Innovation and Cost Efficiency in the Banking Industry: the Role of Electronic Payments[1]

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Abstract

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.

Keywords: electronic payments, ATM, bank cost efficiency, nonparametric regression, ICT adoption.

JEL classification numbers: C14, C33, G2, L8, L11.

I. Introduction

The role of ICT adoption and technological change in banking activity has received remarkable attention in the literature (see, for instance, Berger 2003; Humphrey et al. 2006; Casolaro & Gobbi 2004; Frame & 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 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[2]. Despite the relative importance and 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

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[2]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.

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.

Three previous studies are most related to ours. We depart from each of them in different aspects. Haynes & 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. They estimate an augmented Cobb-Douglas production function where a dummy variable accounts for the adoption of ATMs in a given year. Ou et al. (2005) and Ou et al. (2009) focus on ATMs intensity rather than ATMs adoption by using a quantitative measure of ATMs diffusion (ATMs per employee) in a cross section of 264 banks in Taiwan. OLS estimates show that higher diffusion on ATMs is associated with lower cost inefficiency. Departing from the 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 the total of 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. The beneficial effect of a larger expansion of ATMs relative to branch offices combined with the shift to electronic payments has been found by Carbó-Valverde et al. (2006) 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

2

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 II. we present our model and formulate testable hypotheses for our two measures of IT innovation. Section III. 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 IV.. Section V. concludes with a discussion of the policy implications of this study.

II.   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 & Thompson 2000; Ou et al. 2005; Ou et al. 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:

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

where `OC` indicates operating costs, `TA` total assets, and a lower value of `costratio` corresponds to higher cost efficiency. Our aim is to assess the impact of the IT payment channel innovation on the bank efficiency overall. 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:

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 of payment operations managed by the bank. The use of this variable, which represents a novelty with respect to previous studies, is ex-

pected 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 & Thompson 2000, Ou et al. 2005, Ou et al. 2009). However, cash and other paper based instruments emerge as the most costly instruments on the bank side (Bank of Italy 2012), above all owing to the hefty costs for the management and handling of the paper documents (deposit, transportation, reconciliation, etc.). A number of reasons motivate the inclusion of `elettroratio` in our model. For instance, 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 IV., 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 efficiency 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 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 & 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 & 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

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

efforts to control salary expenses, in line with the empirical evidence provided by several studies, e.g. Spong et al. (1995), Berger & 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% against 1.3% 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.*

III. Data

Our analysis is conducted on a data set provided by the Bank of Italy. We consider an unbalanced panel of 2,708 observations in the period between 2006 and 2010, where we have information about 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. Table 1 provides the definition of all variables included in estimated models.

Table 1 about here

Table 3 shows descriptive statistics for the sample as a whole. Table 4 and Table 5 report the same statistics disaggregated by year and bank size, respectively. Figure 1 depicts the time path of `costratio` controlling for bank size. These descriptive evidence help to highlight some relevant facts occurred over the considered period in the Italian banking system. From Table 4 we observe the sharp increase in salaries. Other

7

things being equal, this effect would imply lower cost efficiency. On the other hand, our two measures of IT innovation show an increasing time trend, thus leading to expected cost efficiency gains. By looking at the relatively flat time trend of `costratio`, one should conclude that, in the full sample, cost savings associated with IT innovation have been offset by the increase in salaries. However, this descriptive evidence should carefully take into account differences across banks, most of them being proxied by `TA`. From 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 pattern seems to be driven by efficiency gains due to IT innovation that compensates for higher salary expenses. The red and black curves shown in Figure 1 illustrate how `costratio` varies as a function of `logTA` in 2006 and 2010, respectively. The two curves are obtained by means of nonparametric local linear regression with cross-validated bandwidth. Only banks after a threshold value of `logTA` have experienced significant cost gains, while below that value we observe an efficiency loss. This descriptive evidence calls for controlling for bank size in our estimated model.

Table 2 about here

Table 3 about here

Table 4 about here

Table 5 about here

Figure 1 about here

Figure 2 about here

8

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).

IV. Estimation and results

We concentrate our attention on the cost-efficiency indicator `logcostratio` against two technological variables, the first (`elettroratio`) takes into consideration the number of ATMs and the second (`atmshare`) takes into account the number of electronic payments. As argued in Section II., 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.[4]

Parametric models

Table 6 about here

We consider the following model

$$\texttt{logcostratio}_{it} = \beta_0 + \beta_1 \texttt{logwage}_{it} + \beta_2 \texttt{elettroratio}_{it} \tag{1}$$
$$+ \beta_3 \texttt{atmshare}_{it} + \beta_3 \texttt{logTA}_{it} + \alpha_i + u_{it}$$

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

where the index i refers to banks and t refers to time.[5] The model is first estimated by pooled OLS. Then, in order to consider the panel features of 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:

$$\texttt{logcostratio}_{it} = \beta_0 + \sum_{x \in A} \beta_1^{(x)} x_{it} + \sum_{x \in A} \beta_2^{(x)} x_{it}^2 + \sum_{x \in A} \beta_3^{(x)} x_{it}^3 + \alpha_i + u_{it} \qquad (2)$$

where $x \in A$ and $A = \{\texttt{logwage}, \texttt{elettroratio}, \texttt{atmshare}, \texttt{logTA}\}$. In order to provide the reader with a better comparison among the various estimators we consider also the Arellano-Bond (AB) estimator (Arellano & Bond 1991).[6] 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% level suggesting the validity of our hypotheses in Section II.. 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).

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[5]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.

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

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

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

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 $x = \{\texttt{logwage}\}$

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

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

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

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 see that 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 7 about here

Table 8 about here

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.[7]

The general nonparametric model we use is defined as

$$y_{it} = m(\mathbf{x}_{it}, i, t) + \varepsilon_{it} \tag{3}$$

where $\mathbf{x}_{it}$ is a set of regressors as in equation (1). By means of a Taylor expansion of

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[7]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.

$m(\mathbf{x}_{it}, i, t)$ about $\mathbf{x}$ we obtain the following approximation

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

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

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

$$\times \sum_{i=1}^{N} \sum_{t=1}^{T} \begin{pmatrix} 1 \\ (\mathbf{x}_{it} - \mathbf{x}) \end{pmatrix} K_{it,\mathbf{h}} y_{it}$$

where $K_{it,\mathbf{h}}$ is a standard product kernel (Li & Racine 2007) that depends also on a vector of bandwidth parameters $\mathbf{h}$.[8] The LLKE provides us with an estimator of the conditional mean for each bank i at time t, this is $\widehat{m}(\mathbf{x}, i, t)$. However, the merit of the LLKE is that it allows us to estimate the marginal effects associated to each variable in $\mathbf{x}_{it}$, $\widehat{\mathbf{g}}(\mathbf{x}, i, t)$. 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 least squares cross-validation (LSCV) method and the Akaike information criterion (AIC). This approach, in conjunction with the LLKE 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

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

continuous regressors enter the model in a linear fashion. Let us specify the vector of regressors as $\mathbf{x}_{it} = (\mathbf{x}_{it}^{c'}, \mathbf{x}_{it}^{o'}, \mathbf{x}_{it}^{u'})'$, where the superscripts c, o and u indicate continuous, discrete ordered and discrete unordered regressors respectively. 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. 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, $x_{it}^{u} = i$ 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 et al. (2011), Henderson & Simar (2005), Gyimah-Brempong & Racine (2010), Gyimah-Brempong & Racine (2014), Czekaj & Henningsen (2013). We compare the results obtained via the LSCV approach with nonparametric estimates that use an improved AIC to calculate the optimal bandwidth (see Hurvich et al. 1998). The results of the nonparametric estimates are collected in Figures 3 to 6.[9] More precisely, Figure 3 contains the LSCV-based nonparametric estimates for the fixed effects model and Figure 4 its associated marginal effects, while Figure 5 contains the AIC-based nonparametric estimates for the fixed effects model and Figure 6 its associated marginal effects. Each figure features a bootstrapped 95% confidence band. Finally, Table 9 contains the bandwidths associated to the nonparametric estimators and

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

to each variable. The variables `bank` and `year` refer to the indices i and t in equation (3) respectively.

Figure 3 about here

Figure 4 about here

Figure 5 about here

Figure 6 about here

From Figure 3, Figure 4 and Table 9 we see that the effect of `electroratio` is linear and, therefore, its marginal effect on `logcostratio` is the same for any value of `electroratio`. We notice that the marginal effect is always negative. On the other hand, the marginal effect of `atmshare` is about zero for nearly all values of `atmshare`. The effect of `atmshare` gets negative for values of `atmshare` close to one. It is worth noticing that the confidence intervals get larger consistently with the fact that there are only few data corresponding to large values of `atmshare`. In those cases Henderson & Parmeter (2007, pp. 214-215) suggest comparing the LSCV results with those obtained via AIC.

Table 9 about here

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 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

15

effects associated to the parametric models (Table 6 and Table 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 to 6 confirm that `elettroratio` always plays a significant role in enhancing cost efficiency, while the marginal effect of `atmshare` could be either approximately constant around zero (Figure 4) or a constant positive value (Figure 6). 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 II.). 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 II., 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 & Lopes 2009).

Savings

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

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

as the cost savings of the bank with respect to a technological variable, ceteris paribus. Figures 7, 8, 9 and 10 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 7, 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 8). Finally, for the nonparametric models in Figure 9 and in Figure 10 we notice that the effect of `atmshare` is nearly zero, while an increasing variation in `elettroratio` produces a decrease in $\Delta \widehat{\texttt{logcostratio}}_i$.

Figure 7 about here

Figure 8 about here

Figure 9 about here

Figure 10 about here

V.   Conclusions

This paper tackles the issue of cost inefficiency reduction associated to the use of full automated payment processing procedures. 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 scale goes beyond inter-bank level and cash management (which also would get benefits), and in specific cases also encompasses interfacing with end-users. Cash

17

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. In this paper we have shown some relevant empirical evidence which confirms the positive impact of full automated processing procedures for overall operating costs. In particular, we find strong evidence that the diffusion of electronic payments effectively reduces cost inefficiency, while ATMs diffusion alone does not. We have obtained these results contrasting results obtained using both parametric and nonparametric estimation techniques. 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 current 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). Our results show that IT innovation is effective in enhancing cost efficiency. This indicates that cost reduction can be achieved by relying heavily on virtual services to depositors (remote banking) and enlarging the supply of electronic payment channels.

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19

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Innovation and Cost Efficiency in the Banking Industry: the Role of Electronic Payments: Figures
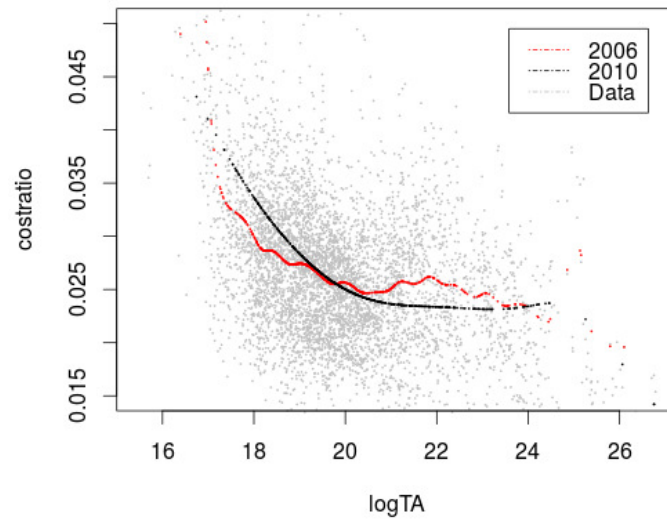
Figure 1. Cost efficiency and bank size in 2006 and 2010
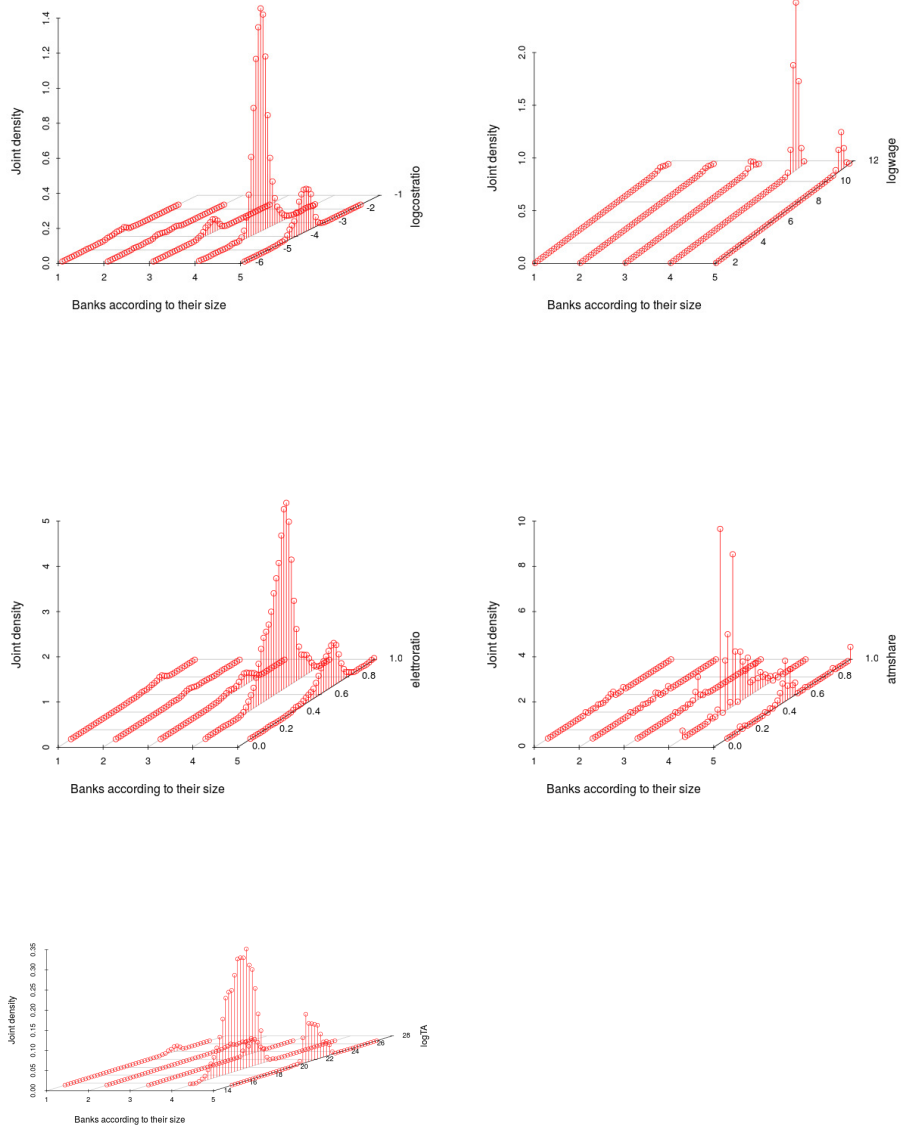
Figure 2. Nonparametric joint densities of `logcostratio`, `logwage`, `electroratio`, `atmshare`, `logTA` and `size`: in the horizontal axis 1 corresponds to major banks, 2 to big banks, 3 to average banks, 4 to minor banks, 5 to small banks.
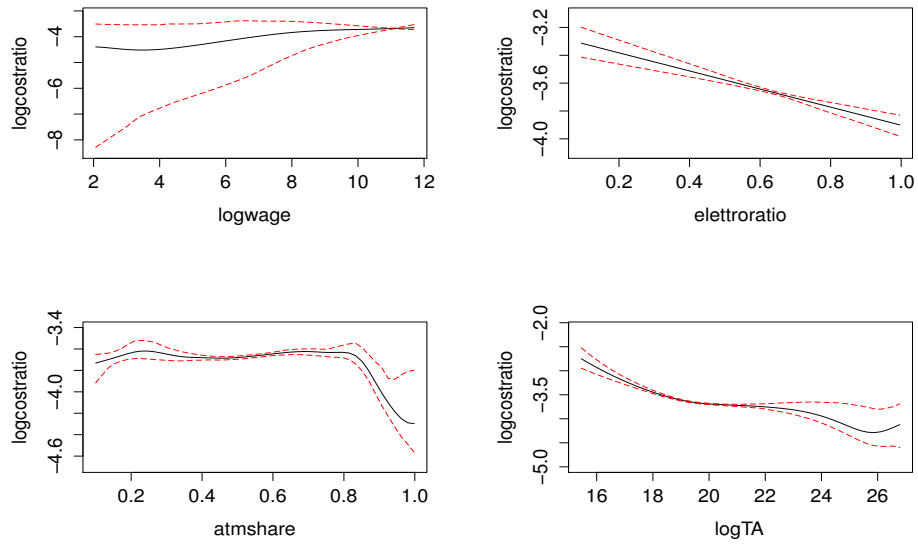
Figure 3. Estimates of FE nonparametric regression with LSCV.
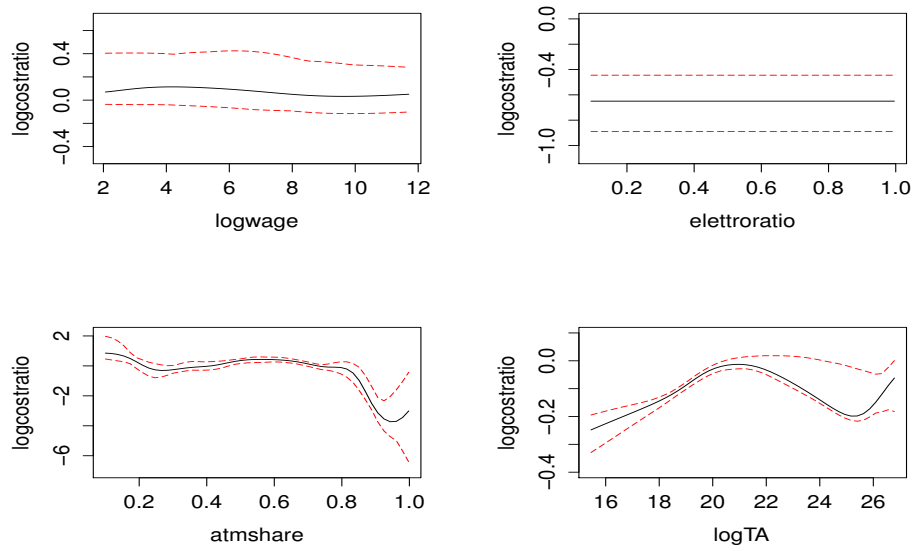
Figure 4. Marginal effects of FE nonparametric regression with LSCV.
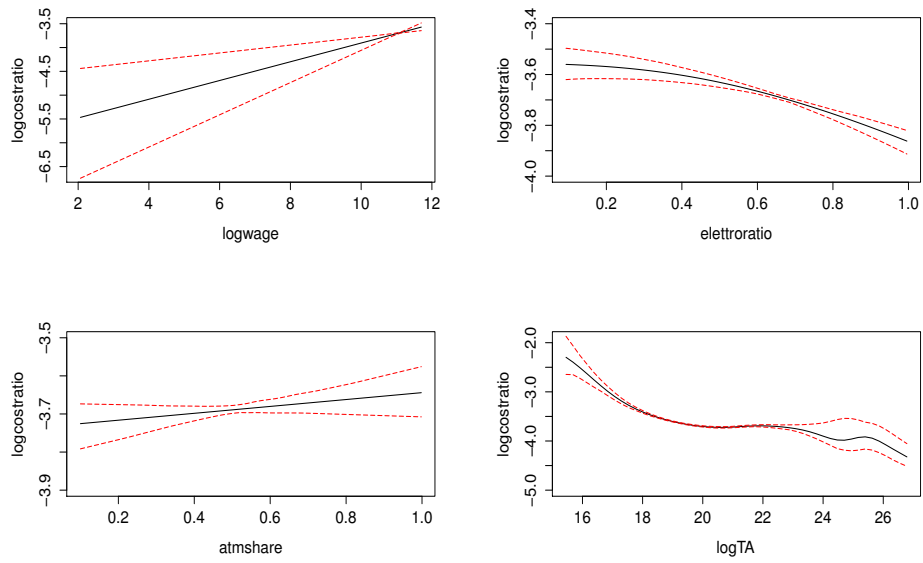
Figure 5. Estimates of FE nonparametric regression with AIC.
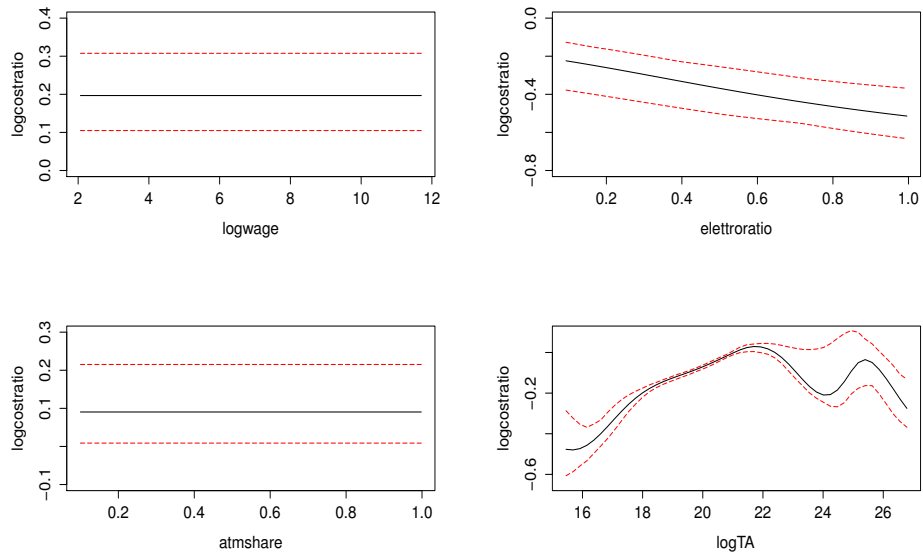
Figure 6. Marginal effects of FE nonparametric regression with AIC.
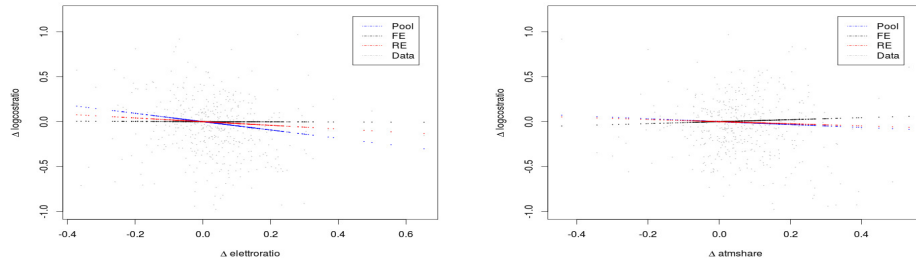
Figure 7. Savings for the linear parametric model.
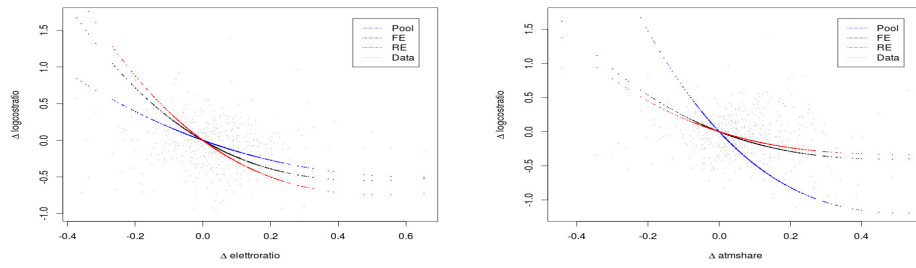
Figure 8. Savings for the cubic parametric model.
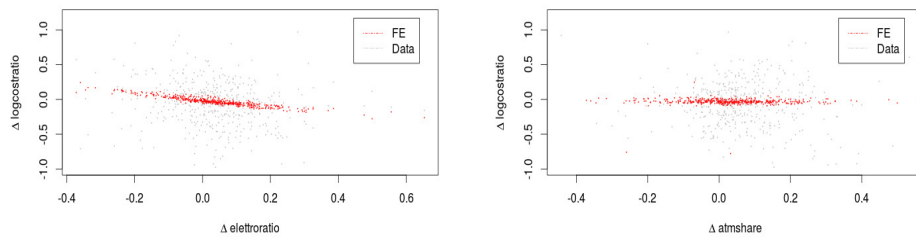
Figure 9. Savings for the nonparametric model with LSCV.
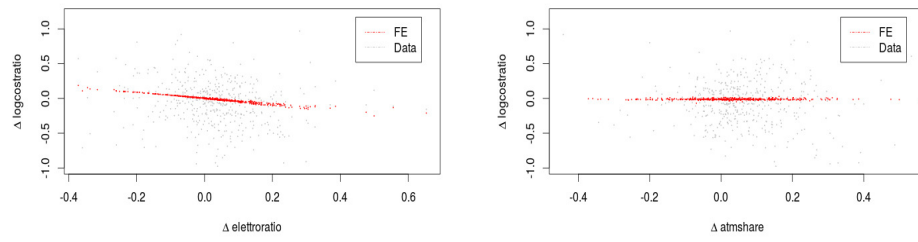
Figure 10. Savings for the nonparametric model with AIC.

Innovation and Cost Efficiency in the Banking Industry:

the Role of Electronic Payments: Tables

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 number of total transactions.
atmshare	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.

TABLE 2

Correlation matrix

	costratio	wage	elettroratio	atmshare	.1
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	1*st* Quantile	Median	Mean	3*rd* Quantile	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.

TABLE 4

Descriptive statistics by year

Variable	Minimum	1*st* Quantile	Median	Mean	3*rd* Quantile	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	0.124	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	63.440	67.940	68.610	72.770	110.900
elettroratio	0.239	0.606	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.

34

TABLE 5

Descriptive statistics by bank size

Variable	Minimum	1*st* Quantile	Median	Mean	3*rd* Quantile	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	4.536	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	0.683	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.

TABLE 6

Parametric regression results

Dependent variable: $logcostratio_{it}$

Static model

	Pooling (1)	FE (1)	RE (1)	Pooling (2)	FE (2)	RE (2)
$logwage_{it}$	0.145*** (0.018)	0.177*** (0.010)	0.144*** (0.010)	-1.176*** (0.338)	-1.200*** (0.191)	-1.769*** (0.201)
$logwage_{it}^2$				0.146*** (0.047)	0.122*** (0.028)	0.223*** (0.029)
$logwage_{it}^3$				-0.005** (0.002)	-0.003*** (0.001)	-0.008*** (0.001)
$elettroratio_{it}$	-0.464*** (0.055)	-0.010 (0.054)	-0.204*** (0.052)	-0.268 (0.895)	-1.887*** (0.674)	-1.990*** (0.701)
$elettroratio_{it}^2$				1.529 (1.602)	4.125*** (1.274)	4.763*** (1.309)
$elettroratio_{it}^3$				-1.654* (0.936)	-2.695*** (0.766)	-3.371*** (0.783)
$atmshare_{it}$	-0.161*** (0.052)	0.110** (0.044)	-0.118*** (0.042)	-3.604*** (0.713)	-1.397*** (0.477)	-1.418*** (0.500)
$atmshare_{it}^2$				8.209*** (1.347)	3.114*** (0.974)	2.706*** (1.007)
$atmshare_{it}^3$				-5.589*** (0.812)	-2.011*** (0.633)	-1.675** (0.648)
$logTA_{it}$	-0.062*** (0.003)	-0.357*** (0.015)	-0.100*** (0.006)	-8.037*** (0.519)	-0.790 (0.698)	-7.015*** (0.595)
$logTA_{it}^2$				0.367*** (0.000)	0.003 (0.034)	0.314*** (0.029)
$logTA_{it}^3$				-0.006*** (0.000)	0.000 (0.001)	-0.005*** (0.000)
constant	-3.643*** (0.206)		-3.076*** (0.150)	56.950*** (3.667)		51.788*** (4.097)
Observations	2708	2708	2708	2708	2708	2708
R^2	0.216	0.281	0.583	0.340	0.438	0.648
Adjusted R^2	0.216	0.213	0.581	0.338	0.331	0.644
F/Wald statistic	186.247*** (df=4;2703)	200.523*** (df=4;2053)	931.816*** (df=4;2703)	115.618* (df=12;2695)	133.022*** (df=12;2045)	404.520*** (df=12;2695)

Dynamic model

	Pooling (1)	FE (1)	RE (1)	AB (1)	Pooling (2)	FE (2)	RE (2)	AB (2)
$logcostratio_{it-1}$	0.783*** (0.013)	0.023 (0.023)	0.607*** (0.016)	0.071*** (0.027)	0.747*** (0.013)	0.007 (0.021)	0.530*** (0.017)	0.060** (0.027)
$logwage_{it}$	0.076*** (0.012)	0.077*** (0.010)	0.081*** (0.0113)	0.152 (0.137)	-0.129 (0.269)	0.775*** (0.212)	0.097 (0.250)	2.196 (1.705)
$logwage_{it}^2$					-0.002 (0.038)	-0.159*** (0.031)	-0.046 (0.036)	-0.367 (0.244)
$logwage_{it}^3$					0.001 (0.002)	0.009*** (0.001)	0.003* (0.002)	-0.017** (0.010)
$elettroratio_{it}$	-0.169*** (0.036)	-0.001 (0.055)	-0.186*** (0.045)	-0.030 (0.318)	0.566 (0.607)	-0.832 (0.671)	-0.667 (0.695)	-7.013*** (2.331)
$elettroratio_{it}^2$					-0.925 (1.088)	1.695 (1.281)	1.464 (1.273)	16.495*** (5.107)
$elettroratio_{it}^3$					0.325 (0.634)	-1.096 (0.773)	-1.136 (0.754)	-11.106*** (3.373)
$atmshare_{it}$	0.010 (0.034)	0.111** (0.046)	0.020 (0.040)	0.261 (0.162)	-2.416*** (0.499)	-1.279** (0.511)	-2.496*** (0.537)	-5.171** (2.086)
$atmshare_{it}^2$					5.016*** (0.928)	3.015*** (1.042)	5.196*** (1.041)	11.515** (4.543)
$atmshare_{it}^3$					-3.166*** (0.552)	-2.008 (0.677)	-3.280*** (0.647)	-7.533*** (1.009)
$logTA_{it}$	-0.014*** (0.002)	-0.332*** (0.019)	-0.026*** (0.003)	-0.675*** (0.108)	-2.153*** (0.398)	-0.749 (1.075)	-4.206*** (0.563)	-2.046 (2.852)
$logTA_{it}^2$					0.100*** (0.019)	-0.005 (0.051)	0.193*** (0.027)	0.054 (0.137)
$logTA_{it}^3$					-0.002*** (0.000)	0.000 (0.001)	-0.003*** (0.000)	-0.001 (0.002)
constant	-1.273*** (0.142)		-1.702*** (0.144)		14.980*** (2.818)		29.161*** (3.952)	
Observations	2013	2013	2013	1348	2013	2013	2013	1348
R^2	0.735	0.214	0.841		0.751	0.377	0.863	
Adjusted R^2	0.733	0.146	0.839		0.745	0.255	0.858	
F/Wald statistic	1111.670*** (df=5;2007)	74.554*** (df=5;1370)	2122.220*** (df=5;2007)	68.890*** (df=5)	463.018*** (df=13;1999)	63.477*** (df=13;1362)	967.221*** (df=13;1999)	390.305*** (df=13)
Sargan test				30.475 (df=25)				59.775 (df=50)

	Static model		Dynamic model	
	(1)	(2)	(1)	(2)
H_0: no FEs				
F statistic	18.778*** (df=650;2053)	20.413*** (df=650;2054)	5.080*** (df=637;1370)	6.391*** (df=637;1362)
H_0: RE is the true model vs. FE				
Hausman χ^2 statistic	348.175*** (df=4)	1102.263*** (df=12)	1220.900*** (df=5)	1092.200*** (df=13)

Note: (1) and (2) refer to equation 1 and equation 2 respectively; standard errors in brackets. *p<0.1; **p<0.05; ***p<0.01

TABLE 7

Marginal effects in the static polynomial model

| | $f(x)$ | | | |
	$x = \bar{x}$	$x = q_{0.25}$	$x = q_{0.50}$	$x = q_{0.75}$
	$x = \texttt{logwage}$			
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)
	$x = \texttt{elettroratio}$			
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)
	$x = \texttt{atmshare}$			
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)
	$x = \texttt{logTA}$			
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_α is the $\alpha-$th quantile of x.
Standard errors in brackets; *p<0.1; **p<0.05; ***p<0.01.

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_α is the α−th quantile of x.
Standard errors in brackets; *p<0.1; **p<0.05; ***p<0.01.

TABLE 9

Bandwidths

	Dependent variable: `logcostratio`	
	LSCV	AIC
`logTA`	1.330	0.795
`logwage`	1.934	3,285,958.000
`elettroratio`	64,888.950	0.367
`atmshare`	0.065	418,817.700
`bank`	0.000	0.001
`year`	0.559	1.000
Observations	2,708	2,708
R^2	0.994	0.973