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Innovation and Cost Efficiency in the Banking Industry: The Role of Electronic Payments

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This paper presents new evidence on the assessment of banks' cost efficiency gains stemming from ICT adoption. With respect to the existing literature we introduce two novelties. First, banking operating costs are explained in terms of a commonly used measure of IT innovation (the relative diffusion of ATMs) and a new variable defined as automated payment transactions. Second, the results obtained via standard parametric estimation methods are compared with those obtained via nonparametric estimation techniques. Using an original dataset of Italian banks observed in the period 2006–2010, we do not find clear cost efficiency enhancing effects due to ATMs diffusion. On the other hand, the diffusion of electronic payments shows a significant effect in terms of cost inefficiency reduction.
(*J.E.L.*: *C14, C33, G2, L8, L11*).

1. Introduction

The role of ICT adoption and technological change in banking activity has received remarkable attention in the literature (see, for instance, Berger, 2003; Casolaro and Gobbi, 2004; Humphrey *et al.*, 2006; Frame and White, 2012 for a survey). In this context, the utilization of ICT for retail payment services is an excellent angle from which to assess the spread of new technologies among economic agents (Hasan *et al.*, 2012). Indeed, innovations in retail payments imply the automation of both the inter-bank procedures and the internal banking processes and products, with

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positive spillovers for bank efficiency and customers' safety (e.g., Fung *et al.*, 2014). Moreover, in the European context, the bank provision of electronic payments in substitution of cash and other paper based procedures—which has been reinforced by the project of a Single European Payment Area (SEPA)—is considered both as an opportunity to reinforce the retail banking activities, and as an important driver for cross selling strategies with loans and deposits.[1] Despite the relative importance of technological innovation in the field of payment markets, the empirical literature on retail payments and banking efficiency is rather scant (Humphrey *et al.*, 2006). The issue is becoming more and more relevant after the last financial crisis, the fall in the net interest income, the new competition challenges worldwide and the more stringent prudential supervision requirements (the so called 'Basel III' requirements) which may further reduce degrees of freedom in searching profits.

The aim of this paper is to provide new evidence on the positive link between fully automated payment processing procedures and overall operating costs at the bank level. To the best of our knowledge, this is the first study using observed data on electronic payments, where the available evidence relies on automated teller machines (ATMs) data. We find evidence of banks' cost efficiency gains stemming from the use of IT payment channels applying nonparametric estimation techniques to an original dataset of 2708 observations on Italian banks or banks operating in Italy observed over the period 2006–2010. We depart from previous studies on IT innovation and bank efficiency in different aspects as briefly discussed below.

Haynes and Thompson (2000) find a positive productivity effect of the adoption of ATMs in a panel of 93 UK building societies observed over the period 1981–1993. In order to isolate the productivity effects of introducing the ATM, the authors estimate an augmented production function in which the innovation is treated as a shift factor whose impact is captured using ATM binary variables.

In particular, a dummy variable accounting for the adoption of ATMs in a given year enters a production function where output (measured as the level of commercial assets) is produced by one labour input (defined by the number of full-time equivalent employees), and two capital inputs measured using fixed and liquid assets. Three alternative functional forms of the augmented production function (Cobb–Douglas, translog and CES) are estimated by OLS and by IV after instrumenting the labour variable. Results suggest that ATM adopters enjoyed large productivity gains over non-adopters by the end

[1] Regarding the screening of European banks, Ayadi *et al.* (2012) find that 'diversified retail' banks (using diversified sources of funding and providing predominantly customer loans) are safer than others allowing for lower default probability and long-term liquidity risks.

of the 1980s. This result appears to be robust to alternative specifications of production function. Ou *et al.* (2009) focus on ATMs intensity rather than ATMs adoption by using a quantitative measure of ATMs diffusion (number of ATMs per employee) at the bank level. OLS estimates on a cross section of 264 Taiwanese banks show that higher diffusion of ATMs is associated with lower values of two alternative cost inefficiency measures computed by dividing operating expenses by total revenue (operating cost ratio) and by total assets (asset management cost ratio). However, the authors point to several limitations of their study: the lack of results on actual savings in operating costs due to IT investment; the incomplete nature of the sample; the lack of control for bank-specific characteristics.

Departing from the two above mentioned studies we use two quantitative measures of the degree of IT innovation at the bank level. The first measure is given by the relative incidence of the number of ATMs owned by the bank to the number of its ATMs and physical branches over the counter (OTC). The second measure is the share of electronic transactions to total payment operations managed by the bank. We believe that the combined use of these two variables provides a more appropriate way to measure the 'actual' degree of IT innovation at the bank level, while the relative endowment of ATMs alone can be regarded only as its 'potential' counterpart. To our knowledge, this is the first study that moves in this direction. Carbó-Valverde *et al.* (2006) have studied the beneficial effect of a larger expansion of ATMs relative to branch offices combined with the shift to electronic payments for a sample of 93 commercial and savings Spanish banks over the 1992–2000 period. These authors use bank-specific information on operating cost, number of ATMs, branch offices, and labour and capital input prices. On the other hand, information on the means of payment (the number of check, giro and card payments) is available only at the aggregate (national) level.

All the aforementioned papers share the common feature of using parametric estimation methods. They need to impose a functional form to the production (cost) function augmented in order to accommodate for the presence of the IT input. We do not need to do so as our estimates are nonparametric. It is worth noticing that the use of nonparametric estimation techniques is a relevant novelty in this field.

The remainder of the paper unfolds as follows. In section 2, we present our model and formulate testable hypotheses for our two measures of IT innovation. Section 3 presents our data, reporting the definitions and descriptive statistics for all relevant variables included in the estimated models. Estimates and results are presented and discussed in section 4. Section 5 concludes with a discussion of the policy implications of this study.

2. Modelling the Impact of Innovation on Bank Cost Efficiency

Studies on the impact of IT innovation on bank efficiency usually consider the diffusion of ATMs as a proxy of innovation (Haynes and Thompson, 2000; Ou *et al.*, 2005, 2009). However, such an approach may lead to overestimating cost savings. Indeed, the availability of ATMs alone does not necessarily imply a lower usage of traditional means of payments which depends on the attitude of clients towards electronic payments.

In line with previous studies (see, for instance, Carbó-Valverde *et al.*, 2006) our measure of cost inefficiency is:

$$\text{costratio} = \frac{\text{OC}}{\text{TA}}$$

where OC indicates operating costs, TA total assets, and a lower value of costratio corresponds to higher cost efficiency.[2] Our aim is to assess the impact of the IT payment channel innovation on cost efficiency. Accordingly, we define a single equation model where the logarithm of costratio (logcostratio) is the dependent variable to be linked to a set of explanatory variables. We assume that in order to assess the impact of IT innovation on cost efficiency one should consider the relative technological endowment of the bank as well as the actual usage of it. The first aspect is captured by the variable atmshare defined as the relative incidence of the number of ATMs owned by the bank to the number of its physical branches OTC and ATMs. This is our first indicator of payment channel innovation in bank services, reflecting the endowment of infrastructure available to the bank as a result of its past IT investment. A higher ratio means a greater ATM intensity and a higher probability to process electronic cash operations, which are more efficient than OTC ones (Bank of Italy, 2012). This variable is expected to affect costratio negatively, according to the following hypothesis:

[2] An alternative proxy for bank cost inefficiency is the ratio between operating cost and total income. However, we use costratio for three main reasons. First, this measure allows us to obtain results comparable with previous studies as the ratio between operating cost and total assets is the most commonly used indicator in the empirical literature on cost savings linked to technological innovation (Bolt and Humphrey, 2007). Second, costratio is more informative for our purposes than efficiency indicators based on bank revenues. As a matter of fact, the ratio between operating costs and total income could lead to misleading and incorrect conclusions as it is both directly linked to profitability and strongly affected by other factors such as interest rate changes, competition issues, and the business cycle. Third, income variables are correlated with e-payment revenues, thus implying additional distortions in measuring cost efficiency gains/losses. For instance, other things being equal, the ratio between operating costs and total income may decrease simply because of an increase of e-payment fees, not because of cost efficiency gains.

Hypothesis 1: *The higher the diffusion of the ATM network, the lower costratio (the higher cost efficiency) due to less costly automated channel for the management and handling of banknotes, ceteris paribus.*

Our second IT innovation explanatory variable is elettroratio, defined by the share of electronic transactions to the total number of payment operations managed by the bank. The use of this variable, which represents a novelty with respect to previous studies, is expected to improve on available evidence as it is more directly linked to the actual usage of electronic transaction technologies. Studies on banking efficiency usually consider the diffusion of ATMs as a proxy of innovation (Haynes and Thompson, 2000; Ou *et al.*, 2005, 2009). A number of reasons motivate the inclusion of elettroratio in our model. Bank of Italy (2012) and Schmiedel *et al.* (2012) claim that indicators referring to the various channels of access to transactions highlight the possible efficiency gains of a shift to the electronic channel: the average unit cost of traditional payment instruments (i.e., paper based credit transfers, checks collecting items) is almost three times that of straight-to-processing (STP) orders, due to administrative costs arising from the large number of manual operations involved in the payment process. Central bankers' speeches (see for instance Panetta, 2013) underline that innovative payment channels can be used for the distribution of highly standardized, low-value-added transaction-based services, such as liquidity management and consumer finance products, especially to the more technologically or financially advanced customers, that can generate more value-added and reduce costs. Accordingly, elettroratio should be consistent with the following hypothesis:

Hypothesis 2: *The higher the share of actual full automated payment transactions managed by the bank, the lower costratio and the higher cost efficiency due to less costly automated channel and positive spillover within the bank, ceteris paribus.*

In section 4, we will specify and estimate several models for a sample of Italian banks observed over the period 2006–2010 in order to test the above hypotheses. First of all, we will estimate the baseline model, including variables measuring the two IT determinants of cost inefficiency described above. In line with previous empirical studies on this issue, we will also estimate an extended model, including other two additional covariates in order to control for bank size and labour cost.

Bank size will be proxied by total assets owned by the bank.[3] The empirical literature on the link between bank size and cost efficiency

[3]Total assets include cash balances, financial assets for trading, loans with banks and customers, financial investments, property, plant and equipment and intangible assets.

includes mixed results. One argument in favour of higher efficiency of larger banks is that with size scale economies also increase. On the other hand, smaller local banks usually operate in small and protected markets, benefiting from a more efficient selection of reliable customers and lower levels of competition. This is also consistent with the view that small banks (especially cooperative and local/rural banks) are less innovative in their business models and more affected by local market specificity (Kwan and Eisenbeis, 1996). Overall, especially in the Italian case, more than size alone, the ownership structure, the geographical location, the type of relationship with customers (relation- vs. transaction-models) matter. For instance, Giordano and Lopes (2009) estimate cost and profit efficiency of Italian banks in 1993–2003 and find that small and medium-sized mutual banks located in the Centre and North of Italy show the best performance in costs and profitability, while large incorporated banks in the South perform worst. Given all the above considerations, in our model the effect exerted by bank size on cost efficiency is expected to be undetermined a priori:

Hypothesis 3: *The higher the total assets owned by the bank, the higher/lower cost efficiency, ceteris paribus.*

We finally maintain the assumption that most efficient banks are those making higher efforts to control salary expenses, in line with the empirical evidence provided by several studies, for example, Spong *et al.* (1995), Berger and Humphrey (1997) and Bikker (2004). This also suits the Italian case as, according to the Bank of Italy (2014), the relative higher ratio of operating expenses to total assets of the Italian banking industry (1.8 per cent against 1.3 per cent of the Euro area average) is largely due to greater relative importance of labour-intensive and branch-based retail business. Thus, we put forward our last testable hypothesis:

Hypothesis 4: *The higher salary expenses of the bank, the higher costratio (the lower cost efficiency), ceteris paribus.*

3. Data

Our analysis uses an original data set provided by the Bank of Italy. We consider an unbalanced panel of 2708 observations in the period between 2006 and 2010, where we have information on 651 banks and other financial institutions operating in Italy. The considered time span allows to identify long-run cost differences among banks rather than short-run anomalies. The use of a more recent dataset could potentially be more

TABLE 1: Variable Definitions

Variable	Definitions
Logcostratio	Natural logarithm of the ratio of operating costs to total assets
Logwage	Natural logarithm of wages
Elettroratio	Ratio of electronic transactions to the total number of transactions
	Ratio of the number of ATMs to the number of physical branches and ATMs
LogTA	Natural log of total assets (TA); TA includes cash balances, financial assets for trading, loans with banks and customers, financial investments, property, plant and equipment and intangible assets

reflective of the recent significant growth in electronic payments in the Italian banking system. Nevertheless, results obtained using this time span are still relevant and reliable. As compared to more recent data, this 5 years period is more homogeneous and not affected by relevant recent changes in accounting methodologies and, as a consequence, more informative from a policy maker perspective. In particular, since 2011 the new International Accounting Standards for bank balance sheets and new prudential requirements have been introduced (Capital Requirements Directives 2 in 2011 and Capital Requirements Directives 3 in 2013 in line with Basel III). Furthermore, after 2010 bank balance sheets were strongly influenced by the sovereign debt crisis.

Table 1 provides the definition of all variables included in the estimated models.

Table 2 shows the correlation among variables, while Table 3 shows descriptive statistics for the sample as a whole. Tables 4 and 5 report the same statistics disaggregated by year and bank size, respectively. Figure 1 depicts the time path of costratio controlling for bank size. Overall, this descriptive evidence helps to highlight some relevant facts occurred over the considered period in the Italian banking system.

Interestingly, we observe in Table 2 that the two technological variables, atmshare and elettroratio, show a particularly weak level of linear association, thus providing additional support to our motivation. Indeed, banks with a low value of atmshare might still be ‘innovative’ by using

TABLE 2: Correlation Matrix

	Costratio	Wage	Elettroratio	Atmshare	TA
costratio	1	0.062	−0.221	−0.195	−0.098
wage	0.062	1	0.147	0.055	0.096
elettroratio	−0.221	0.147	1	−0.005	0.054
atmshare	−0.195	0.055	−0.005	1	0.112
TA	−0.098	0.096	0.054	0.112	1

TABLE 3: Descriptive Statistics (Full Sample)

Variable	Minimum	1st quartile	Mmedian	Mean	3rd quartile	Maximum
costratio	0.003	0.022	0.026	0.027	0.030	0.186
wage	0.008	61.010	66.080	66.440	71.370	126.500
elettroratio	0.093	0.592	0.658	0.644	0.704	0.996
atmshare	0.100	0.455	0.500	0.502	0.550	0.998
TA	0.005	0.155	0.385	3.484	1.242	430.000

Note: The variable wage is expressed in thousands of Euros, while the variable TA is expressed in billions of Euros.

electronic payments more intensely. On the other hand, a high value of atmshare might be associated with a less intense usage of electronic payments. This implies that it is preferable to use both variables as proxies of IT innovation in empirical models.

TABLE 4: Descriptive Statistics by Year

Variable	Minimum	1st quartile	Median	Mean	3rd quartile	Maximum
Year 2006						
costratio	0.003	0.023	0.026	0.027	0.030	0.186
wage	0.528	56.560	61.440	61.210	65.720	111.100
elettroratio	0.126	0.560	0.636	0.620	0.685	0.996
atmshare	0.100	0.422	0.480	0.467	0.525	0.995
TA	0.005	0.131	0.321	2.905	0.970	216.000
Year 2007						
costratio	0.010	0.022	0.026	0.028	0.030	0.152
wage	24.870	59.480	64.180	64.860	68.720	113.900
elettroratio	0.093	0.575	0.645	0.630	0.693	0.994
atmshare	0.182	0.429	0.484	0.472	0.526	0.997
TA	0.006	0.131	0.342	2.901	0.992	395.000
Year 2008						
costratio	0.003	0.022	0.027	0.028	0.031	0.130
wage	11.520	63.150	67.530	68.260	72.370	120.700
elettroratio	0.117	0.606	0.664	0.651	0.706	0.973
atmshare	0.100	0.480	0.525	0.534	0.579	0.998
TA	0.016	0.174	0.433	3.711	1.509	430.000
Year 2009						
costratio	0.009	0.022	0.026	0.026	0.030	0.141
wage	0.008	56.560	67.940	68.610	72.770	110.900
elettroratio	0.239	63.440	0.672	0.659	0.715	0.991
atmshare	0.222	0.483	0.519	0.524	0.565	0.998
TA	0.024	0.186	0.445	3.666	1.419	422.000
Year 2010						
costratio	0.006	0.021	0.025	0.026	0.029	0.125
wage	0.949	65.630	69.390	70.150	74.200	120.500
elettroratio	0.216	0.618	0.679	0.665	0.723	0.991
atmshare	0.111	0.486	0.522	0.524	0.565	0.998
TA	0.019	0.189	0.453	4.396	1.402	416.000

Note: The variable wage is expressed in thousands of Euros, while the variable TA is expressed in billions of Euros.

TABLE 5: Descriptive Statistics by Bank Size

Variable	Minimum	1st quartile	Median	Mean	3rd quartile	Maximum
Minor banks						
costratio	0.003	0.023	0.026	0.028	0.031	0.186
wage	0.528	60.650	65.720	66.140	70.980	120.700
elettroratio	0.117	0.582	0.656	0.638	0.698	0.889
atmshare	0.100	0.440	0.500	0.489	0.540	0.875
TA	0.005	0.117	0.256	0.373	0.509	3.389
Small banks						
costratio	0.008	0.020	0.024	0.025	0.029	0.044
wage	27.500	61.770	66.510	66.880	71.070	120.400
elettroratio	0.093	0.617	0.673	0.659	0.716	0.996
atmshare	0.192	0.508	0.532	0.546	0.566	0.998
TA	0.576	1.788	2.801	3.664	0.992	23.860
Average banks						
costratio	0.015	0.020	0.023	0.023	0.027	0.036
wage	0.008	65.670	70.610	69.250	75.200	95.140
elettroratio	0.471	0.646	0.696	69.250	0.732	0.807
atmshare	0.399	0.519	0.536	0.537	0.562	0.625
TA	8.132	11.170	17.260	17.780	22.240	38.660
Big banks						
costratio	0.007	0.018	0.021	0.021	0.026	0.037
wage	12.380	60.400	66.820	66.850	76.070	90.950
elettroratio	0.532	0.688	0.743	0.716	0.754	0.789
atmshare	0.511	0.536	0.548	0.558	0.568	0.693
TA	10.640	20.390	27.290	27.730	33.460	44.620
Major banks						
costratio	0.007	0.016	0.020	0.021	0.028	0.035
wage	11.520	68.020	74.570	72.570	82.560	108.100
elettroratio	0.502	0.611	0.640	0.660	0.718	0.890
atmshare	0.550	0.570	0.618	0.630	0.696	0.750
TA	22.220	77.250	94.930	167.300	208.000	430.000

Note: The variable wage is expressed in thousands of Euros, while the variable TA is expressed in billions of Euros.

By looking at the relatively flat time trend of costratio in Table 4, one should conclude that the Italian banking system has not achieved any relevant efficiency improvement in the considered period. However, the full picture provided by our descriptive figures highlights at least two facts that deserve some attention and that will be covered by our econometric analysis. First, the variables that according to our hypotheses affect the cost structure of banks have experienced relevant changes. From Table 4 we observe the sharp increase in salaries that, other things being equal, would imply lower cost efficiency, whilst our two measures of IT innovation show an increasing time trend, thus leading to expected cost efficiency gains. Second, the descriptive evidence should carefully take into account differences across banks, most of them being proxied by TA. From

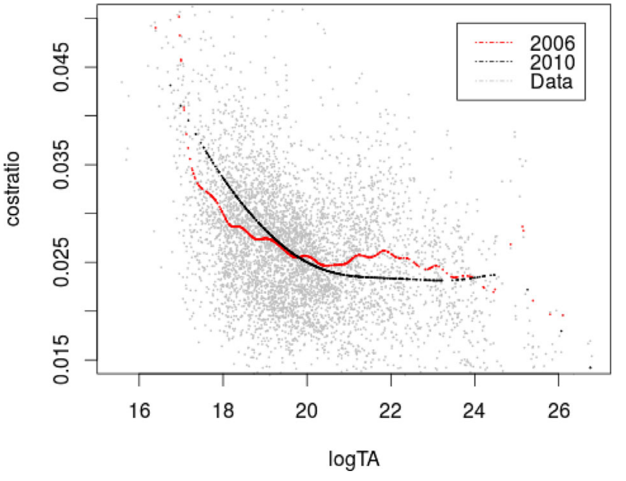

Figure 1: Cost Efficiency and Bank Size in 2006 and 2010

Table 5 we observe that cost efficiency seems to increase with size: the mean of costratio decreases from 0.028 (minor banks) to 0.021 (major banks). Such a difference might mirror structural budget differences among banks of different size. In particular, larger banks tend to have a different asset and liability composition with respect to smaller banks that will be reflected into their operating costs. In general, smaller banks tend to be funded proportionally more by retail deposits than larger banks, which in turn also fund themselves proportionally more in the interbank and bond markets. This means that larger banks fund their assets (loans, bonds, etc.) with a larger share of liabilities that imply lower operating costs (retail branches, salaries, etc.).[4] This argument captures differences between larger and smaller banks from a static point of view showing different cost efficiency levels. However, our data seems to show also differences in cost efficiency gains, thus pointing at differences from a dynamics point of view among banks of different scale. As a matter of fact, the red and black curves shown in Figure 1 illustrate how costratio varies as a function of logTA in 2006 and 2010, respectively.[5] Banks have experienced significant cost gains only after a certain value of logTA, while below such a threshold we observe an efficiency loss. This descriptive evidence calls for controlling for bank size in our estimated model.

[4]We thank an anonymous Referee for pointing to this issue.
[5]The two curves are obtained by means of nonparametric local linear regression with cross-validated bandwidth.

It is finally worth noticing that our variables (with respect to size) show very skewed distributions and their density seems to be higher for minor banks (see Figure 2). The high density for minor and small banks is due to the high fragmentation of the Italian banking system which—despite mergers and acquisitions—is characterized by a large number of credit institutions and a large share of cooperative and local/rural banks (about 700).

4. Estimation and Results

We concentrate our attention on the cost-efficiency indicator logcostratio against two technological variables, the first (atmshare) takes into consideration the number of ATMs and the second (elettroratio) accounts for the number of electronic payments. As argued in section 2, we expect these two variables to have a negative impact on inefficiency. On the other hand, we expect wages (logwage) to have a positive impact on the inefficiency variable.[6]

Our baseline model is a standard linear model estimated by means of classical estimation methods for panel data models (see Table 6). The advantage of this approach is that the properties of the corresponding estimators are well studied in the literature and allow to tackle the problem of endogeneity. On the other hand, a major drawback is assuming that the functional form that links dependent and independent variables is correct. In fact, when the parametric assumption is wrong estimates are generally no longer consistent.

The nonparametric approach allows us to relax the functional form assumption and, therefore, to avoid any problem due to misspecification. Moreover, it allows us to identify potential nonlinear relationships among variables and marginal effects.

4.1. Parametric Models

We consider the following model

$$\begin{aligned} \text{logcostratio}_{\text{it}} &= \beta_0 + \beta_1 \text{logwage}_{\text{it}} + \beta_2 \text{elettroratio}_{\text{it}} + \beta_3 \text{atmshare}_{\text{it}} \\ &\quad + \beta_4 \text{logTA}_{\text{it}} + \alpha_{\text{i}} + u_{\text{it}} \end{aligned} \tag{1}$$

where the index *i* refers to banks and *t* refers to time.[7] The model is first estimated by pooled OLS. Then, in order to consider the panel features of

[6] The numerical results are obtained by means of the R packages plm and np. See Croissant and Millo (2008) and Hayfield and Racine (2008).

[7] Since the panel is unbalanced the time index should be t_i. For ease of notation we decide to drop the index i and use t instead of t_i.

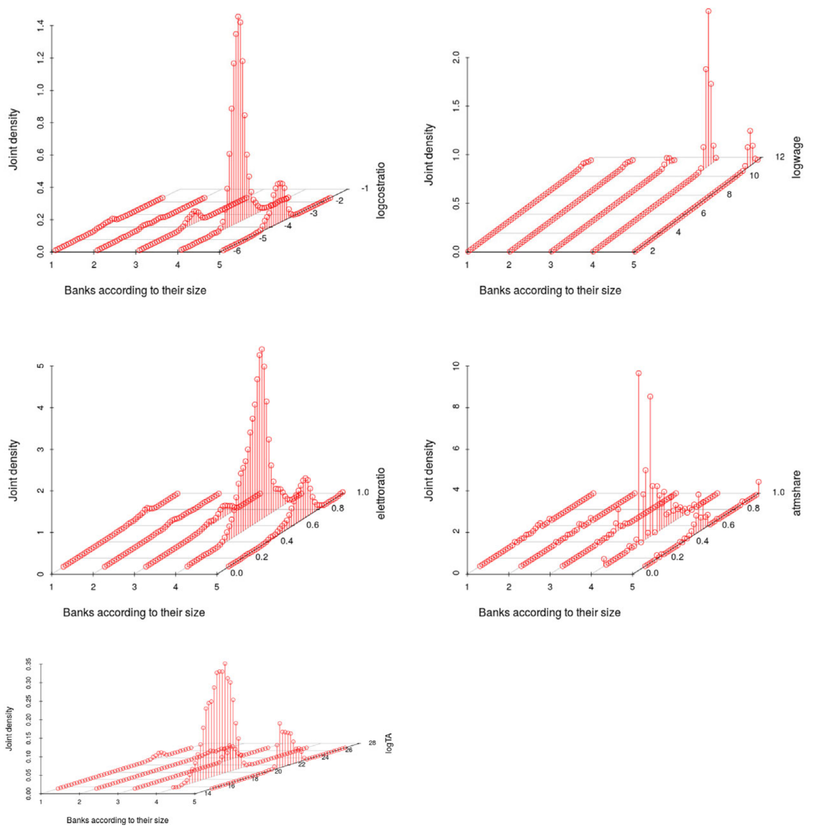

Figure 2: Nonparametric Joint Densities of Logcostratio, Logwage, Electroratio, Atmshare, LogTA and Size: In the Horizontal Axis 1 Corresponds to Major Banks, 2 to Big Banks, 3 to Average Banks, 4 to Minor Banks, 5 to Small Banks

the data we estimate the model both with a fixed effects (FE) estimator and a random effects (RE) estimator. It is possible that the marginal effects may not be linear and vary across the domain of the covariates. Therefore, we augment the model in equation (1) by including squares and cubes of the regressors and estimate the following model:

$$\text{(2)} \quad \text{logcostratio}_{it} = \beta_0 + \sum_{x \in A} \beta_1^{(x)} x_{\text{it}} + \sum_{x \in A} \beta_2^{(x)} x_{\text{it}}^2 + \sum_{x \in A} \beta_3^{(x)} x_{\text{it}}^3 + \alpha_{\text{i}} + u_{\text{it}}$$

where $x \in A$ and $A = \{\text{logwage}, \text{elettroratio}, \text{atmshare}, \text{logTA}\}$. In order to provide the reader with a better comparison among the various estimators we consider also the Arellano-Bond (AB) estimator (Arellano and Bond,

TABLE 6: Parametric Regression Results

	Dependent variable:													
	$Logcostratio_{it}$													
								Pooling (2)		FE (2)		RE (2)		AB (2)
$logcostratio_{it-1}$		0.783***		0.023		0.607***	0.071 ***		0.747***		0.007		0.530***	0.060**
		(0.013)		(0.023)		(0.016)	(0.027)		(0.013)		(0.021)		(0.017)	(0.027)
$logwage_{it}$	0.145***	0.076***	0.177***	0.077***	0.144***	0.081 ***	0.152	−1.176***	−0.129	−1.200***	0.775***	−1.769***	0.097	2.196
	(0.018)	(0.012)	(0.010)	(0.010)	(0.010)	(0.0113	(0.137)	(0.338)	(0.269)	(0.191)	(0.212)	(0.201)	(0.250)	(1.705)
$logwage^2_{it}$								0.146***	−0.002	0.122***	−0.159***	0.223***	−0.046	−0.367
								(0.047)	(0.038)	(0.028)	(0.031)	(0.029)	(0.036)	(0.244)
$Logwage^3_{it}$								−0.005**	0.001	−0.003**	0.009***	−0.008***	0.003**	−0.017**
								(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.010)
$elettroratio_{it}$	−0.464***	−0.169***	−0.010	−0.001	−0.204***	−0.186***	−0.030	−0.268	0.566	−1.887***	−0.832	−1.990***	−0.667	−7.013***
	(0.055)	(0.036)	(0.054)	(0.055)	(0.052)	(0.045)	(0.318)	(0.895)	(0.607)	(0.674)	(0.671)	(0.701)	(0.695)	(2.331)
$elettroratio^2_{it}$								1.529	−0.925	4.125***	1.695	4.763**	1.464	16.495***
								(1.602)	(1.088)	(1.274)	(1.281)	(1.309)	(1.273)	(5.107)
$elettroratio^3_{it}$								−1.654*	0.325	−2.695***	−1.096	−3.371***	−1.136	−11.106***
								(0.936)	(0.634)	(0.766)	(0.773)	(0.783)	(0.754)	(3.373)
$atmshare_{it}$	−0.161 ***	0.010	0.110**	0.111**	−0.118***	0.020	0.261	−3.604***	−2.416***	−1.397***	−1.279**	−1.418***	−2.496***	−5.171**
$atmshare^2_{it}$	(0.052)	(0.034)	(0.044)	(0.046)	(0.042)	(0.040)	0.162	(0.713)	(0.499)	(0.477)	(0.511)	(0.500)	(0.537)	(2.086)
								8.209***	5.016***	3.114***	3.015***	2.706***	5.196***	11.515**
$atmshare^3_{it}$								(1.347)	(0.928)	(0.974)	(1.042)	(1.007)	(1.041)	(4.543)
								−5.589***	−3.166***	−2.011***	−2.008	−1.675**	−3.280***	−7.533**
								(0.812)	(0.552)	(0.633)	(0.677)	(0.648)	(0.647)	(1.009)
$logTA_{it}$	−0.062***	−0.014***	−0.357***	−0.332***	−0.100***	−0.026***	−0.675***	−8.037***	−2.153***	−0.790	−0.749	−7.015***	−4.206***	−2.046
	(0.003)	(0.002)	(0.015)	(0.019)	(0.006)	(0.003)	(0.108)	(0.519)	(0.398)	(0.698)	(1.075)	(0.595)	(0.563)	(2.852)
$logTA^2_{it}$								0.367***	0.100***	0.003	−0.005	0.314***	0.193***	0.054
								(0.000)	(0.019)	(0.034)	(0.051)	(0.029)	(0.027)	(0.137)
$logTA^3_{it}$								−0.006***	−0.002***		0.000	−0.005***	−0.003***	−0.001
								(0.000)	(0.000)		(0.001)	(0.000)	(0.000)	(0.002)
Constant	−3.643***	−1.273***			−3.076***	−1.702***		56.950***	14.980***			51.788***	29.161 ***	

continued

TABLE 6: Continued

Dependent variable:														
Logcostratio_{it}														
								Pooling (2)		FE (2)		RE (2)		AB (2)
	(0.206)	(0.142)			(0.150)	(0.144)		(3.667)	(2.818)			(4.097)	(3.952)	
Observations	2708	2013	2708	2013	2708	2013	1348	2708	2013	2708	2013	2708	2013	1348
R^2	0.216	0.735	0.281	0.214	0.583	0.841		0.340	0.751	0.438	0.377	0.648	0.863	
Adjusted R^2	0.216	0.733	0.213	0.146	0.581	0.839		0.338	0.745	0.331	0.255	0.644	0.858	
FAVald statistic	186.247***	1111.670***	200.523***	74.554***	931.816***	2122.220***	68.890***	115.618***	463.018***	133.022***	63.477***	404.520***	967.221***	390.305***
	(df = 4;2703)	(df = 5;2007)	(df = 4;2053)	(df = 5;1370)	(df = 4;2703)	(df = 5;2007)	(df = 5)	(df = 12;2695)	(df = 13;1999)	(df = 12;2045)	(df = 13;1362)	(df = 12;2695)	(df = 13;1999)	(df = 13)
Sargan test							30:475 (df = 25)							
			Static model			Dynamic model								
			(1)	(2)		(1)	(2)							
H_0: no FEs														
F statistic			18:778***	20:413***		5:080***	6:391***							
			(df = 650;2053)	(ddf = 650;2054)		(df = 637;1370)	(df = 637;1362)							
H_0: RE is the true model vs. FE														
Hausman χ^2 statistic			348:175***	1102:263***		1220:900***	1092:200***							
			(df = 4)	(df = 12)		(df = 5)	(df = 13)							

Note: (1) and (2) refer to equations 1 and 2, respectively; standard errors in brackets. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

1991).[8] The AB estimator is a standard tool in applied econometrics and allows us to consistently estimate our parametric model in the presence of endogeneity.

From the parametric regressions reported in Table 6 the estimated (linear or first order) coefficients have the expected sign and are statistically significant at the 1 per cent level suggesting the validity of our hypotheses in section 2. This is generally true both considering the static models (first column associated to each estimator in Table 6) and the dynamic model (second column associated to each estimator in Table 6). In particular, the estimated regression coefficients of the two technological variables (elettroratio and atmshare) are both negative and significant in most specifications. When it is not the case this could be due to functional misspecification which we tackle by specifying a polynomial form (equation 2).

The inclusion of nonlinear effects (quadratic and cubic terms) significantly improves the fit. It is also worth noticing that the first-order (negative) coefficient of the electronic payment technology variables is always significant. However, it probably does not capture the whole marginal effect. Moreover, adding squares and cubes to our baseline model complicates a little the interpretation of the marginal effects. The marginal effect of x on *logcostratio* in equation 2 is approximated by the following expression

$$\frac{\Delta \text{logcostratio}}{\Delta x} \approx f(x) = \beta_1^{(x)} + 2\beta_2^{(x)} x + 3\beta_3^{(x)} x^2.$$

Since the marginal effect depends on x, it is of practical interest to test whether the marginal effects are zero when evaluated at some particular value of x, say the mean, the median or some other quantile. Let us then consider the following null hypothesis

$$H_0 : f(x) = 0.$$

The alternative hypothesis depends on the variable we are considering. In particular, if $x = \{\text{logwage}\}$

$$H_1 : f(x) > 0,$$

while if $x = \{\text{elettroratio}, \text{atmshare}, \text{logTA}\}$

$$H_1 = f(x) < 0.$$

[8]Notice that the AB estimator requires the inclusion of the lagged dependent variable among the regressors.

TABLE 7: Marginal Effects in the Static Polynomial Model

	$f(x)$			
	$x = \bar{x}$	$x = q_{0.25}$	$x = q_{0.50}$	$x = q_{0.75}$
$x =$ logwage				
Pooling	9:535***	10:089***	9:429***	8:805***
	(0:031)	(0:029)	(0:031)	(0:033)
FE	20:770***	21:779***	20:581***	19:493***
	(0:023)	(0:022)	(0:024)	(0:025)
RE	13:412***	14:397***	13:228***	12:176***
	(0:023)	(0:022)	(0:023)	(0:025)
$x =$ elettroratio				
Pooling	−5:529***	−2:698***	− 6:373***	−8:138***
	(0:064)	(0:072)	(0:063)	(0:071)
FE	1:140	2:234	0:647	−1:466*
	(0:063)	(0:073)	(0:060)	(0:060)
RE	−0:814	1:490	−1:716**	−4:894***
	(0:061)	(0:071)	(0:059)	(0:061)
$x =$ atmshare				
Pooling	6:038	6:081	6:069	4:915
	(0:068)	(0:065)	(0:068)	(0:072)
FE	3:677	3:293	3:668	3:705
	(0:057)	(0:057)	(0:057)	(0:055)
RE	0:564	0:055	0:550	0:681
	(0:056)	(0:056)	(0:056)	(0:055)
$x =$ logTA				
Pooling	−13:147***	−25:717***	−16:674***	−2:389***
	(0:004)	(0:006)	(0:004)	(0:005)
FE	−25:296***	−28:926***	−26:071***	−22:529***
	(0:018)	(0:017)	(0:018)	(0:019)
RE	−12:770***	−22:278***	−14:937***	−5:720***
	(0:007)	(0:008)	(0:007)	(0:007)

Note: $\bar{x}$ is the mean of x while q_a is the a-th quantile of x. Standard errors in brackets; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The results of the tests described above are collected in Table 7 for the static model and in Table 8 for the dynamic model. The results for the two model specifications are similar. We notice that the marginal effect of the atmshare variable is always non significant. With respect to the elettroratio variable we consistently reject the null hypothesis (i.e., whether we consider mean or the three quartiles) only in the case of the pooling estimator. These results are confirmed also by the AB estimator. It is worth noticing that our specification tests suggest that between the FE estimator and pooled OLS we should favour the FE estimator. The same happens when we test FE against RE. In addition to that, the Sargan test suggests that the orthogonality conditions used for the AB estimator are satisfied.

TABLE 8: Marginal Effects in the Dynamic Polynomial Model

	$f(x)$			
	$x=\bar{x}$	$x=q_{0.25}$	$x=q_{0.50}$	$x=q_{0.75}$
$x=$ logwage				
Pooling	9.558***	9.845***	9.500***	9.133***
	(0.023)	(0.022)	(0.023)	(0.025)
FE	17.461***	17.745***	17.406***	17.066***
	(0.027)	(0.025)	(0.027)	(0.029)
RE	12.300***	12.614***	12.238***	11.858***
	(0.026)	(0.025)	(0.026)	(0.028)
AB	11.144***	9.900***	11.325***	11.846***
	(0.043)	(0.045)	(0.043)	(0.043)
$x=$ elettroratio				
Pooling	−4.865***	−3.637***	−5.154***	−5.273***
	(0.045)	(0.051)	(0.044)	(0.048)
FE	−0.205	0.288	−0.417	−1.253
	(0.065)	(0.076)	(0.062)	(0.061)
RE	−3.492***	−1.980**	−3.994***	−5.187***
	(0.056)	(0.065)	(0.054)	(0.057)
AB	2.391	4.773	1.508	−1.456*
	(0.172)	(0.176)	(0.176)	(0.210)
$x=$ atmshare				
Pooling	4.930	4.048	4.917	4.748
	(0.046)	(0.045)	(0.046)	(0.048)
FE	3.890	3.651	3.886	3.790
	(0.059)	(0.059)	(0.059)	(0.056)
RE	4.428	3.623	4.410	4.432
	(0.054)	(0.054)	(0.054)	(0.055)
AB	5.380	5.029	5.379	5.047
	(0.129)	(0.125)	(0.129)	(0.131)
$x=$ logTA				
Pooling	−4.132***	−7.017***	−5.108***	−1.077
	(0.003)	(0.005)	(0.003)	(0.0003)
FE	−19.557***	−22.077***	−20.447***	−15.988***
	(0.022)	(0.022)	(0.022)	(0.025)
RE	−5.721***	−10.966***	−7.313***	−0.856
	(0.005)	(0.007)	(0.005)	(0.005)
AB	−11.397***	−14.381***	−11.957***	−9.641***
	(0.047)	(0.041)	(0.046)	(0.051)

Note: $\bar{x}$ is the mean of x while q_a is the a-th quantile of x. Standard errors in brackets; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

4.2. *Nonparametric Models*

The nonlinear specification in equation (2) allows us to describe the potential nonlinear nature of the marginal effects. However, a more sensible way to capture such nonlinear features is to use nonparametric estimation techniques, allowing us to overcome problems coming from the incorrect specification of the model's functional form.[9]

[9]To the best of our knowledge, no off-the-shelf estimator can simultaneously deal with endogeneity and panel data in a nonparametric fashion. Hence, we rely on the results obtained in the parametric models as for endogeneity robustness checks.

The general nonparametric model we use is defined as

$$y_{\text{it}} = m(x_{\text{it}}, i, t) + \varepsilon_{\text{it}} \tag{3}$$

where x_{it} is a set of regressors as in equation (1). By means of a Taylor expansion of $m(x_{it}, i, t)$ about x we obtain the following approximation

$$y_{\text{it}} \approx m(\mathbf{x}, i, t) + (\mathbf{x}_{\text{it}} - \mathbf{x})' g(\mathbf{x}, i, t) + \boldsymbol{\varepsilon}_{\text{it}}. \tag{4}$$

This approximation allows us to derive not only an estimator for $m(x, i, t)$ but also an estimator for the marginal effects vector function $g(x, i, t)$. For the model in equation (4), we can derive the local linear kernel estimator (LLKE) via standard least squares theory. This is,

$$\begin{aligned} \begin{pmatrix} \widehat{m}(\mathbf{x}, i, t) \\ \widehat{g}(\mathbf{x}, i, t) \end{pmatrix} &= \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \begin{pmatrix} 1 & (\mathbf{x}_{\text{it}} - \mathbf{x})' \\ (\mathbf{x}_{\text{it}} - \mathbf{x}) & (\mathbf{x}_{\text{it}} - \mathbf{x})(\mathbf{x}_{\text{it}} - \mathbf{x})' \end{pmatrix} K_{\text{it},\mathbf{h}} \right)^{-1} \\ &\quad \times \sum_{i=1}^{N} \sum_{t=1}^{T} \begin{pmatrix} 1 \\ (\mathbf{x}_{\text{it}} - \mathbf{x}) \end{pmatrix} K_{\text{it},\mathbf{h}} y_{\text{it}} \end{aligned} \tag{5}$$

where $K_{\text{it},\mathbf{h}}$ is a standard product kernel (Li and Racine, 2007) that depends also on a vector of bandwidth parameters $\mathbf{h}$.[10] The LLKE provides us with an estimator of the conditional mean for each bank i at time t, this is $\widehat{m}(x, i, t)$. However, the merit of the LLKE is that it allows us to estimate the marginal effects associated to each variable in x_{it}, $\widehat{g}(x, i, t)$. It is universally known that the choice of the bandwidth in nonparametric estimation is crucial in determining the final results. Our problem is no exception to the rule. In order to choose the bandwidth we use the Akaike information criterion (AIC).[11] This approach, in conjunction with the LLKE.

Let us specify the vector of regressors as $\mathbf{x}_{\text{it}} = \left(\mathbf{x}_{\text{it}}^{c'}, \mathbf{x}_{\text{it}}^{o'}, \mathbf{x}_{\text{it}}^{u'} \right)'$, where the superscripts c, o and u indicate continuous, discrete ordered and discrete unordered regressors, respectively, delivers some interesting results. According to Hall *et al.* (2007), such a cross-validation procedure is able to smooth away irrelevant regressors and to recognize when continuous regressors enter the model in a linear fashion.The bandwidth's upper bound associated to a continuous variable is infinite. This is clearly a theoretical bound and it cannot be observed in practice.

[10]In the application we use the Gaussian kernel for continuous variables and the Li and Racine kernel for discrete variables. See Li and Racine (2007) and references therein.

[11]In addition to the AIC method we also used the least squares cross-validation criterion. The AIC method, however, seems to deliver more stable results. Therefore, the results associated to the least squares cross-validation are omitted.

TABLE 9: Bandwidths

	Dependent variable: logcostratio
	AIC selection method
LogTA	0.795
Logwage	3,285,958.000
Elettroratio	0.367
Atmshare	418,817.700
Bank	0.001
Year	1.000
Observations	2708
R^2	0.973

However, when the bandwidth is sufficiently large and by graphical inspection, we can argue that the regressor enters the model linearly. This phenomenon can actually be observed in our results in Table 9 and in Figure 3. The case of discrete regressors is quite different. The bandwidth associated to a discrete variable, whether ordered or unordered, takes values between zero and one. When the bandwidth reaches its upper bound the variable is smoothed away and it has no effect on the results. This fact justifies the fixed effects approach in Racine (2008). This is, we consider an unordered discrete variable associated with each bank, say, $x_{\mathrm{it}}^{u} = i$ and, whenever the associated bandwidth hits the upper bound, the variable is smoothed out and the data are poolable. This approach has been applied in a number of contexts by different authors. See for example Henderson and Simar (2005), Gyimah-Brempong and Racine (2010), Henderson *et al.* (2011), Czekaj and Henningsen (2013), and Gyimah-Brempong and Racine (2014). The results of the nonparametric estimates are collected in Figures 3 and 4.[12] More precisely, Figure 3 contains the AIC-based nonparametric estimates for the fixed effects model and Figure 4 its associated marginal effects. Each figure features a bootstrapped 95% confidence band. Finally, Table 9 contains the bandwidths associated to the nonparametric estimators and to each variable. The variables bank and year refer to the indices i and t in equation (3), respectively.

We notice that the marginal effect of elettroratio is an always negative decreasing function. On the other hand, the marginal effect of atmshare is constant and positive.

Given that this is the first study that tackles the issue by means of nonparametric techniques, it is of interest to check whether this new perspective is able to shed new light on the impact of IT innovation on

[12]For ease of exposition, figures only include the results for the continuous variables.

banks' efficiency. Three considerations are in order with this respect. First, to some extent, results tend to agree under the two scenarios, the only notable exception being the behaviour of atmshare. The marginal effects associated to the parametric models (Tables 6 and 7) confirm that banks with higher elettroratio are also the most cost-efficient. On the other hand, the results associated to the variable atmshare are more controversial as the marginal effects in the nonlinear specification are never significantly different from zero. The nonparametric estimates in Figures 3 and 4 confirm that elettroratio always plays a significant role in enhancing cost efficiency, while the marginal effect of atmshare is a constant positive value (Figure 4). Second, these findings support the view that elettroratio is the main driver of cost efficiency gains, rather than the endowment of ATMs alone (See Hypotheses 1 and 2 in section 2). With respect to previous studies, this appears to be a new result. Third, the results for our other two control variables reveal the nonlinear nature for bank size (logTA), while the variable associated to wages (logwage) is approximately linear. This suggests caution about the inclusion of bank size proxies in linear models for banks' cost efficiency. As pointed out in section 2, this corresponds exactly to the Italian case, where the nexus between efficiency and size is complex and depends on many different factors such as the bank's geographical location and its ownership structure (Giordano and Lopes, 2009).

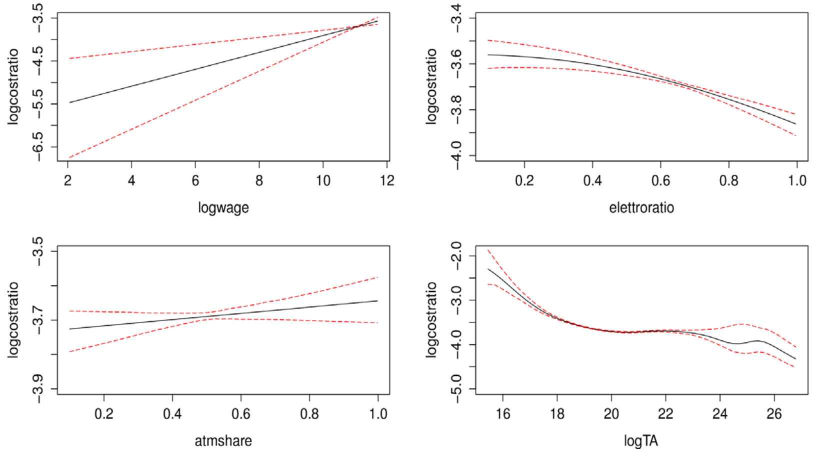

Figure 3: Estimates of FE Nonparametric Regression With AIC

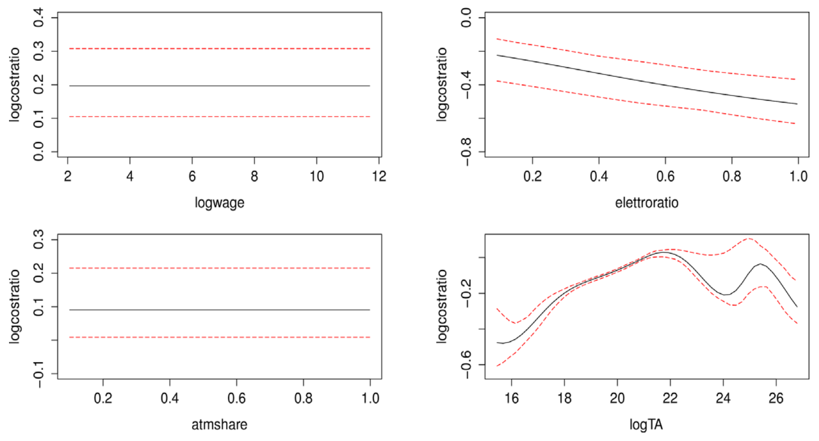

Figure 4: Marginal Effects of FE Nonparametric Regression With AIC

4.3. Savings

The estimates from our models can be used to estimate variations in logcostratio between 2006 and 2010. We can define

$$\Delta \widehat{\text{logcostratio}}_{\text{i}} = \widehat{\text{logcostratio}}_{\text{i,2010}} - \widehat{\text{logcostratio}}_{\text{i,2006}}$$

as the cost savings of the bank with respect to a technological variable, ceteris paribus. Figures 5–7 report estimated savings stemming from a change in atmshare and elettroratio in the linear parametric, cubic parametric and the nonparametric models, respectively. Such a comparison gives rise to interesting insights. We notice a large difference in the results of the two parametric specifications. Looking at Figure 5, one should conclude that atmshare is not able to produce an effect on savings, while increasing elettroratio produces some saving effect. On the other hand, the cubic model displays larger savings for both technological variables (Figure 6). Finally, for the nonparametric model in Figure 7 we notice that the effect of atmshare is nearly zero, while an increasing variation in elettroratio produces a decrease in $\Delta \widehat{\text{logcostratio}}_{\text{i}}$.

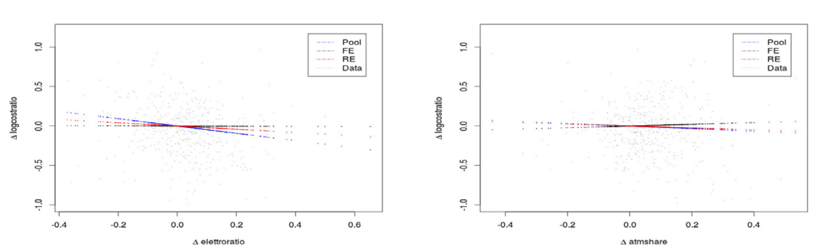

Figure 5: Savings for the Linear Parametric Model

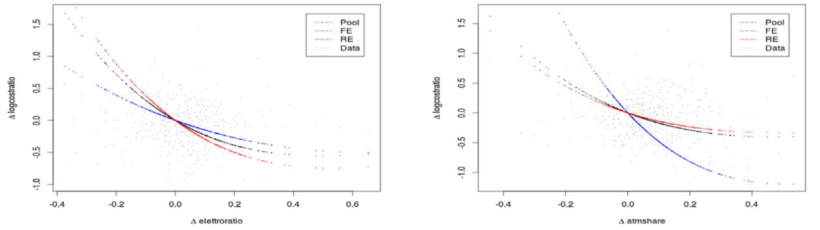

Figure 6: Savings for the Cubic Parametric Model

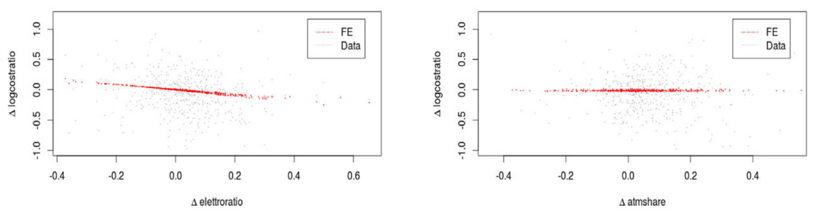

Figure 7: Savings for the Nonparametric Model With AIC

5. Conclusions

This paper provides new evidence on the positive link between fully automated payment processing procedures and overall operating costs at the bank level. We introduce two main novelties in the empirical analysis of this issue. First, we use two quantitative measures of the degree of IT innovation at the bank level based on the relative diffusion of ATMs (atmshare) and electronic transactions managed by the bank (elettroratio). Second, we make use of nonparametric estimation techniques, thus overcoming a number of limitations associated to the exclusive use of parametric approaches. Our results are based on an original panel of Italian banks observed over a 5-year time span. We find strong evidence that the diffusion of electronic payments effectively reduces cost inefficiency, while ATMs diffusion alone does not. This implies that IT innovation is effective in enhancing cost efficiency when it concerns a shift from traditional payment channels to virtual services to depositors (remote banking) and the enlargement of the supply of electronic payment channels. The issue of innovation in payments is at the core of the SEPA project and, more in general, of the Digital Agenda for Europe. The SEPA goes beyond inter-bank level and cash management (which also would get benefits), and in specific cases also encompasses interfacing with end-users. Cash and other paper based payment instruments are still widely adopted in Europe. In this field, the migration from the legacy credit transfer and direct debit schemes to the SEPA products will allow enhancing end-to-end payments, using common message formats in the bank-to-customer/firm domain and customer servicing channels associated with payments initiation, reconciliation and cash management services. In this context, banks can better keep their clients and increase stable liabilities/deposits which are also important to mitigate liquidity risks. The financial industry has a pivotal role in the provision of this kind of services. From a policy point of view, our conclusions are also relevant for the ongoing debate on the declining pattern of operating incomes in the Italian banking system. During the years under investigation, the Italian banking system has experienced a consistent drop in operating net earnings which has been mainly driven by a contraction in the level of revenues from financial services. In the context of the credit crisis (and given the strict regulations imposed by the Basel agreements), such a pattern will be hardly reversed unless banking activities will improve cost efficiency (Panetta, 2013).

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