



Munich Personal RePEc Archive

## **The Impact of the Microchip on the Card Frauds**

Ardizzi, Guerino

Banca d'Italia

20 July 2012

Online at <https://mpra.ub.uni-muenchen.de/41435/>

MPRA Paper No. 41435, posted 19 Sep 2012 11:43 UTC

# THE IMPACT OF THE MICROCHIP ON THE CARD FRAUDS

by Guerino Ardizzi\*

## Abstract

The issue of frauds through payment cards has received a great deal of attention from authorities. A large share of card frauds can be ascribed to the phenomenon of counterfeiting of debit cards, widely used payment instrument in “face-to-face” transactions. With the advent of the Single Euro Payment Area, the European banking community has shared and almost reached the ambitious goal of replacing all the cards (and accepting terminals) with chip compatible ones, which are supposed to be harder to clone than the magnetic stripe card. Using a bi-annual balanced panel data of over one hundred Italian banks, in this paper we estimate for the first time the real impact on card frauds caused by the chip card migration. The results confirm the positive effects of the new technology: the ratio between fraud and ATM-POS transactions (card fraud loss rate) is reduced significantly if the chip card is present.

**JEL Classification:** C22, C23, D12, E21

**Keywords:** fraud, debit card, payment instrument, security, chip, technology, prevention, EMV, SEPA

## Contents

|                                 |    |
|---------------------------------|----|
| 1. Introduction.....            | 2  |
| 2. Literature.....              | 4  |
| 3. Payment card frauds .....    | 5  |
| 4. Dataset .....                | 8  |
| 5. Model of analysis.....       | 9  |
| 6. Estimation of the model..... | 11 |
| 6.1. Results .....              | 12 |
| 6.2. Robustness checks .....    | 13 |
| 7. Conclusion .....             | 15 |
| Tables and figures. ....        | 17 |
| References .....                | 23 |

---

\* Banca d'Italia, Market and Payment System Oversight Department. The views expressed in the article are those of the author and do not involve the responsibility of the Bank.

## **1. Introduction**

The confidence in the means of payment is a public good whose production requires investments in technology. From this point of view, the card fraud represents a serious threat to the functioning of one of the most used payment networks also in the transactions carried out abroad. According to the estimates the fraudulent transactions carried out in Europe on POS and ATM in a year amount to over 1 billion euros; similar figures are recorded in the United States. Much of this amount is used to finance other illegal activities, including international terrorism (Shen et. al. 2007).

The prevention and reduction of risks in the usage of electronic payment instruments are crucial for the integration and integrity of retail payment systems in Europe. The adoption of common security standards, in fact, together with the exchange of information and the financial education, represents one of the fundamental pillars for the prevention, the reduction of the social costs due to frauds and the development of secure electronic payments.

The success achieved in the adoption of new preventive technologies represents a strong incentive for the market operators to continue in the path of modernization. The savings arising from the technological innovation, even when they are not properly perceived by the players of change (typical so called "free riding" problems) are then felt by everyone, banks and consumers.

The adoption of the "microchip" in the countries involved in the creation of the SEPA - Single Euro Payments Area - is an example of how the strategy of cooperation - under the aegis of the authorities, primarily the central banks - could produce positive results. At the end of 2011, in fact, about 90 per cent of the cards and the accepting terminals (POS, ATM) in Europe (70 per cent in Italy), have migrated to the so-called "EMV" microchip technology, developed by Visa Europay-Mastercard already since 1999 and endorsed by the European banking community in view of SEPA. This technology - with respect to the old "magnetic stripe" - makes it more expensive for the fraudster to duplicate the card and, above all, capture sensitive data contained in the microchip.

Ten years ago, with the advent of the euro, the rates of migration to chip in Europe were a tenth of the present ones; in Italy virtually nil. With reference to the physical terminals<sup>1</sup>, the fears of fraud have recently been directed to countries outside the EU. Among these, the United States, which still allow a widespread use of the magnetic stripe technology, stand out. This technology is still combined with the micro-chip of the cards issued in Europe in order to preserve the fundamental principle of full reachability of the payment instruments.

Recently, the "chip only" based solutions have been under scrutiny within the Eurosystem, with cards issued without magnetic stripe and with limited possibilities of use outside of the chip-EMV networks (European Central Bank, 2010). These are more incisive solutions to the problem of the illegal card usages which in the face-to-face transactions concern above all the counterfeit cards used in zones or areas where the "magnetic stripe" is still prevalent (ECB 2011, VII Sepa Report). The 'liability shift rules', issued by the governance authorities of the card payment schemes, which allow to transfer the fraud losses towards the unsafe operators, have given decisive impetus to the European migration. Nevertheless, such rules are not applicable outside in the other contexts. In the countries outside the EU, in fact, the self-regulation bodies – even though in the context of common cards and marks (for example Visa and Mastercard) - pursue different strategies in the protection of the interests of the local bank communities.

The Italian banks, after the initial uncertainties, have accelerated the replacement of cards and terminals with "chip compliant" devices, especially since 2006, when the rate of card fraud (fraud losses out of total operations) has reached the maximum point (Bank of Italy, Report on the 2009).

The debate is still in progress between the opposing positions of the European banking community, which supports the generalized shift towards the chip, and the United States where only recently a serious debate has been launched on the issue so partly overcoming the resistance of those who are not convinced, given the migration costs, that the chip represents an effective solution to the problem of the asymmetries in the security provisions

---

<sup>1</sup> This work does not consider the fraudulent activities carried out using cards in the "virtual" world (so-called "card not present" frauds).

both at national level and at cross-border level. In fact there are no rigorous empirical studies, aimed at demonstrating the effective benefits induced by the micro-chip technology in the reduction of the card fraud.

The objective of this study is therefore to verify empirically the impact of the microchip cards on the frauds, taking into account the Italian case study. In Section 2 a brief review of the available literature on the subject is exposed. In Sections 3 and 4 we show in more detail the problem of the card fraud and the database used in this work. The Section 5 illustrates the model of analysis and the econometric approach, aimed to verify the relationship between microchips and debit card frauds. The results are discussed in Section 6, while the conclusions and some policy indications are reported in Section 7.

## **2. Literature**

The theoretical and empirical literature has addressed the issue of the opportunistic and illegal behaviours in several economic and financial sectors (insurance, accounting, finance). Nevertheless the analyses of the links between fraudulent utilizations and payment technologies are scarce. The analytical approaches to the issue of the fraud in the payments system are essentially twofold. The fraudulent phenomena are evaluated either in terms of their impact on the demand for electronic means of payments, or of their effects on the risk management models.

In the first approach the fraud is an explanatory variable in a micro-founded payment instruments demand equation. The purpose is essentially to evaluate the consumer behaviour during the choice of secure payment instruments. Kosse (2010) demonstrates for example that the fraud significantly reduces the use of payment cards both in the POS, and in the ATM<sup>2</sup>. These works do not deal, however, with the issue of the determinants of the fraud.

In the second approach, instead, the fraud assumes the role of dependent variable. The fraudulent event is in fact the random variable which the analyst has to interpret on the basis

---

<sup>2</sup> The negative impact of the fraud on the use of payment cards is also confirmed in a recent work that for the first time utilizes macro-territorial data for Italy (see Ardizzi and Iachini, 2012).

of a probabilistic model. The probabilistic fraud function can be estimated through various quantitative methods (logistic or neural models, Bayesian approaches, actuarial models). In this context, the analyst's goal is essentially to calculate the probability that a given tool can be used fraudulently (Shen et al., 2007, Paulina and Paba, 2010). At the same time, once identified the probabilistic model of the fraud, the risk manager's goal is to make prevention, intercept anomalies and reduce the risk of losses for the bank (Caimi et al., 2006).

Among the econometric techniques most used for the detection of the risk of fraud there is the binomial logistic regression (Shen et al., 2007) based on high-frequency time series of micro-data, where the dependent variable takes the value 1 when an irregular event occurs (es. theft, loss, cloning) and 0 in all other cases<sup>3</sup>. Among the explanatory variables of the equation, a series of covariates that identify the type of instrument (e.g. debit card), the type of technology (e.g. chip card), the brand (e.g. Visa) and "individual specific" characteristics of the card holder (e.g. expenditure ceilings, age, income, residence, and so on) can therefore be inserted. This type of analysis requires a considerable amount of confidential information, available only in the protected archives of the anti-fraud offices of the companies who either issue or manage payment cards.

However, the regression techniques used by the risk management analysts provide useful insights for applications addressed to the policy maker, taking into consideration bank-level data sets and non-categorical fraud risk indicators.

### **3. Payment card frauds**

The analysts distinguish between "gross fraud" and "net fraud" (Caimi et al., 2006). The "gross fraud" is the total amount of transactions disclaimed by the cardholder (also automatically through card blocking or alert systems) in front of an impairment of the card and of the sensitive information. This one is typically measured, then, from the "issuing" side of the card<sup>4</sup> (so-called "issuing fraud").

---

<sup>3</sup> The most complex models consider multinomial categorical variables, with reference to specific events: theft, loss, interception of the card, etc.

<sup>4</sup> When the irregular transaction is detected, on the contrary, on the side of the operator who accepts the card, we talk about "acquiring fraud". In this paper we do not consider this possibility, since the information

The impairment of the card for fraudulent purposes can be traced back to several causes: theft, loss, cloning, non-receipt, etc. The gross fraud represents the potential loss for the circuit, and does not take its actual economic impact (loss) on the intermediary and on its capital into account. The "net fraud " is instead the accounting loss recorded on the balance sheet by the acquirer or the issuer due to the occurrence of the gross fraud. The incidence of the gross fraud on the net one depends on the mechanisms of transfer of responsibility (liability shift) between the various parties involved (issuer, acquirer, owner, operator).

In this paper we consider the amount of the "gross" fraud, divided by the gross amount of the total card transactions (the so-called card fraud loss rate) as a synthetic indicator of riskiness of the instrument. We moreover consider only the fraudulent uses as a result of card counterfeiting or cloning, namely the interception of sensitive data and the duplication of the physical supports for illicit purposes unknown to the legitimate cardholder. This is the fraud case which has involved the transition to the microcircuit technology so as to oppose its effects. Compared to the magnetic stripe, the "chip" enables in fact both the direct and the protected on-line dialogue (encryption) between the card and the acceptance device (ATM or POS) in the preliminary phase of authentication of the cardholder, and the encrypted storage of the sensitive data once the transaction has been completed.

Cloning is still the main source of card fraud. It is perpetrated by means of "skimming" devices which allow fraudsters to decode the data contained in the magnetic stripe card (e.g. holder's name, card number, etc.) in order to use them in devices duplicated through ATM and POS. Excluding the frauds carried out without the presence of the physical card (the so-called "card not present" fraud, for example via Internet, telephone or mail), the cloning represent in fact about 70 per cent of the whole set of card frauds (Central Office for Means of Payment Fraud-UCAMP Report 2010<sup>5</sup>). The debit cards record lower levels of fraud (about 1/5) than those on average experienced on the credit cards, above all at the domestic level, thanks also to the combination of the PIN code on ATM and POS (Bank of Italy, 2009). However, the issue of the frauds committed through counterfeit cards

---

available on the "acquiring side" are difficult to distinguish by type of card (debit, credit or prepaid card) or channel (Internet, physical).

<sup>5</sup> The Report contains also an illustration of the different types of fraud and of the underlying mechanisms.

used in systems that do not adopt the chip technology has arisen during the last few years even for the debit cards<sup>6</sup> (e.g., ATM, Maestro, Visa Electron circuits).

This study focuses therefore on the debit cards, which are mainly used in the physical world. The credit card, besides not requiring the compulsory matching of the PIN code when the operation takes place, is also used in the “distance” transactions, such as the Internet or telephone ones. This instrument presents, therefore, an area of risk which is more extensive in term of security provisions and necessarily different compared to the debit card (Sahin and Duman, 2011). Furthermore, the higher concentration in the credit card market strongly reduces the statistical numerosity of the information available about the debit card, issued by nearly all Italian banks and more popular among households (Bank of Italy, Survey on Household Income and Wealth, 2010).

Since 2009, after the constitution (Act 166/2005) of the antifraud system at the Ministry of Economy and Finance-Central Office for Means of Payment Fraud (UCAMP), people can rely on the publication of a report on card frauds in Italy, which provides a great deal of systemic level information relative to the size and the dynamics of the frauds with respect to the different types of instrument or channel (debit card, credit, internet, etc.) and underlying causes (cloning, theft, loss, etc.). According to the report, in the biennium 2009-2010 (the latest data available), the credit card fraud losses, divided by the total amount of POS and ATM transactions, have decreased by 11 per cent (UCAMP Report 2010). Those related to the cloning have decreased by 27 per cent. In the biennium in question, the percentage of microchip cards increases by 10 percent points, going from 60 to 70 percent (ECB 2011). Since 2007, in parallel with an acceleration of the migration to EMV chip required by SEPA, the (credit and debit) card fraud rate indicates a downward trend, decreasing from 0.07 per cent (as a share of the level of POS transactions) to 0.05 per cent in 2010 (Bank of Italy, Annual Report 2010).

Similar trends can be inferred even at international level, despite the data relative to the phenomenon of fraud available are subdued. Combining the information released by the East (the European ATM Security Team) on fraud via ATMs and those published by the

---

<sup>6</sup> In the case of the debit cards the proportion of the frauds attributable to the clonings is higher (80%) than that relative to the credit cards (60%).

ECB on the percentages of the compliant chip cards in Europe, an inverse relationship can be inferred: as the proportion of microchip cards increase the rate of fraud decreases<sup>7</sup> (Figure 1).

#### 4. Dataset

In this work we use data drawn from the reports of the intermediaries on the payment services collected by the Bank of Italy from each reporting body (bank or financial company) on an aggregate and anonymous basis, available since 2009. The available information allow us to construct a longitudinal database for the years 2009 and 2010, which includes 108 intermediaries representative of over the 60 per cent of the debit cards market. We have excluded the banks that have missing values<sup>8</sup> as well as those who do not report all the relevant data (e.g frauds, transactions, number of cards issued) in both reference periods. This in order to obtain a strictly balanced panel dataset.

The panel data for the two years under consideration show a decreasing change in the rate of fraud on debit cards - calculated as the ratio between the amount of the gross frauds and the total amount of the transactions processed by the card issuer - in line with the whole banking system (Table 1) as reported by the Central Office for Means of Payment Fraud-UCAMP<sup>9</sup> (2011).

The Figure 2 shows instead the aggregate banking statistics available at the Bank of Italy (but not for individual banks) on the fraud rates relative to the transactions and the share of the migrations to the chip debit cards occurred in Italy between 2003 and 2010; it also shows a sharp increase in the fraudulent transactions in 2006, caused mainly by the

---

<sup>7</sup> On this point see also CapGemini, World Payment 2011.

<sup>8</sup> If we consider also the banks which do not report frauds data (missing), conventionally setting them equal to zero, we run the risk of underestimation of the phenomenon and of selecting intermediaries with a fraud risk equal to zero not in a random way.

<sup>9</sup> In particular, the UCAMP archive collects personal daily data from the single intermediaries (banks, companies issuing credit cards on the basis of information directly coming from the anti-fraud offices of the companies. These information are shared between the reporting institutions for preventive reasons, according to the provisions of the law. The statistics used in the present work, instead, concern semi-annual or annual information, aggregated and signalled by the banks to the Bank of Italy with the aim to provide the information concerning the pattern of the phenomenon.

intensification of the cloning, followed by a gradual reduction occurred in parallel with an acceleration of the migration to the chip.

## 5. Model of analysis

In the literature review we have shown that in the approach adopted by the sector analysts in the study of the card fraud for forecasting purposes it is related to a set of explanatory variables within regression models for categorical data (eg, logit, probit models). The relationship is expressed according to a function like this:

$$y_i = f(x_1 \dots x_n)$$

Where  $y$  is the target variable for the instrument of payment  $i$ , generally expressed as a binomial function. The variables that instead affect the probability of occurrence of the fraud (Caimi et al., 2006) and which represent the arguments (regressors) of the function, consider the number and type of (e.g., credit or debit) cards used, the presence of chip on the card, the type of control over the shipping and activation process of the same, the maximum utilization limit granted to the customer, the licensing and warning systems (e.g. sms alert), and so on.

On the ground of the available data (aggregated to the bank level), you may consider only some of the variables listed above. In particular, the variables available (counted from the side of the issuing bank) are:

- Total number of cards in circulation issued by the reporting institution
- Number of cards with the chip
- Amount of POS transactions and ATM withdrawals through cards issued by the reporting institution
- Amount of transactions carried out through cards issued by the reporting institution at its own acceptance points (so called “on-us transactions”)
- Amount of disclaimed transactions in the case of operations carried out with cards issued by the reporting institution (issuing fraud).

The equation of the model of analysis of the fraud is therefore as follows:

$$\text{FRAUD} = \alpha_0 + \beta_1 \text{CHIP} + \sum_j \beta_j Z_j + u_{it} \quad [1]$$

con  $j=2 \dots n$

The dependent variable (FRAUD) is equal to the ratio of operations disclaimed by the holder (gross fraud) to total transactions (POS and ATM), that is the card fraud loss rate. As the rate of fraud increases, the potential loss and hence the riskness borne by the cards issued by the reporting bank increases. This variable does not follow a dichotomous distribution such as in the logistic models, nevertheless it is distributed continuously in the range [0-1] with a concentrated mass of (positive) values close to zero. Figure 3 shows the empirical distribution of the variable FRAUD calculated from data provided by the Italian banks and pooled for the biennium 2009-2010. Figure 4 shows instead the density function of the same, logarithmically transformed, data, from which a log-normal empirical distribution can be inferred.

The first variable in the right-hand side of equation [1] is equal to the percentage of microchip cards (CHIP). Its coefficient, expected to be negative, aims to capture the effect of the technology believed to be safer on the rate of fraud. This variable is considered exogenous to the model, as the choice to adopt chip cards has been driven by the European Payments Council (EPC, the self-regulatory body of European banks) and the banks are committed to migrate all SEPA cards and terminals to chip EMV standards by the end of 2010<sup>10</sup>.

The summation term among the covariates indicates the set of environmental variables ( $Z_j$ ), and of the relative coefficients, which can influence the indicator of fraud. One of the control variables used in the context of the risk management systems (Caimi et al., 2006) identifies the so-called “on-us” operativeness component (ONUS), equal to the percentage of transactions that are completed at POS and ATM terminals owned by the same bank that issued the card. Therefore, we consider  $Z_1 = \text{ONUS}$ . Even the expected effect of this variable on the fraud rate is negative: the higher the share of transactions within its own

---

<sup>10</sup> The EPC's SEPA Cards Framework (SCF) recognises the EMV standard for SEPA-wide acceptance of payments with cards at very high levels of security (European Payments Council, 2009).

network is, the lower the information asymmetries are and the higher the ability of the intermediary to prevent the frauds promptly would be (Giacomelli, 2008).

The data (Fig. 5) actually show a lower incidence of the "on-us" rate of fraud compared to the overall fraud rate.

A second control variable ( $Z2 = QCARTE$ ) is included to take into account the relative size of the intermediary, expressed as a percentage of the cards issued compared to the overall number of cards in circulation or to the intermediated transactions. The effect on the indicator of fraud can be ambiguous: on the one hand the larger diffusion of the instrument may increase the probability for the bank of having a counterfeited card (positive coefficient); on the other hand, the bank can better diversify the risk (negative coefficient) by extending its market share.

Finally, in the longitudinal models the term  $u_{it}$  in the equation [1] can be decomposed into an individual specific effect, a temporal effect and a stochastic disturbance. In particular, the individual specific effect incorporates the unobservable elements<sup>11</sup> of "firm specific" heterogeneity, reducing the omitted variable bias in the estimates. The temporal specific effect can be captured by providing, instead, a year dummy.

## 6. Estimation of the model

The parameters of the equation [1] were estimated using the balanced panel of 108 intermediaries observed in 2009 and 2010. The dependent variable (FRAUD), i.e, the rate of fraud. is expressed in terms of logarithms (lnFRAUD), in order to reduce the dispersion and the asymmetry. The explanatory variables, instead, are expressed in percentage terms and are:

- a. the percentage of CHIP cards
- b. the percentage of on-us transaction (onus)
- d. the market share (%) of the cards issued (QCARTE)

---

<sup>11</sup> These elements may for example be linked to the internal control and risk management system, to the type of customer, etc. See Giacomelli, 2008

Table 2 describes both the descriptive statistics and the correlation matrix for the above-mentioned variables, from which the presence of collinearities strong enough to endanger the consistency of the estimates does not seem to arise.

First of all, we estimate the “basic” log-linear model<sup>12</sup> which considers only CHIP among the covariates, then we include the control variables and test the stability of the results with respect to disturbances affecting the initial model. In all cases a time dummy variable has been included.

We have used a panel model with "random effects". The Hausman test strongly rejects in fact the hypothesis of 'fixed effects'<sup>13</sup>, while the Breusch-Pagan test refuses that of "poolability" (cross-sectional model instead of panel model).

### **6.1. Results**

The results of the estimates are shown in Table 3. Since the dependent variable is logarithmic, the regression coefficients  $\beta$  must be interpreted as meaning that a one unit change in the regressor X (expressed as a percentage) is associated with a percentage change in Y exactly equal to  $\beta$ .

As expected, the coefficient of the degree of migration to chip cards (CHIP) has a negative and significant sign. The magnitude of the effect, moreover, is significant: an increase of ten (percentage) points of the number of chip-compliant cards is associated with a reduction in the rate of fraud in the order of 6/7 per cent<sup>14</sup>.

---

<sup>12</sup> The log-linear models are usually applied in the presence of dichotomous explanatory variables. In this case, the independent variables are all continuous but fall within the range [0-1], being expressed in percentage terms.

<sup>13</sup> The lower accuracy of the "fixed effect" estimator, which considers time-invariant individual characteristics, moreover, is also detected when the "within" (intra-group) variability is dominated by the "between" (inter-group) variability, see Cameron and Trivedi 2005. This is exactly the case under consideration (see Table 2). In addition, we have conducted the J-test for overidentifying restrictions (fixed vs. random effects), which is also robust to heteroschedasticity: also in this case the fixed effect model is rejected.

<sup>14</sup> Based on the estimated coefficient, ceteris paribus, EMV technology would have resulted in fewer debit card fraud losses for about 35 million euro from 2006 (the year of the pick of frauds) to 2010, freeing potential resources to continue to innovate in prevention.

The incidence of the ONUS transactions turns out to be not significant<sup>15</sup>, instead; however, the market share (QCARTE) shows a significant negative impact on the rate of fraud. Nevertheless, this variable may also be a proxy of the probability that the intermediary intercepts at its own points of acceptance its own issued cards and of the ability of the intermediary to diversify the risk and reduce the potential loss. This effect partly offsets the low significance of the estimated coefficient for the variable “ONUS”

This is true even if we replicate the regression exercise within the ambit of homogeneous circuits, that is distinguishing between domestic fraud rate (card issued and used in Italy) and cross-border fraud rate (usage abroad). The results are reported in Table 4<sup>16</sup>.

## **6.2. Robustness checks**

We conducted robustness checks of the outcomes illustrated in the previous paragraph, using alternative estimation methods that control for the presence of: 1) heteroskedasticity and autocorrelation of the residual terms; 2) non-normal distribution of the variables, 3) simultaneous causality. Each of the above-named points highlights a violation of the assumptions underlying the regression models and can make the results inconsistent.

The method used to control the first distortion factor (1-PCSE) considers an OLS estimator of the parameters which nevertheless allows to take into account the possible autocorrelation within the panel and the contemporaneous heteroscedasticity of the residual terms<sup>17</sup>.

---

<sup>15</sup> The variables representative of the acceptance infrastructure of the cards (ATM, POS, chip-compliant devices) located in the same seat of the issuing intermediary have not turned out to be significant on the contrary. This is consistent with the approach followed which just carries out a census of the phenomenon from the perspective of the issuer of the card and not from the perspective of the intermediary who manages the POS or the ATM terminal (acquirer). For the sake of brevity we do not present these estimations.

<sup>16</sup> The estimations are in this case carried out on the unbalanced panel, since the breakdown between Italy and foreign countries entails a loss of statistical information and of sample numerosity in the considered period.

<sup>17</sup> Beck and Katz (1995) suggest this approach, of the so-called OLS panel-corrected standard error PCSE model, with OLS estimators, preferring it to the "generalised least square" (GLS) generalized model, which instead requires  $T > n$ . On this point see also Hoechle (2007) and Podestà (2002). We apply also a random effects panel model that admits the presence of "clustered standard errors" that is of errors correlated "between" (per unity of the panel) and robust against heteroskedasticity. This method does not control also for,

In addition, we also consider a so called “quantile” regression estimator (2-quantile method) where the relationship between  $y$  and  $x$  is not expressed by the variation of the conditional mean of  $y$  given  $x$  (classical linear model), but by the variation of one of its quantiles (e.g. median). This approach is useful in the presence of non-normal distributions of the dependent variable, or of high statistical dispersion, which may make the mean value less significant. Furthermore, it may be interesting to calculate the impact of the chip on the median fraud rates of the distribution computed at the level of the riskier intermediaries (i.e. 75th percentile). For this method we have also resorted to the non-parametric bootstrap to calculate the standard errors and test the significance of the estimated coefficients without necessarily making assumptions about the probabilistic model and the reference distribution of the sample. The results reported in Table 5 consider the regression on the median value and on the 75th percentile of the dependent variable<sup>18</sup>.

The third factor of distortion (simultaneous causality) is the possibility that the relationship between the rate of fraud and chip cards is bi-directional. For example, the trend of the rate of fraud in the period can also accelerate the choice of the bank to migrate to the chip card. Hence, also an OLS regression (3-OLSlag method) of the rate of fraud (always expressed in logarithmic form) on the one year lagged values of the CHIP variable has been taken into account. Such solution should reduce this problem<sup>19</sup>: the rate of fraud reported in the year  $t$  can be influenced by the migration rate in the period  $t-1$ , whereas the opposite is not logically true.

---

however, the contemporaneous presence of serial and cross sectional correlation. The estimated coefficients for the variable CHIP are however always significant and comparable in intensity with each other; also the results of these estimations are available in Appendix (Tables 5 and 6).

<sup>18</sup> The estimation for quantiles is conducted on the "pooled" panel, in order to gain degrees of freedom. The quantile regression applied to panel models in fact requires a high sample size to unbundle the unobservable individual specific effects and produce consistent estimates (see Koenker, 2004).

<sup>19</sup> The general approach to follow for dealing with the problem of the simultaneous causality or endogeneity of the regressors is the one of the regression with instrumental variables. However, in this case there are no instrumental variables that simultaneously satisfy the requirements of relevance and of exogeneity available (see Cameron and Trivedi, 2005)

The Table 5 shows a comparison between the different estimators, applied to the basic model<sup>20</sup>, which includes the impact of the chip and the time dummy among the explanatory variables::

$$\ln FRAUD = \alpha_0 + \beta_1 CHIP + \beta_2 d_{anno} \quad [2]$$

The basic model has proved to be sufficiently robust to perturbations of the same (see par. 6.1), has the advantage of parsimony in the parameters to be estimated.

The robustness checks seem to be more than satisfactory. In all the methods adopted the significance and the intensity of the CHIP effect on the rate of fraud ( $\ln FRAUD$ ) is confirmed. The magnitude of such effect is higher in the regression estimated with the 75th percentile method, compared to that estimated on the 50th (median), suggesting that the benefits derived from the micro chip are most evident in the presence of high rates of fraud<sup>21</sup>.

## 7. Conclusion

The issue of the frauds through payment cards is the focus of growing attention, especially after the initiation of the Single Euro Payments Area - SEPA. The phenomena of cloning and counterfeiting significantly affect the segment of the debit cards (eg ATM), where some asymmetries in the field of the security systems both between banks and between domestic and international systems are exploited. Among these asymmetries the non uniform migration of the card schemes to the micro-chip technology, especially in countries outside the Eurosystem, stands out. In this work an empirical exercise aimed at assessing the benefits arising from the microchip cards in terms of reduction of the rate of

---

<sup>20</sup> The results relative to the whole model obtained through the different estimation methods are reported in Table 6.

<sup>21</sup> Final tests concerns the robustness of the results obtained even apart from the log normal model, considering the absolute values of the rate of fraud as the dependent variable (FRAUD). We use a Tobit regression model: unlike the standard panel regression with individual random effects, this model can accommodate the particular distribution of the dependent variable, which is censored (non negative) and has a concentrated mass of positive values very close to zero. The results confirm the significance of the coefficient (negative) the degree of migration to the chip on the rate of fraud. Moreover, all results are robust aggregating the information of the intermediaries who belong to the same banking group, in order to control for possible "group" specific effects. For the sake of brevity, we do not present the results of these tests, available on request from the author.

fraud in Italy has been for the first time carried out. The results confirm the positive effects of the new prevention technology: faced with an increase of 10 percentage points (in absolute terms) in the cards migrated to the chip, the ratio of frauds to transactions is reduced by 6/7 per cent, on average. That would implies in Italy since 2006, the year in which the frauds reached their maximum peak, the chip technology has resulted in a fall in the losses arising from frauds of several tens of millions of euros on the transactions carried out through ATM and POS with payment cards, freeing potential resources that can be devoted to the prevention innovations.

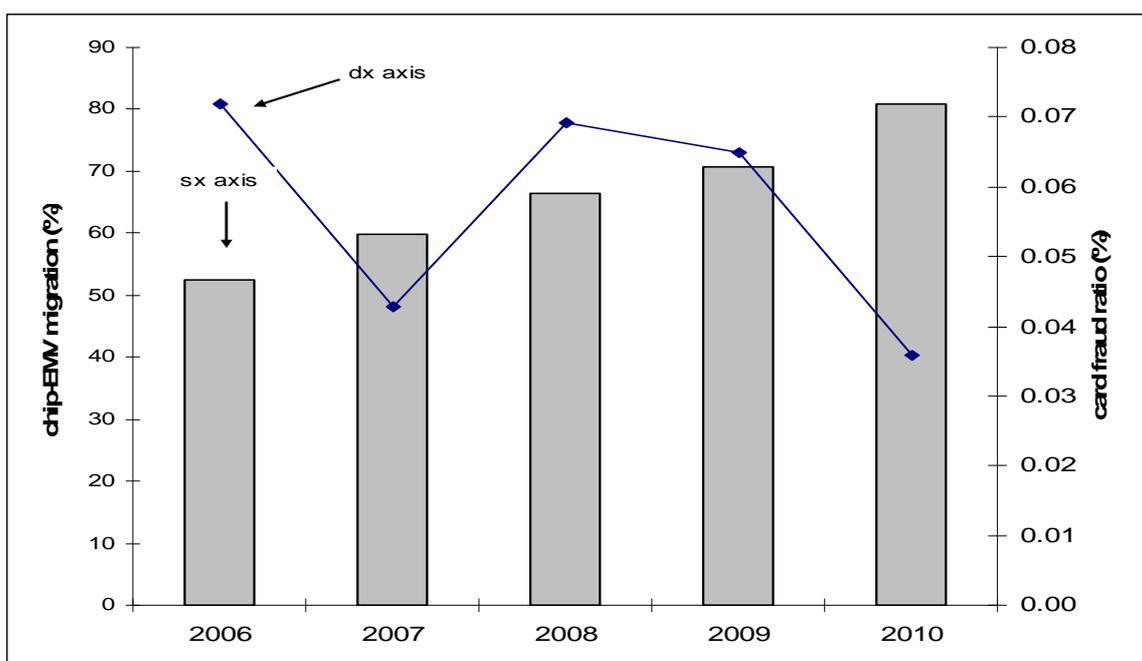
It is therefore necessary to strengthen the international commitments aimed at promoting the widest possible adherence to the new technology standards, planning also the so-called "chip only" option, opportunely accompanied by (incentivating) rules on the transfer of responsibility so as to support the more reliable operators<sup>22</sup> (so called "liability shift rules").

---

<sup>22</sup> See the considerations of the Eurosystem in the seventh Report (2010) on the state of the art of the Single Euro Payment Area (SEPA), p. 7.

## Tables and Figures

Figure 1: Pattern of the fraud rate (issuing side) and % of EMV cards in Europe (issuing side) and % of EMV cards in Europe



Source: EAST, ECB

Table 1: Card fraud (clonation):

| Description                       | Panel   | Total Italy (1) |
|-----------------------------------|---------|-----------------|
| Fraud rate (clonation): year 2010 | 0.016%  | 0.015%          |
| % change 2009-2010                | -22.79% | -17.14%         |

(1) – Source: Ministry of Treasure, Antifraud Office

Table 2: Panel dataset - descriptive statistics

| Variable |         | Mean   | Std. Dev. | Min     | Max    | Observations |
|----------|---------|--------|-----------|---------|--------|--------------|
| lnFRAUD  | overall | -8.956 | 1.405     | -16.367 | -5.492 | N = 216      |
|          | between |        | 1.192     | -13.357 | -6.227 | n = 108      |
|          | within  |        | 0.748     | -11.966 | -5.946 | T = 2        |
| CHIP     | overall | 0.684  | 0.320     | 0.000   | 1.000  | N = 216      |
|          | between |        | 0.284     | 0.000   | 1.000  | n = 108      |
|          | within  |        | 0.150     | 0.184   | 1.184  | T = 2        |
| ONUS     | overall | 0.113  | 0.138     | 0.000   | 0.943  | N = 216      |
|          | between |        | 0.120     | 0.001   | 0.836  | n = 108      |
|          | within  |        | 0.068     | -0.163  | 0.389  | T = 2        |
| QCARTE   | overall | 0.005  | 0.022     | 0.000   | 0.175  | N = 216      |
|          | between |        | 0.021     | 0.000   | 0.174  | n = 108      |
|          | within  |        | 0.003     | -0.026  | 0.035  | T = 2        |
| FRAUD    | overall | 0.000  | 0.000     | 0.000   | 0.004  | N = 216      |
|          | between |        | 0.000     | 0.000   | 0.003  | n = 108      |
|          | within  |        | 0.000     | -0.001  | 0.002  | T = 2        |

Correlation matrix

| Variable | CHIP   | ONUS  | QCARTE |
|----------|--------|-------|--------|
| CHIP     | 1      |       |        |
| ONUS     | -0.103 | 1     |        |
| QCARTE   | 0.066  | 0.150 | 1      |

Dependent variable: lnFRAUD

Source: Bank of Italy, banking statistics

Figure 2: Rate of fraud and chip-EMV indicator in Italy

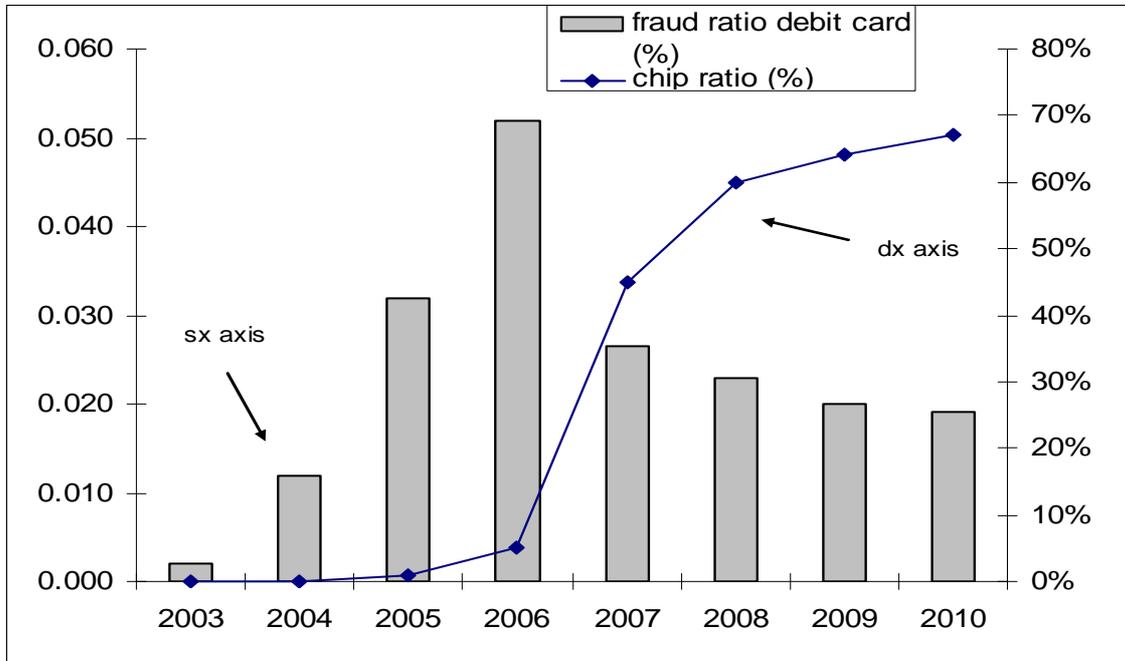


Figure 3: Empirical distribution (number of banks) rate of fraud on debit cards

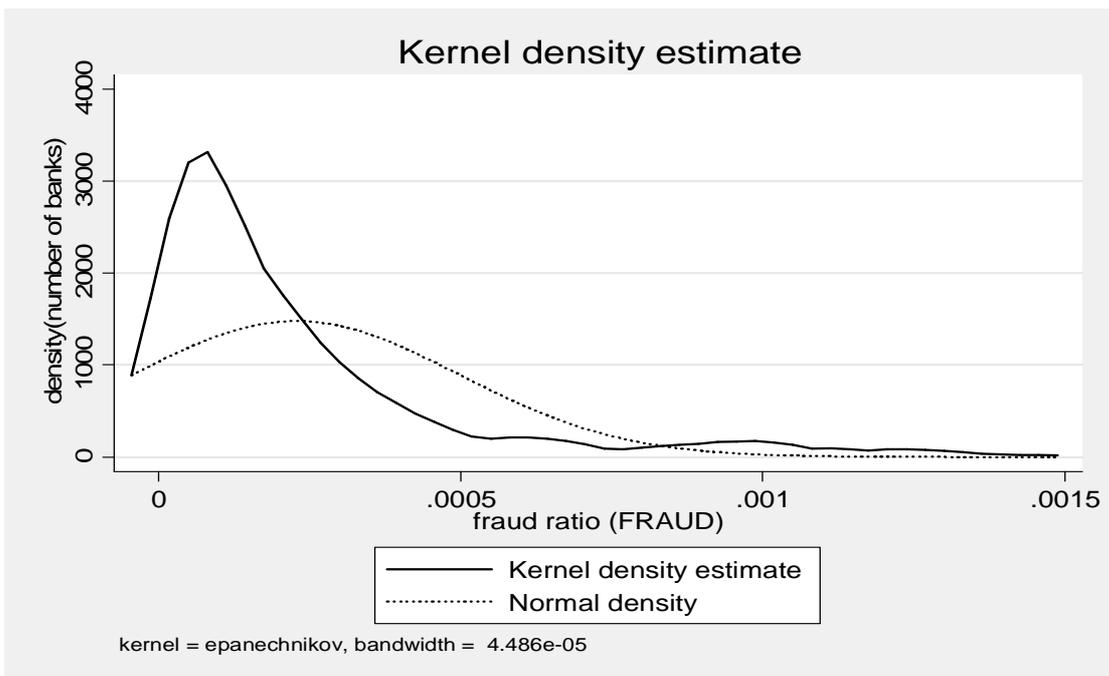


Figure 4: Empirical distribution (number of banks) of the log - fraud rate

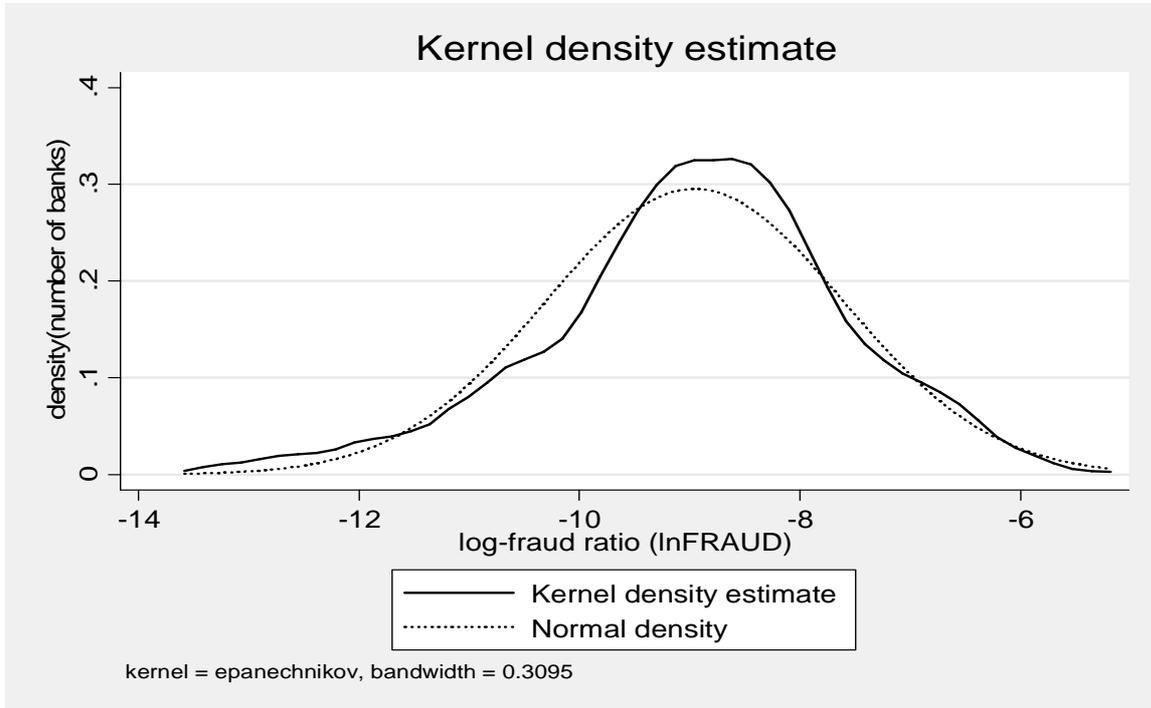


Figure 5: “Onus” card fraud rate vs total card fraud rate

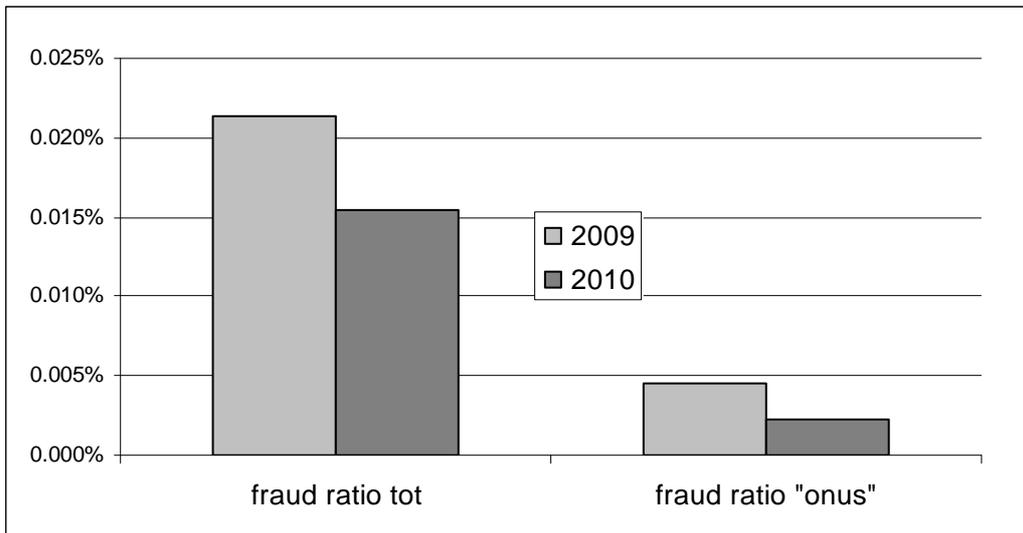


Table 3: Estimation of the log-linear equation model 1 and 2; panel random effect (balanced panel)

| Regressor    | Random Effect<br>Base  | Random Effect<br>Full |
|--------------|------------------------|-----------------------|
| CHIP         | -0.665***<br>(-0.265)  | -0.641***<br>(-0.266) |
| d_anno       | 0.292**<br>(0.149)     | 0.309*<br>(0.157)     |
| ONUS         |                        | 0.271<br>(0.780)      |
| QCARTE       |                        | -15.319*<br>(8.281)   |
| Constant     | -594.93***<br>(300.53) | -629.8<br>(317.22)    |
| Observations | 216                    | 216                   |
| Groups       | 108                    | 108                   |

Table 4: Estimation of the log-linear equation model with cross-border or domestic frauds as dependent variable (unbalanced panel)

| Regressor    | Cross-<br>border fraud<br>rate (log) | Domestic fraud<br>rate (log) |
|--------------|--------------------------------------|------------------------------|
| CHIP         | -0.692*<br>(0.412)                   | -0.702***<br>(0.2514)        |
| d_anno       | -0.018<br>(0.208)                    | 0.151<br>(0.120)             |
| ONUS         | 1.042<br>(0.670)                     | 0.130<br>(-0.565)            |
| QCARTE       | -13.573*<br>(7.204)                  | -10.828<br>(9.218)           |
| Constant     | 26.540<br>(419.581)                  | -310<br>(-241.421)           |
| Observations | 201                                  | 336                          |
| Groups       | 108                                  | 108                          |

Table 5: Robustness checks against violations of the linear regression assumptions  
(base model)

| Regressori   | 1-PCSE                | 2-QUANTILE           |                     | 3-OLS_lag           |
|--------------|-----------------------|----------------------|---------------------|---------------------|
|              |                       | 50° percentile       | 75° percentile      |                     |
| CHIP         | -0.622***<br>(-0.078) | -0.418**<br>(-0.211) | -0.831*<br>(-0.487) |                     |
| CHIPt-1      |                       |                      |                     | -0.920**<br>(0.418) |
| d_anno       | 0.296***<br>(0.067)   | -0.233<br>(0.206)    | 0.292<br>(0.051)    |                     |
| Constant     | -604.0***<br>(133.85) | -476.19<br>(369.10)  | -254.78<br>(327.61) | -8.512**<br>(0.266) |
| Observations | 216                   | 364                  | 364                 | 165                 |
| Groups       | 108                   | 108                  | 108                 | .                   |

Table 6: Robustness checks against violations of the linear regression assumptions  
(all variables)

| Regressore   | PCSE                 | re cluster             | q50                  | q90                  | OLS_lag               |
|--------------|----------------------|------------------------|----------------------|----------------------|-----------------------|
| CHIP         | -0.647***<br>(0.197) | -0.641**<br>(0.268)    | -0.433*<br>(0.2271)  | -0.726**<br>(0.3037) |                       |
| chip t-1     |                      |                        |                      |                      | -0.885**<br>(-0.4113) |
| anno         | 0.303***<br>(0.038)  | 0.309*<br>(0.163)      |                      |                      |                       |
| QCARTE       | -14.75**<br>(3.917)  | -15.32*<br>(8.197)     | -15.47*<br>(8.275)   | -0.121<br>(9.979)    | -5.683<br>(5.806)     |
| ONUS         | 0.125<br>(0.299)     | 0.271<br>(0.848)       | 0.0610<br>(0.8405)   | -0.0391<br>(0.6391)  | -1.138*<br>(0.6174)   |
| costante     | -616.6<br>(75.928)   | -629.8***<br>(326.831) | -8.540***<br>(0.175) | -6.822***<br>(0.218) | -8.385***<br>(0.278)  |
| Observations | 206                  | 216                    | 331                  | 331                  | 165                   |
| Groups       | 108                  | 108                    | .                    | .                    | .                     |

Standard errors in parentheses: p<0.10, \*\* p<0.05, \*\*\* p<0.01

Legend: PCSE= panel corrected standard errors regression (balanced data); re cluster = random effect panel with robust cluster standard errors (balanced data); q50 e q90=quantile (pooled) regression (50° e 90° percentile); OLS\_lag=ordinary least square regression with lagged control variable (chip t-1).

## References

- Ardizzi G. e E. Iachini (2012). “Why are Payment Habits so Heterogeneous Across and Within Countries? Evidence From Europe and Italy, Unpublished, Banca d’Italia.
- Banca Centrale Europea (2010). “Seventh single euro payments area (SEPA) progress report”, October.
- Banca d’Italia (2012), “Survey on Households Income and Wealth”, January.
- Banca d’Italia (2010), “Annual Report 2009”, May.
- Banca d’Italia (2011), “Annual Report 2010”, May.
- Beck, N. e J. Katz (1995), “What to do (and not to do) with time-series cross-section data”, *American Political Science Review* 89: 634–647.
- Cameron C. e K. P. Trivedi, (2005), “Microeconometrics: Methods and Applications”, Cambridge University Press, New York.
- Caimi C., Ghisellini R. e A. Giacomelli (2006). “Forecasting model of fraud”, unpublished Si Holding.
- Capgemini (2011). “World Payment, Report 2011”.
- Central Office for Means of Payment Fraud, (2010). “Rapporto statistico sulle frodi con carte di pagamento”, 1/2011, Ministry of Treasury.  
[http://www.dt.tesoro.it/it/antifrode\\_mezzi\\_pagamento/rapporti\\_statistici/carte\\_pagamento.html](http://www.dt.tesoro.it/it/antifrode_mezzi_pagamento/rapporti_statistici/carte_pagamento.html)
- European ATM Security Team-EAST (2011). “ATM Fraud Analysis Report”, version 18/7/11.  
<http://www.european-atm-security.eu>

- European Payments Council (2009), “SEPA Cards Framework, version 2.1”, Brussels.  
[http://www.europeanpaymentscouncil.eu/knowledge\\_bank\\_detail.cfm?documents\\_id=330](http://www.europeanpaymentscouncil.eu/knowledge_bank_detail.cfm?documents_id=330).
- Giacomelli A. (2008), “Non si gioca con le carte”, in *Internal Audit*, May-August.
- Hoechle D. (2007) “Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence”, *The Stata Journal*.
- Kosse A. (2010). “The Safety of cash and debit cards: a study on the perception and behaviour of Dutch consumers“, DNB Working paper 245, De Nederlandsche Bank.
- Kosse A. (2011). “Do Newspaper Articles of Card Fraud Affect Debit Card Usage?”, ECB Working paper, no. 1389.
- Paulina M., e A. Paba (2010), “A discret choice approach to model credit card fraud”, MPRA Paper No. 20019.
- Podestà F., (2002). “Recent Developments in Quantitative Comparative Methodology: the Case of Pooled Time Series Cross-Section Analysis”, *DSS Papers Soc* 3-2002.
- Koenker R., (2004). “Quantile Regression for Longitudinal Data”, *Journal of Multivariate Analysis*, vol 91, Issue 1, October, 74-79.
- Sahin Y. e E. Duman (2011). “Detecting Credit Card Fraud by Decision Trees and Support Vector Machines“, *IMECS*, March 16-18.
- Shen A., Tong R. e Y. Deng (2007). “Application of Classification Models on Credit Card Fraud Detection, *IEEE*.