The Usage of Credit Cards: An Empirical Analysis on Italian Households Panel Data

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Abstract
Credit cards, both as mean of payment and borrowing, rise many economic issues. The credit card services can be viewed as a two-sided network platform affected by indirect network externalities. The distribution of prices faced by the two sides influences market participation and the overall volume of demand. Consumers may hold or use credit cards from multiple networks leads to a 'multi-homing' effect that is of great importance in determining the outcome of the industry. Moreover, some studies show that the multiple credit cards can be seen as a device to access to more financing, making family bankruptcy more likely. In this paper we model the number of credit cards held by a panel of Italian household over the period 1991-2010 using demographic, socio-economic and geographical variables as potential predictors and panel data techniques for count data. The reached results can be of interest for implementing market strategies in credit card industry and, in particular, to investigate peculiar effect such as "multihoming" and "co-holding".
Keywords: Credit cards, Panel data, Count-data models

1. Introduction

A credit card is a system of payment since it allows the cardholder to pay for goods and services without using cash. This presupposes that the card issuer has granted a line of credit, mostly uncollateralized, from which the user borrows to either pay to the seller or withdraw cash from an ATM. In case of revolving credit card, the cardholder does not pay his balance in full each month, but in installments and the issuer charges an interest rate (Bullock, 2010).

These characteristics of credit cards entail many economic issues. Firstly, from an industrial organization perspective, the credit card services can be viewed as a network industry, like electricity supply, telecommunications and railroads (Economides, 1996). In fact, the participation of a new economic agent to the network involves positive externalities for other participants.

More precisely, credit cards are two-sided network services (Rochet and Tirole, 2004; Rysman, 2009) as the benefits for the users depends on the number of sellers in the network and, similarly, the benefits for the sellers increase with the number of the users (Chakravorti, 2003). In turn, these network effects give rise to competition policy issues (Carlton and Frankel, 1995; Lemley and McGowan, 1998).

In this context, the fact that consumers hold or use credit cards from multiple networks, known as "multi-homing", is extremely relevant in determining the outcome of the industry (Rochet and Tirole, 2003; Guthrie and Wright, 2007). However, from an empirically point of view, it is not clear what should be exactly intended for multi-homing (Snyder and Zinman, 2008). More precisely, two main issues arise. First, one should establish whether what matters is merely the possession of multiple credit cards or even their actual use. The second question concerns the substitutability between debit cards and credit cards in deciding whether a given cardholder is a multi-homer or not.

Since credit cards allow borrowing without applying for personal loans, there exists an incentive in building up large debts (Loke et al., 2011). Possibly, the sharp increase in bankruptcy filing rates in the United States from 1980 to 2004 has been due to the growing credit card debt of families (White, 2007). Thus, the multiple credit cards can be seen as a device to access to more financing.

Although borrowing by means of credit cards could seems irrational, given the high interest rates charged and the large profits earned by issuers (Ausubel, 1991), some authors have maintained that this behavior is nonetheless consistent with economic theory (Zywicki, 2000). Brito and Hartley (1995) show that consumers could be willing to pay high interest rates on credit card debts in order to avoid the costs of bargaining with financial institutions or those associated with precautionary money holding.

If so, another apparent contradiction emerges. Data show that many consumers simultaneously hold costly credit card debts and low-return liquid assets, so that it would be rational to repaying their outstanding balances (Gross and Souleles, 2002; Telyukova and Wright, 2008). However, this action (known as "co-holding") can be explained as an attempt to self-control compulsive buying or the need to complete transactions for which a credit card cannot be used (Gathergood and Weber, 2013).

In the light of these considerations, it is of interest to study the factors affecting the choice of holding multiple credit cards. On one hand this could be a first step toward a more in deep understanding of multi-homing.1 On the other hand, the factors influencing the number of credit cards held could help in predicting family bankruptcy end explaining the "co-holding" phenomena. Besides, our results could be of help in designing marketing strategies by firms operating in such market, aiming to capture new consumer segments.

Therefore, our interest is to investigate, thought an econometric models, those effects in a real data set.

In the literature, several econometric techniques have been used to model the credit card ownership of individuals or households as briefly reported in the following. If the focus is on the choice between to use or not use credit cards, the natural choice is the logit or probit models (Yayar and Karaca, 2012). Other studies, such as (Pulina, 2011), try to identify the factors affecting the type of credit card used by means of a multinomial logit model. When data on the number of credit cards held are available, several authors (Kinsey, 1981; Chien and Devaney, 2001; Tan et al., 2011) have used the tobit model. However, since the variable under consideration is a nonnegative integer, it can be better to resort to count data models as, for example, in (Loke et al., 2011).

Following the previous literature we propose a new approach employing a panel data techniques for count data. This approach allows as to take into account the heterogeneity of the information. In this context, modeling heterogeneity is quite important since there is no theory to guide the choice of variables affecting the number of credit card held.

Aim of the paper is to investigate the determinants driving the credit card ownership and analyses the implication of socio-economic, demographic and geographic variables in the card payment system. We estimate several Poisson regression models and compute the marginal effects of the covariates on the number of credit cards held. The data used in the empirical analysis come from several waves of the Survey of Household Income and Wealth (SHIW) conducted by the Bank of Italy. We found that factors such as age, income, wealth, sex, geographic location, education and marital status are effective in explaining the number of credit cards held by Italian household.

The rest of the paper is organized as follow. The next section illustrates the econometric models used, while Section 3 is devoted to the description of data and variables. Results are presented and discussed in Section 4. Finally, the last section draws some conclusions.

2. Methodology

In the literature business failure has been defined in many different ways, although it there is not a widely accepted definition (Crutzen and van Caillie, 2007).

In many studies, business failure is defined as a series of different situations that lead to the closing down of the firm due to relevant financial problems (Morris, 1997). However, this definition only concentrates on the financial disease without taking into account other difficulties that can affect the firms' health in the early stages of the failure process (Argenti, 1976).

Therefore, it is necessary to clarify the meaning of business failure our study refers to. In a predictive prospective, the empirical literature distinguishes between two main aspects of the definition of business failure: economic and juridical.

A widely used technique for modeling count data is the Poisson regression (for an introduction to count data models, see Cameron and Trivedi, 1998 and Long and Fresse, 2001). Given a set of N independent observations $(\mathrm{y}_{\mathrm{it}}, \mathrm{x}_{\mathrm{it}})$ where y_{it} is a count and x_{it} is a vector of covariates, assume that y_{it} given x_{it} is distributed as a Poisson, that is

$$f(y_{it}|\boldsymbol{x}_{it}) = \frac{e^{-\mu}\mu^{y_{it}}}{y_{it}!} \quad (y_{it} = 0, 1, 2, \dots). \tag{1}$$

The conditional mean is parameterized as

$$\mathrm{E}(\mathrm{y}_{\mathrm{it}}|\mathrm{x}_{\mathrm{it}}) = \mu_{\mathrm{it}} = \exp(\mathrm{x}_{\mathrm{it}}'\beta), \tag{2}$$

where β is a vector of parameters to be estimated (note that, by (2), $\mu > 0$).

Since $\mathrm{Var}(\mathrm{y}_{\mathrm{it}}|\mathrm{x}_{\mathrm{it}}) = \mathrm{E}(\mathrm{y}_{\mathrm{it}}|\mathrm{x}_{\mathrm{it}}) = \mu_{\mathrm{it}}$, the model is heteroskedastic. It can be easily estimated by maximum likelihood.

The equality between the mean and the variance of the Poisson distribution, also known as equidispersion

[1] The two concepts are not overlapping but clearly multiple credit cards are a necessary, although not sufficient, condition for multi-homing.

property, is very often rejected by data, since the variance exceeds the mean. One simple solution to this problem is to use robust standard errors. Then, first we estimated a Poisson regression on the pooled sample.
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

$$\text{MEM}_j = \frac{\partial E(y|\boldsymbol{x})}{\partial x_j} = \beta_j \exp(\bar{\boldsymbol{x}}\,'\boldsymbol{\beta}). \tag{3}$$

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

$$\text{AME}_j = \frac{1}{N}\sum_{i=1}^{N} \beta_j \exp(\boldsymbol{x}_i{}'\boldsymbol{\beta}). \tag{4}$$

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_i is the dummy variable. Then

$$\text{AME}_j = \frac{1}{N}\sum_{i=1}^{N} \{\exp(\boldsymbol{z}_i{}'\boldsymbol{\beta}_{\boldsymbol{z}} + \beta_d) - \exp(\boldsymbol{z}_i{}'\boldsymbol{\beta}_{\boldsymbol{z}})\}. \tag{5}$$

If the assumption of independence of y_{it} is relaxed, one can resort to the population-averaged Poisson regression in order to model the correlation $\rho_{ts} = \text{Cor}\{[y_{it} - \exp(x_{it}{}'\beta)][y_{is} - \exp(x_{is}{}'\beta)]\}$. We estimated this model assuming ρ_{ts} can vary freely between t and s. Even in this case, we used robust standard errors to cope with over dispersion.
In order to modelling the heterogeneity of the cross-sectional units (households) we refer to a panel data models. In this case, including an intercept for each cross-sectional unit, the conditional mean is parameterized as

$$\text{E}(y_{it}|\alpha_i, \boldsymbol{x}_{it}) = \exp(\gamma_i + \boldsymbol{x}_{it}{}'\boldsymbol{\beta}) = \alpha_i \exp(\boldsymbol{x}_{it}{}'\boldsymbol{\beta}) \tag{6}$$

where $\gamma_i = \ln\alpha_i$.
The standard random-effects model can supports two different assumptions. Generally assumes that α_i is distributed as a Gamma with mean 1 and variance η. As an alternative, one can assume that $\gamma_i = \ln\alpha_i$ is normally distributed with mean 0 and variance σ_α^2.
If the individual effects are not random, but additional parameters to be estimated, one obtains the fixed-effects model. One shortcoming of this model is that it does not allow time-invariant covariates. Since most regressors discussed in the next section have this characteristic, we did not consider the fixed-effect model.

3. Data and variables

The data used in this study come from the Survey of Household Income and Wealth (SHIW) conducted by the Bank of Italy since 1977 and every one or two years.

The survey involved about 8000 households in each wave, which were representative of the Italian population. The respondent was the head of the household, who supplied information on composition of the family and the socio-demographic characteristics of its members, employment, income and consumption, wealth, use of the payment instruments and relationship with the financial intermediaries. While some questions concern every member, some others involve the household as a whole.

Due to lack of data, we limited our analysis to the period 1991-2010, during which nine waves have been carried out. We also excluded households for which less than three observations were available. The final sample consists of 26340 observations on 6279 households. The panel is unbalanced, and includes about 4 observations for each household.

The variables drawn or constructed from the dataset [1] are described below, while their descriptive statistics are shown in Table 1 and 2

CRECAR is the number of credit cards held by the household and represents our dependent variable. On average, each family in the pooled sample holds 0.36 credit cards. However, about the 75% of the sample have no credit cards, while a large portion (about 23%) holds one or two. The maximum number of credit cards held is 10. The variable is over dispersed, since its variance is equal to 0.73.

As regressors we consider two distinct sets of variables [2]. The first set includes the following variables:
- the age of the head of household (AGE). It is expected that households whose head is older held more credit

[1] The dataset is freely available at http://www.bancaditalia.it/statistiche/indcamp/bilfait/dismicro.
[2] Before proceeding, it is worth noting that CRECAR is available only at a family level, while most of the variables we are going to discuss in the text concerns the head of household (see Table 3). Then we are assuming that the latter variables give a good description of some characteristics of the household considered as a whole. This seems to us to be a better solution with respect to resort to some index based on all family members' data.

cards. However, behind a certain threshold value the relationship should invert and become negative. To test this hypothesis, we include the square of AGE (labelled as AGESQ) as an additional regressor;
- the number of the household members (NCOMP). Larger families are likely to own more credit cards, so the expected sign of the corresponding coefficient is positive;
- household net wealth (WEALTH). A larger wealth should reflect a higher standard of living and thus the propensity to hold more payment instruments. Moreover, for wealthy people, increasing the number of credit cards held could be a way of showing their social status (Gan et al., 2008). Then we expect a positive coefficient for this variable;
- the household net disposal income (INCOME). Households that earn more should fulfill the income requirement for credit card eligibility more easily, so it is expected that this variable positively affects the credit card ownership.
The second set of covariates aims to capture the effect of geographic and other socio-demographic factors and consists of the following groups of dummy variables:
- *Geographic location* (NORTH, CENTRE and SOUTH). This group of dummies records the location where the household resides. As it is well known, in Italy the level of social and economic development reduces going from North to South. Thus, assuming NORTH as the reference group, we expect the sign of the SOUTH coefficient to be negative, that is households located in the southern regions should possess less credit cards. By the same reasoning, the CENTRE variable should negatively impact on the number of credit cards, but its effect should be lower in magnitude;
- *Municipality size* (SMUN, MMUN, LMUN). These variables consider whether a given household resides in a small (up to 40,000 inhabitants), medium (from 40,000 to 500,000 inhabitants) or large (more than 500,000 inhabitants) municipality, respectively. Considering SMUN as reference, both MMUN and LMUN coefficient are expected to be positive, since living in a more dynamic social and economic environment - as it occurs in larger cities - should foster the credit card ownership;
- *Sex* (MAL, FEM). Both variables are either zero or one depending on the gender of the family head, being MAL the omitted category. The sign of the FEM coefficient is not a priori determinable;
- *Education* (NSC, CSC, HSC, BDP). By means of this group the effect of education is considered. The head of family could have no education (NSC), attended the compulsory school (CSC), hold a high school diploma (HSC) or attained a Bachelor/post-graduate degree. Again, considering the first variable as the reference group, the coefficients of the remaining dummies should exhibit a positive sign. Indeed, more educated individuals are expected to be more confident in using a larger number of credit cards and managing additional bills;
- *Marital status* (MAR, SIN, SDW). Here we take into account whether the head of family is married (MAR), single (SIN) or separated/divorced/widower/widow (SDW). Married people could possess multiple credit cards in order to manage the family balance sheet more efficiently. On the other hand, not married individuals (especially singles) could be more prone to credit card ownership because of a more free lifestyle. Thus for this variables we have no a priori knowledge about the sign of their coefficients. As before the omitted category is the first one (MAR).

Summing up, and jointly considering the reference groups defined above, the "base" head of household is a married male, with no educational qualification and living in a small municipality located in the North of the country.

Moreover, on the basis of the figures reported in Table 2, we can state that in 2010 the most frequent profile in the sample is a married male, who has completed the compulsory school and residing in a small sized city of northern Italy.

Table 1. Summary statistics

Variable	Mean	Std. Dev.	Min.	Median	Max.
CRECAR[a]	0.36	0.73	0	0	10
AGE[b]	56.65	14.37	20	56	98
NCOMP[a]	2.81	1.31	1	3	12
WEALTH[c]	0.28	0.5	-0.64	0.17	28.56
INCOME[d]	41.62	32.11	-75.68	34.08	811.09
Observations	26340				

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

Table 2. Dummy variables summary statistics – years 2010

	Variable	Obs.	Perc.
Geographical location	NORTH*	1341	48.8
	CENTRE	517	18.8
	SOUTH	890	32.4
Municipality size	SMUN*	1369	49.8
	MMUN	1212	44.1
	LMUN	167	6.1
Sex	MAL*	1735	63.1
	FEM	1013	36.9
Education	NSC*	111	4.0
	CSC	1617	58.8
	HSC	744	27.1
	BDP	276	10
Marital status	MAR*	1779	64.7
	SIN	248	9.0
	SDW	721	26.2
	Total	2748	100

**Reference group*

4. Empirical results and discussion

Using the data set described above, the pooled, population-averaged and random-effects Poisson (both with gamma and normal distributed intercepts) regression models have been estimated by means of maximum-likelihood. Results are reported in Table 3. In all models, most parameters results to be highly significant.

For sake of brevity, we focus the discussion on the reached results on the random-effects model with normally distributed intercepts.

The coefficient of AGE is positive, while that of AGESQ is negative, which implies an inverted U relationship between the age and the number of credit cards. Put differently, this means that the number of credit cards held increases as age increases, but only up to a certain value, from which it decreases. From the estimated coefficients, this value is equal to 0.1068/(2*0.0011) = 48.55.

Average marginal effects (AME) are shown in Table 4. For AGE the AME is -0.0131, which means that, on average, one more year of age is associated with 0.0131 fewer credit cards. Thus the impact of the age on the credit card ownership is fairly small.1 The NCOMP parameter is not significant, meaning that the number of credit cards is unaffected by the household size. Maybe, this variable would be better measured if it was net of the number of children in the family. Actually, they are not legally able to own a credit card.

[1]However, since the relationship is not linear, the marginal effect varies with the age.

Table 3. Estimation results – Dependent variable: CRECAR

Variable	Pooled	Population-averaged	Random-effects (Gamma)	Random-effects (Normal)
AGE	0.0918***	0.0817***	0.1023***	0.1068***
	(0.0111)	(0.0113)	(0.0095)	(0.0101)
AGESQ	-0.0010***	-0.0009***	-0.0010***	-0.0011***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
NCOMP	-0.0402*	0.0329	0.005	-0.0083
	(0.0211)	(0.0217)	(0.0194)	(0.0203)
WEALTH	0.0436**	0.0539***	0.0877***	0.0892***
	(0.0219)	(0.0122)	(0.0226)	(0.0219)
INCOME	0.0041***	0.0030***	0.0039***	0.0039***
	(0.0006)	(0.0006)	(0.0005)	(0.0005)
CENTRE	-0.1841***	-0.1980***	-0.2546***	-0.2406***
	0.0462	0.0544	0.0476	0.0516
SOUTH	-0.6732***	-0.7069***	-0.8611***	-0.9443***
	(0.0518)	(0.0573)	(0.0541)	(0.0598)
MMUN	0.1045***	0.1482***	0.1372***	0.1380***
	(-0.0394)	(-0.0441)	(-0.0426)	(-0.0475)
LMUN	0.1662***	0.2533***	0.1682***	0.2119***
	(0.0633)	(0.0697)	(0.0623)	(0.0720)
FEM	-0.0583	-0.0502	-0.1248**	-0.1172**
	(0.0518)	(0.0572)	(0.0510)	(0.0545)
CSC	2.1327***	1.5414***	2.0705***	2.0069***
	(0.2889)	(0.1985)	(0.3083)	(0.3102)
HSC	3.2014***	2.3281***	3.0708***	3.1227***
	(0.2906)	(0.2019)	(0.3068)	(0.3107)
BDP	3.4304***	2.7008***	3.4425***	3.5728***
	(0.2932)	(0.2036)	(0.3105)	(0.3175)
SIN	-0.4097***	-0.1721**	-0.2521***	-0.2909***
	(0.0810)	(0.0741)	(0.0648)	(0.0718)
SDW	-0.3779***	-0.2980***	-0.3341***	-0.3477***
	(0.0711)	(0.0809)	(0.0645)	(0.0690)

Significant at: *** = 1% level; ** = 5% level; * = 10% level. S.E. of the parameters in parentheses..

The household net wealth (WEALTH) is significant and, as expected, it exerts a positive effect on the quantity of credit card. The magnitude of the marginal effect, however, is negligible: if wealth increases by one million, then number of credit cards increases by only 0.0892. The number of credit cards also increases with income (INCOME) by 0.0039 for each additional thousand euros or, which is the same, by 4 for each million euros. Thus, when considering the economic well-being of households, the decision on how many credit cards to hold seems to be driven mainly by income, although its effect is not so high.

Turning to the dummy variables included in the model, those associated to the geographic location (CENTRE and SOUTH) are both strongly significant and negative, confirming that, as one moves from North to South along the country, households tend to hold fewer credit cards. As already noted, this can be explained by the lower level of socioeconomic development prevailing in the southern part of Italy. Particularly, households living in the South own 0.9443 fewer credit cards than those residing in the North (which represents the reference group). The same applies to families located in the central Italy, but the effect is much lower (0.2406). Among the variables recording the size of the municipality where the household lives, MMUN and LMUN, they are both significant and shows a positive sign. Looking at the magnitude of the marginal effect, we can state that the number of credit cards held by families living in medium sized cities increases by 0.1380 with respect to that held by families residing in small municipalities. For large cities the marginal effect is 0.2119.

We also found that a household whose head is a woman possesses fewer credit cards than households with a male head, although the difference is quite small (0.1172). The number of credit cards held is higher when the head is more educated, as shown by the positive sign of the coefficient CSC, HSC e BDP. Particularly, families whose head attended the compulsory school hold 2.0069 more credit cards than those whose head has no education. If the head of household attained a high school diploma or a Bachelor/post-graduate degree, then the family holds 3.1227 and 3.5728 credit cards, respectively, more than the reference group. In other word, an increasing relationship between the number of credit cards held and the level of education seems to exist. Finally, households held fewer credit cards, if their heads are single or separated/divorced/widower/widow. The marginal effects are 0.2909 and 0.3477 respectively.

Table 4 Average marginal effects for the random effects (normal) model

Factors	Variable	AME
	AGE	-0.0131*** (0.0020)
	NCOMP	-0.0083 (0.0203)
	WEALTH	0.0892*** (0.0219)
	INCOME	0.0039*** (0.0005)
Geographic location	CENTRE	-0.2406*** (0.0516)
	SOUTH	-0.9443*** (0.0598)
Municipality size	MMUN	0.1380*** (0.0475)
	LMUN	0.2119*** (0.0720)
Sex	FEM	-0.1172** (0.0545)
Education	CSC	2.0069*** (0.3102)
	HSC	3.1227*** (0.3107)
	BDP	3.5728** (0.3175)
Marital status	SIN	-0.2909*** (0.0718)
	SDW	-0.3477*** (0.0690)

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

5. Conclusion

In this paper we have studied the determinants of the use of one of the major electronic banking services (credit cards) by Italian families. Using data from the Survey of Household Income and Wealth (SHIW) conducted by the Bank of Italy and panel count data models, we have found that factors such as wealth, income and geographic location of the household and socio-demographic characteristics of the head of household are effective in predicting the number of credit cards held. Among those factors, those exerting a stronger impact are the location where the household resides and the level of education of the head of household. More precisely, families living in the South of Italy possess fewer credit cards, while families whose head is more educated held more credit cards.

Our results could be of interest for implementing marketing strategies in the credit card industry and specifically to concentrate effort on particular customer segments. Moreover, they could be of help in understanding some characteristics of the credit card market such as “multi-homing” and “co-holding”.

Our proposed approach can benefit of some further extensions that can help to better investigate same peculiar characteristics of this market. First, can be of interest taking into account the dynamic and possible serial correlation among observations. In other words, the number of credit cards could depend on the number of credit cards held by the household in the previous year. Another interesting extension would be the use of zero inflated and hurdle models to accommodate the large proportion of households not holding a credit card. We plan to work on those aspects in future research.

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