \mu_i$, the model is heteroskedastic. It can be easily estimated by maximizing the log-likelihood function, which is given by

$$\ln L(\beta) = \sum_{i=1}^{N} \{y_i x_i'\beta - \exp(x_i{}'\beta) - \ln y_i!\}. \tag{3}$$

The equality between the mean and the variance of the Poisson distribution, also known as equidispersion property, is very often rejected by data, since the variance exceeds the mean. A simple solution to this problem is to assume a Negative Binomial (NB) distribution for y_i (given x_i), which allows a more flexible modeling of the variance. The NB distribution is given by

$$f(y_i|x_i) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(y_i + 1)\Gamma(\alpha^{-1})} \times \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu}\right)^{\alpha^{-1}} \left(\frac{\mu}{\alpha^{-1} + \mu}\right)^{y_i} \quad (\alpha > 0;\ y_i = 0, 1, 2, \dots) \tag{4}$$

[5] Note that, by (2), $\mu > 0$.

where $\Gamma(\cdot)$ is the gamma function and α is an additional parameter to be estimated. The mean and variance are now $E(y_i|x_i) = \mu_i$ and $Var(y_i|x_i) = \mu_i + \alpha\mu_i^2$. If the conditional mean is still parametrized as in (2), then the log-likelihood becomes

$$\ln L(\beta) = \sum_{i=1}^{N} \left\{ \sum_{j=1}^{y_i-1} \ln(j+\alpha^{-1}) - \ln y_i! - (y_i+\alpha^{-1})\ln[1+\alpha\exp(x_i'\beta)] + y_i \ln\alpha + y_i x_i'\beta \right\}. \tag{5}$$

Note that if $\alpha = 0$, (4) reduces to the Poisson distribution (1), which means that the Poisson model is nested within the NB model. Then one can choose between the two models by means of an LR test of $H_0: \alpha = 0$ against $H_1: \alpha > 0$. Given the expression of the conditional variance of the NB model, this is equivalent to test for over dispersion (Long and Freese 2001, p. 246).

Alternatively, both a Wald test and an LM test are available. The former can be performed using the t test statistic of the estimated α parameter, while the latter requires testing the significance of α in the following auxiliary OLS regression:

$$\frac{(y_i - \hat{\mu}_i)^2 - y_i}{\hat{\mu}_i} = \alpha\hat{\mu}_i + u_i, \tag{6}$$

where $\hat{\mu}_i = \exp(x_i'\hat{\beta})$ are the fitted values of the Poisson model and u_i is an error term (Cameron and Trivedi 1998, pp. 77 ss.).

With the estimated parameters at hand, marginal effects can be calculated. The effect of one-unit change in the j-th regressor on the conditional mean, evalueted at the sample mean of the covariates, is given by

$$MEM_j = \frac{\partial E(y|x)}{\partial x_j} = \beta_j \exp(\bar{x}'\beta). \tag{7}$$

A better approach (Bartus 2005) is to use (7) (with x_i in place of $\bar{x}$) to compute the marginal effect over all individuals and then taking their average, that is

$$AME_j = \frac{1}{N}\sum_{i=1}^{N} \beta_j \exp(x_i'\beta). \tag{8}$$

Besides, for a dummy variable, one should use the finite difference method. In this case the marginal effect is the change in the conditional mean when the variable changes from 0 to 1. Formally, let $x_i = [z_i \;\; d_i]$ and $\beta = [\beta_z \;\; \beta_d]$, where d is the dummy variable. Then

$$AME_j = \frac{1}{N}\sum_{i=1}^{N} \{\exp(z_i'\beta_z + \beta_d) - \exp(z_i'\beta_z)\}. \tag{9}$$

5. Data and Variables

The empirical analysis is carried out on a data set, Survey of Household Income and Wealth (SHIW), released periodically by the Bank of Italy. In particular we use the 2012 Survey that contains a representative sample of 8151 households in Italy. In particular the survey includes socio-demographic variables, economic indicators such as employment, income, consumption and wealth, provided by the head of the family. In addition the survey investigates financial aspects giving specific information on innovative banking services and payment instruments. We refer to this last subsection and select the number of credit cards (labeled with CRECAR) held by the household as dependent variable of the model.

Figure 1 depicts the number of credit cards held by the family in the sample. It shows an asymmetric distribution between the 71% of the sample that has no credit cards and the 27% of them that holds one or two cards. A small number of families hold up to eight credit cards which is the maximum in the sample. Then, on average, each family holds 0.42 credit cards each but with a variance of 0.77.

As regressors we select form the original dataset the most relevant variables and, in addition, we generate further indicators from the original data. In particular, in the selected set of variables we include continuous and discrete variables that describe the characteristics of the family in the sample. Furthermore, to include in the analysis socio-demographic factors we compute also a group of dummy variables.

The variable selection procedure is mainly based on theoretical research hypothesis and empirical evidence. The considered hypothesis and the selected variables are illustrated in the following.

H1. Households in which the head of the family is older held more credit cards.

The age of the head of the household has been taken into consideration. In order to include the potentially nonlinear effect of the age we also compute the square of age as an additional regressor .

H2. Larger families are likely to own more credit cards.

The number of the household members is included expecting a positive effect.

H3. Larger wealth leads to larger number of credit cards held.

More wealth should reflect a higher standard of living and thus the propensity to hold more payment instruments. So we expect a positive coefficient for this variable;

H4. Households that earn more satisfy the income requirement for credit card eligibility more easily.

The household net disposable income should positively affect the credit card ownership.

As we said we also include a second set of dummy variables intended to take into account some peculiar characteristics of the country. Namely we consider: Geographic location, Municipality size, Education, Gender and Marital Status.

The selected variables are synthetized in Table 4 reporting the label and the meaning for each of them. Table 5 and 6 report the descriptive statistics. From a first reading we can state that the Italian cardholder profile is a married male, who has completed the compulsory school and resided in a medium sized city of northern Italy.

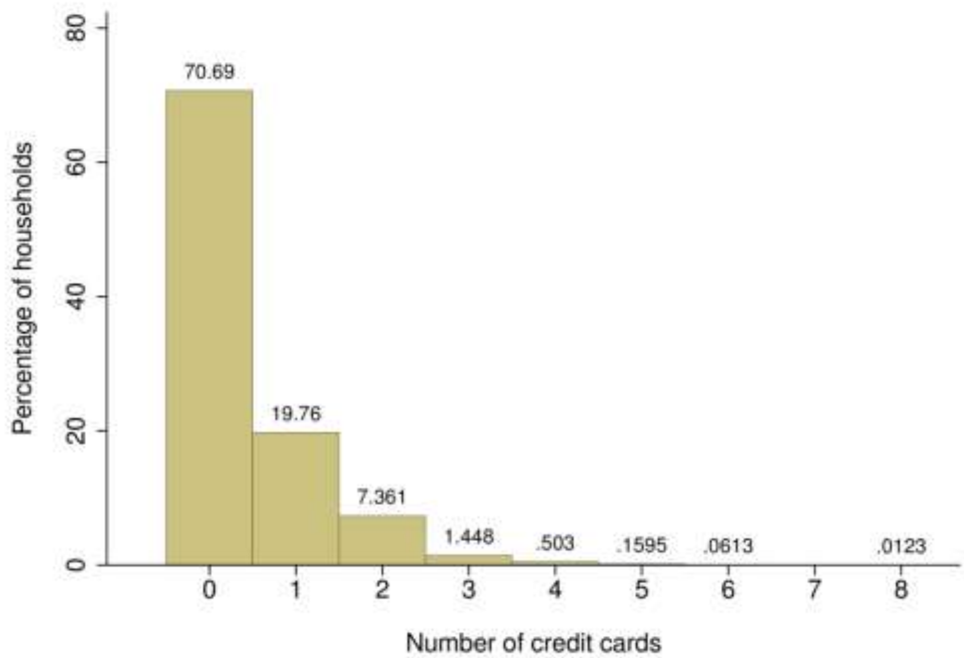

Figure 1. Sample distribution of the number of credit cards

Table 4. Description of the variables

Variable	Description
CRECAR[a]	Number of credit cards held by the family members (dependent variable)
AGE[b]	Age of the head of household
NCOMP[a]	Number of the household members
WEALTH[a]	Net wealth (real assets + financial assets - financial liabilities)
INCOME[a]	Net disposale income of the household
DUMMY VARIABLES	
Geographic location[a]	
NORTH[*]	North
CENTRE	Centre
SOUTH	South
Municipality size[a]	
SMUN[*]	Small municipality (up to 40,000 inhabitants)
MMUN	Medium municipality (from 40,000 to 500,000 inhabitants)
LMUN	Large municipality (more than 500,000 inhabitants)
Gender[b]	
MAL[*]	Male
FEM	Female
Education[b]	
NSC[*]	No educational qualification
CSC	Compulsory school degree
HSC	High school degree
BDP	Bachelor's degree or post-graduate qualification
Marital status[b]	
MAR[*]	Married
SIN	Single
SDW	Separated/divorced or widower/widow

[a]Variable (or group) refers to the household as a whole.
[b]Variable (or group) refers to the head of household.
[*] Reference group.

Table 5. Summary statistics

Variable	Mean	Std. Dev.	Min.	Median	Max.
CRECAR[a]	0.42	0.77	0	0	8
AGE[b]	59.28	15.71	18	60	99
NCOMP[a]	2.46	1.27	1	2	11
WEALTH[c]	0.26	0.44	-0.81	0.16	11.81
INCOME[d]	31.89	23.96	-1	26.01	368.69
Observations	8151				

[a]Units – [b]Years – [c]Millions Euro - [d]Thousands Euro

Table 6. Dummy variables summary statistics

Variable	Obs.	Perc.
Geographic location		
NORTH[*]	3512	43.1
CENTRE	1720	21.1
SOUTH	2919	35.8
Municipality size		
SMUN[*]	3514	43.1
MMUN	3928	48.2
LMUN	709	8.7
Gender		
MAL[*]	4457	54.7
FEM	3694	45.3
Education		
NSC[*]	365	4.5
CSC	4662	57.2
HSC	2157	26.5
BDP	967	11.9
Marital status		
MAR[*]	4981	61.1
SIN	1033	12.7
SDW	2137	26.2
Total	8151	100

[*]Reference group

6. Results and Discussion

Using the data described above, both the Poisson and the Negative Binomial models have been estimated using maximum-likelihood. The results are reported in Table 7. In the Poisson model most of the estimated coefficients are significant at least at a 5% level. However, the test based on the auxiliary OLS regression (6) rejects the null hypothesis of equidispersion ($\alpha = 0$). The same applies to the result of the Likelihood Ratio test. Furthermore, the AIC and BIC criterions are higher in the case of the Poisson model. Thus, the NB model has to be preferred to the Poisson model and in discussing results we will focus on the former of the two. Nevertheless, the over dispersion is not severe. In fact, the estimated α is small (0.14 in the auxiliary OLS regression and 0.13 in the negative binomial model) and the standard errors of the two models are very similar. From the second column of Table 7, we see that, in the NB model, 14 regressors out of 16 have a statistically significant impact - generally at the 1% level – on the number of credit cards held by Italian households.

In order to address the research hypothesis H1 we analyse the relationship between the age of the cardholder and the number of credit cards held and we introduce the age square as an additional variable. The sign of the coefficient of AGESQ is negative while the coefficient of AGE is positive, this highlights that, as expected, as age increases the number of credit card also increases but only up to a certain threshold after that it starts to decrease. This threshold value results in being equal to 0.0981/(2*0.0010) = 49.05, as depicted in Figure 2, which plots the number of credit cards as a function of the age.

The estimated average marginal effects (AME) computed according to equation (8) and (9) are reported in Table 8. We can observe that for the variable AGE we have a AME=-0.006, that indicates, on average, a not so relevant effect since one more year of age is associated with 0.006 fewer credit cards. The nonlinear relationships also imply that the marginal effect varies with the age.

The H2 hypothesis is not satisfied since the NCOMP parameter is not significant, meaning that the number of credit cards is unaffected by the household size. The same arises for the household net wealth (WEALTH) where the corresponding parameter is not significant. On the contrary, the INCOME parameter is strongly significant and positive. The number of credit cards increases with income (INCOME) by 0.006 for each additional thousand euros. Thus, when considering the economic well-being of households, the decision on how many credit cards to hold seems to be driven only by income, although its effect is not so high.

Moving to the analysis of the dummy variables included in the model the residence of households is particularly relevant. In Italy the level of social and economic developments is different in the three main areas of the country (North, Centre and South).

Considering NORTH as the reference group, we expect that the households located in the southern regions should possess less credit cards. The estimated parameters are significant and negative according to the socio economic characteristics of Italy, where the gap between North and South is still relevant. In particular, households in the South own 0.224 fewer credit cards than those in the North. The same effect can be registered for the Centre even if with a much lower value (0.046).

We include in the analysis a categorical variable that takes into account the size of the municipality where the household is. Three different sizes (SMUN, MMUN, LMUN) have been considered: small (up to 40,000 inhabitants), medium (from 40,000 to 500,000 inhabitants) and large (more than 500,000 inhabitants).

The medium and large size result to be both significant with positive sign indicating that living in larger cities encourages the credit card ownership since a more dynamic social and economic environment occurs . Looking at the marginal effect the number of credit cards held by families living in medium sized cities increases by 0.049 with respect to that held by families residing in small municipalities and of 0.084 for large municipalities.

The educational level should have a positive effect on credit card number. We consider an indicator variable for four different education levels: no education (NSC), level of compulsory school (CSC), high school diploma (HSC) or Bachelor/post-graduate degree. Assuming no education as the reference group, in households were the head attended a compulsory school there were 0.171 more credit cards. If the head of the household had a high school diploma or a Bachelor/post-graduate degree, then the family held 0.517 and 0.572 credit cards, respectively, more than the reference group.

The gender (MAL, FEM) also have an effect on the number of credit cards. As expected, in families in which the head is a woman, there are less credit cards then in families where the head is a man, even if the difference is not so relevant (0.083).

Finally a relationship between the number of credit cards held and the marital status seems to exist. Here we take into account whether the head of family is married (MAR), single (SIN) or separated/divorced/widower/widow (SDW). Fewer credit cards results if the heads are single (AME=0.121) or separated/divorced/widower/widow (AME=0.125).

Table 7. Estimation results–Dependent variable: CRECAR

Variable	Poisson	Neg.Binomial
Constant	-4.9834*** (-0.4489)	-4.9006*** (-0.4419)
AGE	0.1013*** (-0.0104)	0.0981***(-0.0105)
AGESQ	-0.0010***(-0.0001)	-0.0010*** (-0.0001)
NCOMP	0.0151 (-0.0202)	0.0045 (-0.0194)
WEALTH	-0.0468(-0.0639)	-0.0363 (-0.0352)
INCOME	0.0101***(-0.0012)	0.0130***(-0.0009)
Geographic location		
CENTRE	-0.0954**(-0.0449)	-0.0934** (-0.0447)
SOUTH	-0.5901*** (-0.0494)	-0.5706***(-0.0482)
Municipality size		
MMUN	0.1015***(-0.0378)	0.1132***(-0.0397)
LMUN	0.1905***(-0.0623)	0.1874***(-0.0628)
Gender		
FEM	-0.1921***(-0.0371)	-0.1944***(-0.0403)
Education		
CSC	1.2091***(-0.3625)	1.1657***(-0.3376)
HSC	2.1291***(-0.3641)	2.0382***(-0.3385)
BDP	2.2286***(-0.3656)	2.1263***(-0.3401)
Marital status		
SIN	-0.3129***(-0.0629)	-0.2969***(-0.0699)
SDW	-0.3310***(-0.0603)	-0.3076***(-0.0631)
Overdispersion test	0.14(0.0000)	-
F test	-	33.14 (0.0000)
Log-likelihood	-5682.87	-5666.31
N. of parameters	16	17
AIC	11397.75	11366.61
BIC	11509.84	11485.71
Pseudo R^2	0.2177	0.1950
N. of observations	8151	8151

Significant at: *** = 1% level; ** = 5% level; * = 10% level. Standard errors of the parameters and p-values of the tests in parentheses. For the Poisson model standard errors are robust.
Reference groups: NORTH, SMUN, MAL, NSC, MAR.

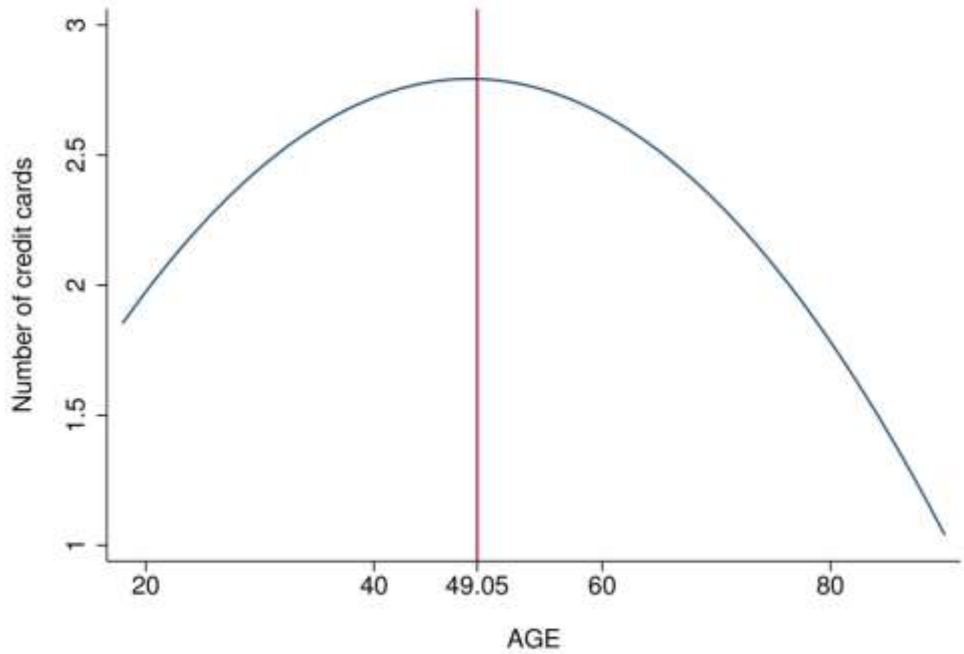

Figure 2. Number of credit cards as function of AGE

Table 8. Average marginal effects of the negative binomial model

Variable	AME
AGE	-0.0058*** (-0.0007)
NCOMP	0.002(-0.0085)
WEALTH	-0.016 (-0.0154)
INCOME	0.0057***(-0.0005)
Geographic location	
CENTRE	-0.0460**(-0.0217)
SOUTH	-0.2242*** (-0.0177)
Municipality size	
MMUN	0.0487***(-0.017)
LMUN	0.0837*** (-0.0296)
Gender	
FEM	-0.0831*** (-0.0168)
Education	
CSC	0.1709*** (-0.0273)
HSC	0.5169***(-0.031)
BDP	0.5716***(-0.0362)
Marital status	
SIN	-0.1214***(-0.0258)
SDW	-0.1251***(-0.0233)

Significant at: *** = 1% level; ** = 5% level; * = 10% level. Standard errors of the elasticities in parentheses. Reference groups: NORTH, SMUN, MAL, NSC, MAR.

7. Concluding Remarks

In this paper we have investigated the determinants that affect the use of credit cards by Italian families. The empirical analysis is based on count data models on data collected by the Bank of Italy in the Survey of Household Income and Wealth. This data set provides detailed information on wealth holdings, consumption, income at the household level and few other socio economic information. The reached results show that economic well-being slightly affects the respond variable however some other factors seem to play a relevant role. In particular the geographic location of the household results to be very peculiar for Italy together with socio-demographic characteristics such as the educational level and the marital status.

Finally, we can say that a single man living in the South of Italy holds fewer credit cards compared to a family of the North whose head is more educated. These results could be useful in understanding the characteristics of different segment of consumers and investigating market effect such as “multi-homing” and “co-holding”.

Possibly, other factor may be included among the determinants of the number of credit cards, but the availability of data and the absence of a theory that could guide this choice are quite binding. A possible solution would be the use of zero inflated and hurdle models to accommodate the large proportion of households not holding a credit card. We leave this for future research.

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