

Semiparametric methods for causal inference: the effect of debit cards on households' spending

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Abstract Motivated by recent findings in the field of consumer science, the paper proposes an application of some semiparametric causal methods to evaluate the effect of debit cards (*carte Bancomat*) on Italian household consumption. The analysis is based on exogeneity conditions (unconfoundedness and overlap) requiring the adoption of debit cards to be independent on the potential consumption given a set of covariates. This offers the advantage of avoiding the introduction of assumptions regarding the link between observable and unobservable quantities, and it also improves the precision relative to other main methodological options. The analysis results in positive effects on household monthly spending during the nineties.

Key words: Causal Inference, Unconfoundedness, Semiparametric methods.

1 Introduction

In this paper, some semiparametric causal inference methods recently proposed to correct for self-selection due exclusively to observable variables are applied to assess whether and how debit cards affect Italian household spending. Debit cards are defined as cards enabling the holder to have purchases directly charged to funds on his account at a deposit-banking institution, and in Italy they are usually called "*carte Bancomat*". This application allows us to verify whether this non-cash payment instrument can drive the consumer behavior so as to encourage spending. The past few years have seen an increasing global trend in the use of non-cash payment instruments such as credit, debit, charge and prepaid cards as well as electronic money. However, the proliferation of non-cash payment instruments has been accompanied by relatively little research on the psychological effects they have on

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consumer spending. Even if from the point of view of economic theory, the payment mechanism has no role in the rational evaluation of a purchase, research on the psychology of consumer behavior provides a theoretical basis for supporting the thesis that payment instruments can play a significant role in consumer decisions. Possibly the most important concept to come out of this field of research is *mental accounting*, that is, the set of cognitive operations used by individuals and households to organize, evaluate, and keep track of financial activities (Thaler, 1985). Starting from this concept, recent research in the psychology of consumer behavior has proposed theories on prospective accounting, coupling, retrospective evaluations and financial resources accessibility (for example: Soman, 2001), which stimulate deeper investigation on the effects of non-cash payment instruments, in particular debit and credit cards, on consumption. There is also substantial evidence that consumers who have cards overspend compared to those who do not. However, the observed relationships between the level of spending and the possession of cards have not been sufficient to state the existence of causal links because of plausible biases due to individuals self-selection. In this paper, the interest in estimating the effect of debit card is principally motivated by the fact this payment instrument does not allow consumers to incorporate additional long-term sources of funds, as in the case of credit card. It is therefore possible to eliminate the confounding inter-temporal reallocations of wealth from the psychological effects on spending.

To evaluate the impact of debit cards possession on spending, we apply recently proposed semiparametric causal inference methods (based on power series) to a dataset from a large Italian survey. According to the author's knowledge, there are no other studies with these objectives based on data from broad surveys. The approach to causality here adopted is that based on the concept of Potential Outcomes. Following this approach and adopting the usual experimental terminology, the causal effect of a treatment is defined by a comparison, typically made by differences, between the potential outcomes that would be observed under different levels of the treatment. The semiparametric methods here applied have the advantage of a functional specification that is flexible to the sample sizes (at the contrary of standard parametric models) without losing efficiency. Under the assumptions illustrated in Section 3, results from these methods are asymptotically the same; so that the more stable the estimated effects across methods are, then the greater the final reliability of the analysis is.

2 The data

The analysis is based on data from the panel component of the Survey on Household Income and Wealth run by the Bank of Italy every two years from 1965 (except for a delay in one year causing the survey on 1997 to be shifted to 1998). Here the aim is to evaluate the effects of debit cards on the monthly household spending observed in five of the last few years, t : 1995, '98, 2000, '02 and '04. The target population has been defined as the set of households having at least one bank current account but

no debit cards at survey's time $t - 1$. The treatment D is posed equal to 1 if, at the subsequent survey's time t , the household possesses at least one debit card, equal to 0 otherwise. Therefore, a household for which $D = 1$ is characterized by having acquired their first debit card during the span $(t - 1) \rightarrow t$. The outcome, Y , on which to evaluate the treatment effect is the monthly average spending of the household on all consumer goods observed at t . Table 1 reports the sizes for each of the five samples.

Table 1 Sample sizes.

$(t - 1) \rightarrow t$	$D = 1$	$D = 0$	Total
1993 $\rightarrow$ 95	257	805	1062
1995 $\rightarrow$ 98	226	396	622
1998 $\rightarrow$ 00	197	539	736
2000 $\rightarrow$ 02	195	442	637
2002 $\rightarrow$ 04	150	474	624

The basic assumption is unconfoundedness that requires the receipt of a treatment to be independent on the potential outcomes given a set of pre-treatment variables, $\mathbf{X}$, that here includes: the lagged outcome; the monthly average money inventories held by the household; the number of banks and the yearly based average interest rate in the province where the household lives; the overall household income and wealth; the Italian geographical macroarea and the number of inhabitants of the town where the household lives; the householder age, education, working status, and sector of activity.

The relevant causal effect to be estimated will be that due to the treated (Population Average causal effect of Treatment on the Treated: PATT): the subset of the population holding the payment instrument under study and to which the causal effect on spending must be ascribed.

Table 2 shows the results, for a subset of the previously proposed variables $\mathbf{X}$, from a descriptive explorative cross-sectional analysis aimed to explain the probability that a household has at least one debit card. Using a logit regression model, we observe the probability a household has at least one debit card increases with the income, the householder education, while it decreases with the householder age.

3 Assessing the assumptions

A preliminary step in the analysis is to consider the plausibility of the Stable Unit Treatment Value Assumption (SUTVA). The assumption is necessary for the Potential Outcomes Approach, and it states that potential quantities for each unit have to be unrelated to the treatment status of other units. SUTVA is not testable, however it is typically implausible when individuals are permitted to interact with each other,

Table 2 MLE*; dep. var.: logit of the probability an household has at least one debit card.

	1995	1998	2000	2002
Intercept	-1.25 (0.00)	0.003 (0.99)	-0.821 (0.02)	-1.319 (0.00)
Income:	$1.3 \cdot 10^{-5}$ (0.00)	$8.4 \cdot 10^{-6}$ (0.00)	$5.5 \cdot 10^{-6}$ (0.00)	$2.4 \cdot 10^{-5}$ (0.00)
Householder education:				
none (intercept)				
elementary school	0.335 (0.08)	0.115 (0.58)	0.597 (0.00)	0.512 (0.01)
middle school	0.880 (0.00)	0.696 (0.00)	0.986 (0.00)	1.084 (0.00)
profess. second. sc.	0.920 (0.00)	0.753 (0.00)	1.272 (0.00)	1.276 (0.00)
high school	1.179 (0.00)	1.156 (0.00)	1.551 (0.00)	1.676 (0.00)
university	1.186 (0.00)	1.227 (0.00)	1.656 (0.00)	1.694 (0.00)
Householder age:				
<31 (intercept)				
31-40	-0.094 (0.55)	-0.168 (0.38)	0.181 (0.34)	0.416 (0.05)
41-50	-0.494 (0.00)	-0.551 (0.00)	-0.125 (0.49)	0.116 (0.57)
51-65	-0.781 (0.00)	-0.780 (0.00)	-0.643 (0.00)	-0.352 (0.09)
>65	-1.617 (0.00)	-1.869 (0.00)	-1.672 (0.00)	-1.200 (0.00)

* *p-values* in parenthesis.

such as in trading or in market analysis. Here, the individual treatment is the holding of debit cards, which does not seem plausible to affect the potential spending of other individuals. The effects of this treatment can be reasonably thought to act only within individuals, and consequently SUTVA can be supposed.

The further assumption of unconfoundedness, firstly introduced by Rosenbaum and Rubin (1983), states that treatment has to be independent on the couple of potential outcomes given the vector of pre-treatment variables: $D \perp (Y_1, Y_0) | \mathbf{X} = \mathbf{x}$. The authors joined the unconfoundedness with the assumption of overlap in which every unit in the population has to have a chance of receiving each treatment: $0 < \Pr(D = 1 | \mathbf{X} = \mathbf{x}) < 1$. To make unconfoundedness plausible, the choice of the pre-treatment variables has been driven by economic theory for what concerns those variables usually adopted to explain the choice of non-cash payment instruments: interest rate, cash inventories, number of banks in the province, consumption. The rest is a set of demographic and social variables introduced as proxies for the remaining unobservable heterogeneity. The unconfoundedness assumption is not testable, nevertheless there are some indirect ways to assess its plausibility. Particularly interesting is a recent contribution by Crump et al. (2008): unconfoundedness can be assessed by a semiparametric test which is based on quantifying the causal effect of the treatment on a variable known to be unaffected by it, typically the lagged outcome. If the treatment effect on the lagged outcome is estimated to be close to zero, then it is plausible the unconfoundedness assumption holds. The test is based on a power series approach to estimation for average treatment effects (Hahn, 1998). Given the particular order term k in the power series expansion, the null hypotheses of interest can be formulated as equality restrictions: $\beta_{1,k} - \beta_{0,k} = 0$, where $\beta_{d,k}$ is the parameter vector in the regression model for the outcome under the treatment d , $\mu_{D=d}(\mathbf{x})$, $d = 0, 1$. Asymptotically the test statistics, Q , are usual quadratic forms

in the differences in the parameter estimates with critical values from a chi-squared distribution: $Q = (\hat{\beta}_{1,k} - \hat{\beta}_{0,k})' \hat{V}_k^{-1} (\hat{\beta}_{1,k} - \hat{\beta}_{0,k}) \rightarrow \chi^2(k)$, with $\hat{V}_k$ be an appropriate estimate (Crump et al. 2008) of the covariances matrices for $\hat{\beta}_{1,k} - \hat{\beta}_{0,k}$. Of particular concerns is the choice of the order term k . Here we propose to fix the part of the power series expansion concerning the dummies variables at the simplest linear specification. Let $\mathbf{X} = (\mathbf{X}_c, \mathbf{X}_d)$, where $\mathbf{X}_c$ is the vector of the pre-treatment continuous variables and $\mathbf{X}_d$ the vector of pre-treatment dummies: the model for Y will be specified as a partially linear regression model

$$\mu_{D=d}(\mathbf{x}) = \mu_{D=d}(\mathbf{x}_c, \mathbf{x}_d) = E(Y|\mathbf{x}_c, \mathbf{x}_d, d) = g(\mathbf{x}_c) + \mathbf{x}_d' \beta,$$

where $g(\mathbf{x}_c)$ is the nonparametric part.

Table 3 shows the values for Q (along with their respective p -values) under the null of unconfoundedness for two values of $l = 2, 3$; where l is the maximum power term $\mathbf{x}_c$ in the power series expansion of the nonparametric part $g(\mathbf{x}_c)$. We find evidence of zero treatment effects on the lagged outcome for the first three periods, $1993 \rightarrow 95$, $1995 \rightarrow 98$ and $1998 \rightarrow 00$, for both values of l . For the other two periods, $2000 \rightarrow 02$ and $2002 \rightarrow 04$, the results are sensitive to the choice of l : the null hypothesis of unconfoundedness is supported only when $l = 3$.

Table 3 Results from the tests to assess unconfoundedness.

	1993 $\rightarrow$ 95	1995 $\rightarrow$ 98	1998 $\rightarrow$ 00	2000 $\rightarrow$ 02	2002 $\rightarrow$ 04
$l = 2$					
k	47	50	58	54	50
Q	48.54	49.15	53.28	79.11	68.55
p -value	0.410	0.507	0.651	0.014	0.041
$l = 3$					
k	52	55	63	59	55
Q	52.39	54.9	56.9	53.5	50.2
p -value	0.458	0.478	0.692	0.675	0.653

Finally, a simple and affordable method to assess the overlap condition is to plot the distribution of the propensity score, $\Pr(D = 1|\mathbf{x})$, in both treatment groups, which can reveal lack of overlap in the multivariate pre-treatment variables distributions. A main concern can be here that misspecification of the propensity score may lead to failure in detecting a lack of overlap; we then undersmooth the estimation of the propensity score by adopting a semiparametric logit including higher order terms in a series expansion (Imbens, 2004). The resulting histograms of estimated propensity scores for treated and untreated (here not reported for brevity) show a satisfactory overlap.

4 Estimation methods

The first method relies on the estimation of the regression function for the untreated $\mu_{D=0}(\mathbf{x})$, from which the counterfactual outcome for the generic treated unit i can be estimated as $\hat{\mu}_{D=0}(\mathbf{x}_i)$. The estimated PATT is obtained from averaging $[y_i - \hat{\mu}_{D=0}(\mathbf{x}_i)]$ on the treated. A simple parametric regression estimator, however, may be very sensitive to differences in the distributions of the pre-treatment variables between the treated and the untreated. Such differences indeed make causal effects estimation relies heavily on extrapolation and consequently on the functional specification. More flexible and reliable is the method recently proposed by Imbens et al. (2005) and based on power series estimation of $\mu_{D=0}(\mathbf{x})$; the authors show the resulting estimator achieves the semiparametric efficiency bound for PATT illustrated in Hahn (1998).

Another option to attain the efficiency bound (Imbens, 2004) is by weighting on the Series Logit Estimates of the propensity scores $\hat{p}_{SLE}(\mathbf{x}_i)$:

$$\left[\sum_i d_i y_i / \sum_i d_i \right] - \left[\sum_i (1 - d_i) y_i \frac{\hat{p}_{SLE}(\mathbf{x}_i)}{1 - \hat{p}_{SLE}(\mathbf{x}_i)} / \sum_i (1 - d_i) \frac{\hat{p}_{SLE}(\mathbf{x}_i)}{1 - \hat{p}_{SLE}(\mathbf{x}_i)} \right].$$

Since these two methods are asymptotically linear, their asymptotic variances can be calculated by bootstrapping (Imbens, 2004).

The third class of estimators are those where the generic treated unit i is matched to the closest m untreated according to a specific metric in the space of the pre-treatment variables. However, if the number of matches is fixed and matching is done with replacement, Abadie and Imbens (2006) show the bias is $O(N^{-\frac{1}{h}})$, where h is the number of continuous pre-treatment variables, while the variance of the estimator is $O(N^{-1})$. In our study $h = 6$, so that asymptotically the bias will not disappear and the standard confidence interval will not be necessarily valid. To improve the asymptotic proprieties of matching estimators, Abadie and Imbens (2006) propose a mixed method where for each treated unit, matching is followed by a regression adjustment:

$$\hat{y}_{i0} = \frac{1}{\#\delta_M(i)} \sum_{j \in \delta_M(i)} (y_j + \hat{\mu}_0(\mathbf{x}_i) - \hat{\mu}_0(\mathbf{x}_j)),$$

where $\#\delta_M(i)$ is the set of m untreated units closest to i according to the specific metric. If this adjustment is made by series estimation of the regression function, $\hat{\mu}_{D=0}(\mathbf{x})$, the authors show the resulting PATT estimator is consistent and asymptotically normal, with its bias dominated by the variance. This mixed method has been here applied, with: the number of matched units been fixed at 10; the metric been defined as $\|\mathbf{x}\| = (\mathbf{x}'\mathbf{V}\mathbf{x})^{1/2}$, where $\mathbf{V}$ is the diagonal matrix of the inverses

of the pre-treatment variables' variances; the standard errors calculated using the variance estimator proposed by Abadie and Imbens (2006)¹.

5 Results and conclusions

Table 4 reports the calculated effects of debit cards on household monthly consumption as determined by the proposed estimators. Like in Table 3, we propose the results for two values of the power term l in the series expansion of the nonparametric parts of $\mu_{D=d}(\mathbf{x})$ and of the Series Logit estimates of the propensity scores: $l = 2, 3$.

For any of the first three periods, $93 \rightarrow 95$, $95 \rightarrow 98$ and $98 \rightarrow 00$, we obtain positive and quite similar values of the estimated PATT. The period $95 \rightarrow 98$ emerges for the particular high estimated PATT. This result can be justified by observing the period is one year longer (the planned survey for 1997 was delayed one year and shifted to 1998), therefore the use of debit cards could have benefited from the longer span to more strongly affect consumers' behaviors. Overall, the results for these three periods support current psychological theories about the effects of debit cards on spending. The peculiarity of debit cards to no allow the consumer to incorporate an additional long-term source of funds, such as a line of credit, eliminates the potential confounded effect of an inter-temporal reallocation of wealth. Therefore the estimated effects on spending can be ascribed to other reasons like those pertaining to some recently proposed theories in the field on psychology of consumer behavior. In particular two of them emerges as particularly persuasive: the rehearsal of the price paid (Soman, 2001) and the accessibility of financial resources (Morewedge et al., 2007). The former extends the psychological theories of mental accounting and coupling by supposing that payment instruments can influence the memory for and the impact of past expenses on spending behavior. The latter suggests that consumers perceive a unit of consumption to be smaller when large financial resources such as the money in ones bank saving account (to which debit cards provided a direct access) were made temporarily accessible compared to the case when only small financial resources were made temporarily accessible.

On the contrary, the results for the other two periods, $00 \rightarrow 02$ and $02 \rightarrow 04$, are not stable. Table 4 reports very different p -values of the estimated PATT for the two proposed values of l . Moreover, results from Table 3 on the plausibility of unconfoundedness are very sensitive to the value of l . The assumption of unconfoundedness requires that all the variables affecting both the outcome and the treatment are observed, or that the unobserved variables are collinear to the observed ones. Then, the unstable results for the two periods, $00 \rightarrow 02$ and $02 \rightarrow 04$, could be ascribed to a higher variability in the distribution of the unobserved variables. A justification can be in the higher variability of income expectations we have been experiencing in the current decade compared to the nineties.

¹ The authors show bootstrapping is not appropriate for the mixed method due to discreteness in the distributions introduced by the computational procedure.

A direction for future extension of the paper may be towards a deeper investigation on the sensitivity of results to different values of the power term. Even if the choice of the power term in the semiparametric evaluation of treatment effects is an open field of research, the investigation could initiate by analyzing the results from different Cross-Validation criteria, like those usually applied to guide the choice of order term in semiparametric regression models.

Table 4 Estimated PATT*, in Euro.

	Regression	Weighting on the Series Logit est. prop. scores	Mixed method (matching and regression)
<i>l</i> = 2			
1993 → 95	62.20 (0.044)	63.19 (0.049)	58.92 (0.051)
1995 → 98	116.38 (0.052)	122.71 (0.046)	137.17 (0.010)
1998 → 00	80.87 (0.019)	80.68 (0.023)	77.97 (0.025)
2000 → 02	89.94 (0.199)	82.79 (0.238)	80.01 (0.166)
2002 → 04	91.04 (0.091)	85.88 (0.095)	83.21 (0.172)
<i>l</i> = 3			
1993 → 95	60.38 (0.025)	60.38 (0.049)	55.01 (0.047)
1995 → 98	126.27 (0.047)	110.67 (0.039)	142.62 (0.000)
1998 → 00	73.16 (0.023)	81.73 (0.049)	70.98 (0.046)
2000 → 02	75.94 (0.018)	71.74 (0.063)	62.72 (0.090)
2002 → 04	87.58 (0.015)	77.02 (0.047)	78.68 (0.074)

* *p*-values in parenthesis.

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