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A long-term analysis of efficiency in the Italian banking system from 1861 to 2010

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ABSTRACT

In this paper, we analyse the performance of the Italian banking system in the 1861–2010 period. In this regard, we apply a stochastic frontier analysis cum ARDL procedure. First, we implement stochastic frontier analysis to the cost function of the Italian banking system in order to identify the years in which the banking system allocated its resources most efficiently. To this end, we propose a version of the stochastic frontier in which the inefficiency term is modelled as a linear function of the capital ratio and of the non-core ratio. The underlying hypothesis is that the efficiency of the banking system is guided by its degree of solvency and stability (capital ratio and non-core ratio, respectively). Finally, in order to verify the existence and stability of a long-term relationship between banking efficiency and capital ratio and non-core-ratio, we implement ARDL estimation. In so doing, we verify whether solvency and stability are two important factors in determining the efficiency of the Italian banking system in the long run. We show that the efficiency of the banking system is influenced negatively by the non-core ratio and positively by the capital ratio, respectively. Finally, only the non-core ratio influences the efficiency of the Italian banking system in the long run.

1. Introduction and background of literature

The banking sector plays an increasingly critical role in the development of the financial system. The efficiency and quality of the service offered by banks not only have significant effects on a country's economic growth, but also affect every aspect of people's daily lives (Wang et al., 2014). Banks are essential for the economic development of a country as they perform the fundamental function of selecting entrepreneurs and allocating financial and real resources. Given the prominent role of banks in the growth process of a country, the relevance of the studies on the performance of banks is evident (Lucchetti et al., 2001).

The banking industry has been the object of efficiency analyses by a significant number of researchers and it is probably the most heavily studied of all business sectors. Various methods have been applied in performance assessment problems, and banks complex production processes have further motivated the extension and improvement of these techniques (Paradi and Zhu, 2013). "Amongst the wide spectrum of modelling techniques in the banking sector Data Envelopment Analysis (DEA) is one of the most successfully used operational research technique in assessing bank performance," followed by other non-parametric techniques (Free Disposal Hull analysis (FDH)) and parametric techniques (e.g., Stochastic Frontier Analysis (SFA), Thick Frontier Approach (TFA), etc.) (for a survey, see Kumar and Gulati, 2014). From the survey by Paradi and Zhu (2013) on the performance studies of banks conducted with the DEA, it emerges that out of 195 published studies at the bank level, the main applications are: 1) efficiency changes over time due to banking liberalization and deregulation, market structure and economic environmental changes; 2) effects of ownership and bank types; 3) bank performance benchmark and improvement; and 4) international comparison. Instead, in a larger study, which considers a-parametric and parametric methods applied to the analysis of banks performance, Kumar and Gulati (2014) identify four broad non-mutually exclusive research areas in which scholars have focused on recent years. The first research area includes those empirical works which examined the impact of deregulation and liberalisation measures on the efficiency of the banking system. The second key area focuses on the issue of bank ownership and efficiency. The third significant area covered in this survey concentrates on the cross-country comparisons of bank efficiency. The final research area which has been explored by the scholars centres on the effects of mergers and ac-

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quisitions on the efficiency and productivity of acquiring banks. Obviously, other works have been developed over time and other possible research areas have been explored even though they have not emerged in the aforementioned surveys. This demonstrates the boundless scientific interest in analysing the efficiency of banks and equally suggests that more work is needed on the subject.

The interest in the study of the performance of banking industry is linked, in addition to its pre-eminent role in economic growth and development of the economics, to its continuous exposure to the numerous institutional developments and changes occurring in the history of countries and which emerge more clearly when studying long-term dynamics. The European banking scenario, more than any, appears to have been subject to numerous institutional changes, especially in the last century, and the effects and results on the performance of the banks of the related countries have been varied and subject in numerous studies (see Maudos et al., 2002; Casu and Girardone, 2010). Most of the studies conducted on the efficiency of European banks consider the bank production function, leaving the cost function of banks to the margin (see Paradi and Zhu, 2013). Furthermore, the analyses move from cross-sectional data to panel data from European countries, and the same data is used to conduct performance analyses on banks in individual European countries. In the latter case, the analyses are more detailed because the individual institutional categories of banks are considered, making it possible to assert the hypothesis that each category of bank has its own technology (see Paradi and Zhu, 2013; Kumar and Gulati, 2014). Some contributions analyse the individual institutional categories of bank (see amongst others, Destefanis, 1996; Lucchetti et al., 2001; Barra et al., 2016). One the one hand, this approach yields gains in data accuracy. On the other hand, it constrains the focus of the analysis on not very long historical periods, which implies losing information on the relevant institutional changes that occur in a given economy over time.

In light of the foregoing, the aim of our study is to fill some gaps in the empirical literature that examines the efficiency of banks. In this regard, we implement a stochastic frontier approach cum ARDL procedure on the data of the Italian banking system for the years 1861–2010. A single-stage approach is first applied to the measurement of efficiency and of its determination. Then, the dynamic relationship between efficiency scores and its determinants is explored within an ARDL setup. Specifically, *first* we study the performance of the Italian banking system as a whole, not distinguishing by institutional bank category, in order to implement a very long-term efficiency analysis (1861–2010). On this subject, Feng and Zhang (2012) note that little effort has been made in analysing the performance of large banks and the body of literature studying them has basically focused on the efficient use of hard production technologies based on information (for more details see Coles et al., 2004, Berger et al., 2005). *Secondly*, we are the first, to our knowledge, to conduct an efficiency analysis using historical series data by stochastic frontier analysis. Only Richmond (1999) and da Silva e Souza et al. (2020) propose the efficiency analysis on time series data but using Data Envelopment Analysis. The efficiency analysis on time series will allow us to trace the dynamics of the performance of the Italian banking system and to link the periods of greater or lesser efficiency to historical and economic events, and to institutional changes that affected Italy in the period 1861–2010. *Third*, we intend to study the microeconomic cost efficiency of the Italian banking system as a proxy of its ability to recognise the best customers and to support the real economy in the process of economic growth. The microeconomic cost efficiency is suitable for grasping the allocative function of banks as the ability to correctly use the available technology and optimally combine the inputs of the banking production process can be considered as necessary conditions for a correct allocation of resources. *Fourth*, the analysis of the long-term performance of the Italian banking system places us in front of historical and economic events, as well as institutional changes that may have influenced the efficiency of the Italian banking system. In order to take this issue into account, we model the inefficiency component of the cost function of the Italian banking system by adding dummies to control the historical events that have affected the Italian economy and, conversely, the Italian banking system; in addition, we calculate for the first time two indicators that will respectfully approximate the solvency and stability component of the Italian banking system (i.e., the capital ratio and the non-core ratio, see Hahm et al., 2013). The study of the bank efficiency and its relationship with the capital ratio and the non-core ratio are particularly relevant with respect to the Italian financial system, which has always been bank-orientated, while stock exchange has played a more marginal role, both in recent years and historically (Bartoletto and Garofalo, 2014; Rajan and Zingales, 2003). These two indicators, in addition to being a novelty in the field of bank efficiency studies, are two key factors in explaining the dynamics of the performance of the Italian banking system (see Hahm et al., 2013). *Finally*, when analysing a long-term period, it is fair to wonder whether the degree of solvency and stability are factors that influence the performance of the Italian banking system in the short and long term. This is a noteworthy result because it allows us to evaluate which effect of the two factors is to be considered temporary (short term) or permanent (long term), consequently alternating definitively the steady state of the performance of the Italian banking system. To this end, we implement an AutoRegressive Distributed Lag (ARDL) cointegration technique, a tool that will allow us to break down the effect of regressors on the efficiency scores of the Italian banking system in both short- and long-term effects. In addition, it will allow us to consider non-stationarity and potential endogeneity problems due to the dynamic nature of the efficiency scores. A different way of proceeding would have been to apply the efficiency analysis using the specification of the ARDL; unfortunately, this is not possible because the ARDL does not allow to obtain, at the same time, a measure of the performance of the Italian banking system. Therefore, this paper represents an enrichment of the literature on efficiency analysis and also a stimulus in theoretical and empirical research in the search for more efficient tools, from a computational point of view, to be applied to the dynamic efficiency analysis of time series.

The paper is organised as follows Section 2. introduces the historical evolution of the Italian banking system in order to identify the critical historical periods (e.g., World Wars, financial crises and institutional changes) that could have influenced the efficiency of the Italian banking system Section 3. deals with the empirical strategy adopted, presenting the methodological aspects of Stochastic Frontier Analysis and ARDL procedure Section 4. introduces the data used in the analysis and presents some stylised facts Sections 5 and 6 elaborate the main empirical findings and provide policy implications Section 7. concludes.

2. Historical evolution of the Italian banking system

In this section, we trace the main historical and economic events and institutional changes that have affected the Italian economy and that have had possible effects on the performance of the Italian banking system during the period 1861–2010. Specifically, we identify the following three sub-periods:

2.1. The period 1893- First World war (WWI)

The 1888–1893 banking crisis was largely due to the burst of the housing bubble in 1888. In this regard Bartoletto et al. (2018) in line with Reinhart and Rogoff (2009) showed that the banking crisis occurred around the peak of the cycle of housing price, confirming also for Italy the existence of a relationship between the banking crisis and the cycles of housing price. Several scandals in which issuing banks were involved, in particular the scandal of Banca Romana, also affected negatively the stability of the banking system. As a reaction to the severe financial crises, an important reform of the banking system was carried out with the new banking act of 1893, which led to the establishment of the Bank of Italy as new issuing bank together with the Bank of Naples and the Bank of Sicily (Bonelli, 1991). The stability and solvency of the Italian banking system was also affected by the international crisis of 1907, that caused a rapid decline in the equity price cycle. Banks that had invested large capitals in the Stock exchange registered increasing losses in their balance sheets. Panic and bank runs characterized this period, with a worsening of the performance of the banking system (Bonelli, 1971). The first World War represented a major shock for the economic and financial system. The slowdown of the economy since 1914 produced negative effects on the stability of the banking system. Indeed, many banks had solvency problems because of the high amounts of loans granted to companies that, in the meantime, had entered a crisis and could not repay the sums borrowed. For better understanding, we have to take into consideration that from 1894 to the eve of 1929 great contraction, the Italian financial system was characterised by the model of universal banks (mixed banks) that granted both short-term and long-term loans and this model were very active in the establishment of new industrial enterprises and in the expansion of the existing ones. This means that industrial crises had a major impact on the banking system because the model of mixed banking (banca mista) was characterised by a very close bank-industry relationship (Bianchi, 2013). Indeed, after the approval of the banking law in 1936, the expression “Special Credit Institutions” (Istituti di Credito Speciale) was introduced: such institutions mainly provided long-term credit, issuing bonds and deposits with agreed maturity, without collecting current accounts (De Bonis and Silvestrini, 2014).

2.2. The period 1929 - Second World War (WWII)

Second World War (WWII) captures the effect of the 1929 crisis, which led to the reorganization of the banking system through the banking law of 1936. This law, enacted during the severe economic and financial crisis of 1929–1935 (Ferri and Garofalo, 1994), has continued to regulate the Italian banking system even after the end of the fascist period and World War II, until the eve of the signing of the Maastricht Treaty. The banking law of 1936 sanctioned the end of the universal banking model and segmented the banking sector into two parts, namely short-term and long-term liability institutions (Gigliobianco and Giordano, 2010).

2.3. The period 1993 onwards

The period 1993 onwards captures the effects on 1993 banking law: the Italian banking system recorded a reduction in profitability margins which in 1994 reached the lowest levels recorded in the previous 30 years (Farabullini and Gobbi, 1996). The reduction in margins has resulted in large losses for banks. Indeed, during that period, the banking system was more vulnerable due to the difficulties linked to the reorganisation of services offered and to changes in the structure of costs under increasing competitive pressures. The crisis, which culminated in the deep recession of 1993, led to a sharp increase in non-performing loans, resulting in losses in both interest and capital, especially for those banks operating in the market segments most affected by the recession. Added to this were the effects of the currency crisis of 1992, which contributed to capital losses. Meanwhile, the banking system was undergoing a major restructuring resulting from the transposition of the new European directives. With the Amato law of 1990 and the new 1993 banking act, the Institute for the Industrial Reconstruction (Istituto per la Ricostruzione Industriale)'s public banks were first converted into joint-stock companies and then privatised (Bianchi, 2013). It was established the return to the universal bank and the overcoming of the specialization for maturities of the credit intermediation. This in-depth restructuring of the credit system has strongly impacted on bank efficiency because the increasing competition on national and international markets led to new strategies, such as mergers between different credit institutions and new tensions within the banking industry.

3. Methods

In this section we present the methods of analysis. In the first step, we apply the stochastic frontier to the cost function of the Italian banking system in order to identify the years in which the banking system allocated its resources most efficiently. To this end, we also propose a version of the stochastic frontier in which the inefficiency term is modelled as a linear function of the capital ratio and of the non-core ratio. The underlying hypothesis is that the efficiency of the banking system is guided by its degree of solvency and stability. In the second step, in order to verify the existence and stability of a long-run relationship between banking efficiency and capital ratio and non-core-ratio, we implement ARDL estimation. In this way, besides verifying the presence variable omission in the determination of banking system efficiency, we test whether solvency and stability are two relevant drivers of inefficiency in the long run.

3.1. Stochastic frontier analysis

Lucchetti et al. (2001), in their study on the effects of the efficiency of the banking system on economic growth, highlight the difficulty of having a single and shared measure of efficiency. They review the concepts of macroeconomic allocative efficiency, microeconomic technical efficiency, and microeconomic efficiency (for more details, see Lucchetti et al., 2001). The concept of microeconomic efficiency, in addition to representing a better proxy for the development of the financial system, allows to overcome the measurement problems inherent in the other two concepts of efficiency. For this reason, in this work, we will refer to the notion of microeconomic efficiency. Therefore, we analyse the cost efficiency of the Italian banking system in the period 1861–2010. Cost efficiency analysis allows to measure the ability to produce, in the most economical possible way, a given set of outputs, compatibly with the available technology and input prices (see Lucchetti et al., 2001). In particular, cost-efficiency analysis allows to measure the ability of the banking system to use the available technology correctly while minimising costs. The latter is a necessary condition for a correct allocation of resources on the part of the banking system. In other words, given our analysis of aggregate national data over 150 years of Italian history (from the Unification of Italy to 2010), we identify the years[1] in which the Italian banking system has efficiently allocated its resources and the years in which its efficiency has shown negative/positive trends, trying to justify them through the numerous historical, economic, and institutional events that have taken place during the period under investigation.

As part of the cost efficiency analysis, the representation of the production process can be expressed implicitly as follows:

$$TC = TC(p,\ q,\ u) \tag{1}$$

[1] Our decision-making units are the years of analysis.

Where TC represents variable total costs, p is the vector of input prices, q is the vector of the quantities produced and u are the residuals, formed by a component that measures inefficiency and by a component that captures the random error.

The efficiency analysis for the Italian banking system will be implemented through Stochastic Frontier Analysis (SFA). Before proceeding with the definition of the equation to estimate, it is necessary to define the technology underlying Eq. (1). In general, a Cobb-Douglas specification is assumed, although the empirical literature favours a more flexible functional form such as the translog function. Unfortunately, the latter generates very serious multicollinearity problems, whose effect (as in our case) hinder the convergence of the maximum likelihood estimator (in this regard see Lucchetti et al., 2001). Based on the above, we propose a Cobb-Douglas cost function linearised using logs:

$$\begin{aligned} ct_t &= a_0 + b_1 q_{1t} + b_2 q_{2t} + b_3 p_{1t} + b_4 p_{2t} + b_5 p_{31t} + b_6 p_{32t} + \varepsilon_t \\ \varepsilon_t &= u_t + v_t \\ v_t &\sim N\left(0, \sigma_v^2\right) \\ u_t &\sim \mathcal{F} \end{aligned} \quad (2)$$

where, the dependant variable ct_t is the natural log of total costs at time t, while q_{1t} and q_{2t} are respectively the natural log of total loans and deposits and the natural log of the total revenues from services to customers at time t. The use of stock variables to approximate the value of production can be justified considering that the balance sheet components (loans and deposits) entail a continuous production of services, so as to constitute themselves acceptable proxies of bank production (see Lucchetti et al., 2001). Furthermore, in addition to loans and deposits, some income statement items (**revenues from customer services**) were also considered, to capture the contribution to production deriving from those services provided by banks that do not find an adequate response in the movements of loans and deposits.

Instead, with p_{1t}, p_{2t}, p_{31t} and p_{32t} we indicate the natural log of the price of fixed capital at time t (**fixed assets**, p_{1t}), the natural log of unit cost of labour (p_{2t}), the natural log of the **interest rates on loans** (p_{21}) and the natural log of the **interest rates on security** (p_{22}) at time t. The last two variables represent a proxy of the price associated with the fundraising at time t (see Sealey and Lindley, 1977; Beccalli et al., 2006). Finally, the composed error term ε_t is the sum of a normally distributed disturbance, v_t, representing measurement and specification error, and a one-sided disturbance, u_t, representing inefficiency. Moreover, u_t and v_t are assumed to be independent of each other and independent and identically distributed across observations.

A convenient parameterisation includes the variance decomposition as $\sigma^2 = (\sigma_u^2 + \sigma_v^2)$, $\lambda = \frac{\sigma_u}{\sigma_v}$. If $\lambda \to +\infty$, we get the deterministic frontier. If $\lambda \to 0$, there is no inefficiency in disturbances, so every statistical unit lays on the frontier and the model can be estimated by OLS. In particular, a deterministic frontier involves that any shift from the frontier (both from random noise or misspecification of the functional form or data errors) is treated as inefficiency. Thus, the error term contains cost the volatility (albeit temporary) of the production units: the best-practice frontier is then stochastic and depends on various random occurrences, not all under the direct control of researcher. Based on the above, an assumption about the $\mathcal{F}$ distribution of the inefficiency term is needed to estimate the model Aigner et al. (1977). assumed a half-normal distribution, that is, $u_t \sim N^+(0, \sigma_u^2)$, while Meeusen and van den Broeck (1977) opted for an exponential distribution, $u_t \sim \varepsilon(0, \sigma_u)$. Other commonly adopted distributions are the truncated normal distribution (Stevenson, 1980) and the gamma distribution (Greene, 2003; for more details see Belotti et al., 2013).

Given the length of the historical period analysed, it is important to check, in addition to historical and economic events, and institutional changes, for factors that could have influenced the stability and solvency of the Italian banking system over the years (Jordà et al., 2017). For this reason, we estimate a further model (model (3)) that will take these two factors into account. As suggested by Jordà et al. (2017), a measure of the financial strength of the banking system is given by the Tier 1 capital ratio, given by the following ratio: $Capital\ ratio = \frac{Capital}{Total\ assets}$, while a measure of the stability of the banking sector is given by the non-core ratio, given by the following ratio: $Non-core\ ratio = \frac{Other\ liabilities}{Deposits + Other\ liabilities}$. The Tier 1 Capital Ratio is a variable, defined by the Basel Committee, which identifies the main components of a bank's equity capital. It represents a proxy of the amount of capital that allows to absorb losses without affecting the interests of depositors. Therefore, it determines the ability to operate in conditions of solvency. It follows that its increase is intended as an improvement of the banking system's health. On the contrary, an increase in the non-core must be read as a clear sign of a deterioration in the health of the banking system: Hahm et al. (2013) shows that an increase in the inflows of non-core funds can destabilise the banking system. Furthermore, we consider dummies that allow us to check for the most significant historical and economic events, and institutional changes that could have influenced the efficiency of the Italian banking system (see Section 2). In particular, we consider: 1) the 1893-WWI dummy which captures the effects of the crisis of 1893 and the First World War; 2) the 1929-WWII dummy which captures the effects of the 1929 crisis and the Second World War; 3) the dummy which takes into account the effects caused by the introduction of the 1993 Consolidated Banking Act (CBA). The first two dummies represent the joint effect of two crises close to each other, for this reason we have considered two rather than four. The choice of combining two crises in a single dummy follows two orders of reason: 1) too many dummies generate a multicollinearity problem; 2) every crisis has a trigger period which must be sought in the causes that precede it and which determine it, and a period of propagation that goes beyond the year of the identification of the crisis itself. Since each of the first two dummies is characterised by two relevant crises, which started before the same date and which lasted over time, we considered it appropriate to merge two dummies into one, obtaining a dummy that extends from 1893, but which starts earlier, up to the First World War, and a dummy that extends from 1929, but which starts before, up to the Second World War. The relationship amongst these variables and the efficiency of the banking system can be tested, by including both variables in the inefficiency component u_t. In other words, in the case of half-normal distribution, the inefficiency term would be modelled as follows: $u_t \sim N^+(m_t, \sigma_u^2)$. The same reasoning can be extended to the other distributions of the inefficiency term. In other words, it is possible to model the inefficiency component as a linear function of the above variables. Specifically, we will have:

$$\begin{aligned} m_t = {} & \delta_0 + \delta_1 Capital\ ratio_t + \delta_2 Non-core\ ratio_t + \delta_3 1893 \\ & - WWI + \delta_4 1929 - WWII + \delta_5 CBA\_1993 \end{aligned}$$

This is the *inefficiency function*. It differs from the cost function defined in Eq. (2), which we will define as *frontier function*. It is important to bear in mind that in the case of the inefficiency function, a negative sign of the parameter associated with the Capital Ratio will mean a reduction in the inefficiency of the banking system in the allocation of resources. On the contrary, in the case of a positive sign of the coefficient associated with the non-core ratio, it must be interpreted as an increase in the inefficiency of the banking system in terms of resource allocation. For the dummies, which reflect the effect of the periods of crisis and wars considered, we expect a positive sign as they reduce the efficiency of the Italian banking system.

Models (2) and (3) will be implemented to estimate the cost function; furthermore, we will use Akaike's Information Criterion (from now on AIC) and the Bayesian Information Criterion (from now on BIC) and the log-likelihood criterion in order to select the best model.

3.2. ARDL approach

In this section we present the ARDL approach, which will be applied to the efficiency scores obtained from the first model. Therefore, we will consider raw efficiency scores, i.e., the efficiency scores obtained without removing the effect of capital ratio and non-core ratio.

In order to verify the existence of a long- and short-run relationship between efficiency scores (eff) and capital ratio and non-core ratio, we implement the AutoRegressive Distributed Lag (ARDL) cointegration technique. Introduced by Pesaran and Shin (1999) and Pesaran et al. (2001), this method features several advantages over the residual-based approach proposed by Engle and Granger (1987) and the maximum likelihood-based approach proposed by Johansen and Juselius (1990) and Johansen (1988). One of the important features of this approach is that it is free from unit-root pre-testing and can be applied regardless of whether variables are integrated of order zero, order one or fractionally integrated. In addition, it does not matter whether the explanatory variables are endogenous (see Pesaran and Shin, 1999).

The ARDL cointegration procedure involves three steps:

1. **Determination of the Existence of a Long-Run Relationship amongst the Variables.** In the first stage, the existence of a long-run relation amongst the variables under investigation is tested by computing the Bound F-statistic (bound test for cointegration). The bound F-statistic is computed on each of the variables individually, as they stand as endogenous variables while all others are assumed to be as exogenous. In practice, testing the relationships amongst the forcing variable(s) in the ARDL model leads to testing the long-run relationship amongst the underlying variables. In doing so, current values of the underlying variable(s) are excluded from the ARDL model approach to cointegration.
2. **Choosing the Appropriate Lag Length for the ARDL Model/Estimation of the Long-Run Estimates of the Selected ARDL Model**. If a long-run relationship exists between the underlying variables, while the hypothesis of no long-run relationship between the variables in the other equations cannot be rejected, then the ARDL approach to cointegration can be applied. Selecting the appropriate lag length for each of the underlying variables in ARDL models is very important as it affects the properties of the error terms which are required to be Gaussian (i.e. standard normal error terms that do not suffer from non-normality, autocorrelation, heteroskedasticity, etc.). In order to select the appropriate model of the long-run underlying equation, it is necessary to determine optimum lag length(k), using model order selection criteria, such as the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) or the Hannan-Quinn Criterion (HQC). In our analysis, we use the AIC criterion, so that the model with the lowest AIC is considered as the "best" option amongst all models specified.
3. **Reparameterisation of the ARDL Model into an Error Correction Model**. When non-stationary variables are regressed in a model, we may get results that are spurious. One way to solve this problem is to differentiate the data in order to achieve stationarity. In this case, parameter estimates are correct, and the spurious relation problem is resolved. However, the regression equation only produces the short-run relationship between the variables. It does not provide any information about the long-run behaviour of the parameters in the model. This constitutes a problem since researchers are mainly interested in long-run relationships between the variables under consideration. In order to resolve this, the concept of cointegration and the error correction model (ECM) become imperative. With the specification of ECM, we now have both long-run and short-run information incorporated.
In particular, the error correction model of the ARDL model related to our case is as follows:

$$\begin{aligned}\Delta eff_t = {} & \alpha_0 + \alpha_1 eff_{t-1} + \alpha_2\ capital\ ratio_{t-1} \\ & + \alpha_3 non-core\ ratio_{t-1} + \alpha_4 1893 - WWI_{t-1} \\ & + \alpha_5 1929 - WWII_{t-1} + \alpha_6 CBA\_1993_{t-1} \\ & + \sum_{i=1}^{n} \beta_{1i} \Delta eff_{t-i} + \sum_{i=1}^{n} \beta_{2i} \Delta capital\ ratio_{t-i} \\ & + \sum_{i=1}^{n} \beta_{3i} \Delta non-core\ ratio_{t-i} + \sum_{i=1}^{n} \beta_{4i} \Delta 1893 \\ & - WWI_{t-i} + \sum_{i=1}^{n} \beta_{5i} \Delta 1929 - WWII_{t-i} \\ & + \sum_{i=1}^{n} \beta_{6i} \Delta CBA\_1993_{t-i} + \varepsilon_t \end{aligned} \tag{3}$$

Where *eff* is the efficiency score of the first model, capital ratio, non-core ratio, 1893-WWI, 1929-WWII, CBA_1993 are the same variables defined above, Δ is the first difference operator, α_0 the drift component and ε_t is the usual white noise error term. Coefficients $\alpha_1,\ \alpha_2, \alpha_3, \alpha_4,\ \alpha_5\ and\ \alpha_6$ represent long-run relationships, whereas the remaining expressions with summation sign ($\beta_1,\ \beta_2,\ \beta_3, \beta_4, \beta_5\ and\ \beta_6$) represent the short-run dynamics of the model.

Eq. (3) may also be written in the following way:

$$\begin{aligned}\Delta eff_t = {} & \alpha_0 + \sum_{i=1}^{n} \beta_{1i} \Delta eff_{t-i} + \sum_{i=1}^{n} \beta_{2i} \Delta capital\ ratio_{t-i} \\ & + \sum_{i=1}^{n} \beta_{3i} \Delta non-core\ ratio_{t-i} + \sum_{i=1}^{n} \beta_{4i} \Delta 1893 \\ & - WWI_{t-i} + \sum_{i=1}^{n} \beta_{5i} \Delta 1929 - WWII_{t-i} \\ & + \sum_{i=1}^{n} \beta_{6i} \Delta CBA\_1993_{t-i} + \rho EC_{t-1} + \varepsilon_t \end{aligned} \tag{4}$$

where ρ is the speed-of-adjustment parameter and EC is the residual obtained from the estimated cointegration model of Eq. (3). The error correction coefficient (ρ) is expected to be lower than zero and implies the cointegration relationship.

In order to investigate the existence of long-run relationships amongst the variables in the system, the bound test approach developed by Pesaran et al. (2001b) was employed. The bound test is based on the Wald or F-statistic and follows a non-standard distribution. The null hypothesis of no cointegration $H_0: \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = 0$ is tested against the alternative hypothesis of cointegration $H_1: \alpha_1 \neq \alpha_2 \neq \alpha_3 \neq \alpha_4 \neq \alpha_5 \neq \alpha_6 \neq 0$ Pesaran et al. (2001). provide the two sets of critical values in which the lower critical bound assumes that all the variables in the ARDL model are I(0) and the upper critical bound assumes that the variables are I(1). If the calculated F-statistic is greater than the appropriate upper bound critical values, the null hypothesis is rejected, implying cointegration. If the above statistic is below the lower bound, the null cannot be rejected, indicating the lack of cointegration. If, however, it lies within the lower and upper bounds, the result is inconclusive.

Cointegration does not necessarily mean that the estimated coefficients are stable. If the coefficients are unstable, the results

Table 1
Statistical summary.

Variables	Observations	Mean	Standard Deviation	Min	Max
Total Costs (cv)	150	4233.417	7198.668	16.464	24,620.23
Total Loans and Deposits (q_1)	150	11.791	1.897	7.516	14.809
Total Revenues from Services to Costumers (q_2)	150	8.016	2.281	3.493	11.419
Fixed Assets (p_1)	150	7.126	1.924	3.255	10.593
Unit cost of labour (p_2)	150	69.036	8.946	47.052	91.883
Interest rates on Loans (p_{31})	150	1.256	0.528	0.144	2.710
Interest rates on Security (p_{32})	150	1.832	0.391	1.065	3.009
Inefficiency Components					
Non-Core Ratio	150	0.171	0.090	0.029	0.447
Capital Ratio	150	0.124	0.055	0.021	0.200
1893_WWI	150	0.233	0.424	0	1
1929_WWII	150	0.126	0.333	0	1
CBA1993	150	0.12	0.326	0	1

will be unreliable (Bahmani-Oskooee and Chomsisengphet, 2002). In order to test long-run parameter stability, Pesaran and Pesaran (1997) suggest applying the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of recursive residuals squared (CUSUM squared) tests proposed by Brown et al. (1975) to the residuals of the ECMs to test for parameter constancy.[2]

4. Data

The empirical analysis of the cost function of the banking system requires to identify the variables necessary to implement econometric estimates. In this regard, variable selection is a very thorny issue (for more discussion, see Favero and Papi, 1995). In line with Lucchetti et al. (2001), we choose to follow a hybrid approach, considering amongst bank outputs both flow variables and stock variables. Unlike bank efficiency studies conducted on recent years and on shorter data series, by using long-term series we are unable to distinguish banks by institutional category and, consequently, we use the aggregate data. Obviously, it would have been appropriate to work on data that distinguish banks by institutional category as the empirical literature shows that there are substantial differences in the efficiency dimension amongst the different categories; unfortunately, when working on long-term series we have to use highly aggregated data which causes the loss of much valuable information in the study of banking efficiency (see Destefanis, 1996; Barra et al., 2016). In our work time series of the Italian banking system covers all the institutional categories. In particular, the time series include both commercial banks that could raise short-term funds (aziende di credito) and special credit institutions (istituti di credito speciale), two institutional categories that existed until the 1990s.

Table 1 shows the statistical summary of the variables.

Our analysis is based on the Bank of Italy's historical dataset of assets, liabilities, costs and revenues of the Italian banking sector from 1861 to 2010. The reconstruction of historical data was operated by De Bonis et al. (2012), who have estimated total assets and total liabilities. Total assets are given by the sum of loans, debt securities held, shares and other equity and fixed assets. Total liabilities are given by the sum of deposits, debt securities issued, capital and reserves. The series includes all the institutional categories of banks operating in Italy and the branches of foreign banks. Unfortunately, the Bank of Italy's historical dataset does not include the labour costs of the banking sector. As explained by De Bonis et al. (2012), this is due to the lack of economic accounts (*conti economici*) of the banks and to the prevalence of patrimonial sheets. Only for issuing banks labour costs were available from 1927. For this reason, we have reconstructed the unit labour costs and the number of workers of the banking sector from 1975 to 2010, starting from the Annual reports of the Bank of Italy.[3] Finally, we have estimated the missing values of unit labour costs from 1861 to 1974 (for more details on the estimate of the series of unit labour costs, see the Appendix).

In Fig. 1, we show the long-run pattern of loans and deposits is Italy from 1861 to 2010 expressed in real terms. Since the data on loans and deposits in De Bonis et al. (2012) are expressed in current values, we had to deflate. For this purpose, we used the GDP deflator calculated by Baffigi (2017).

During the first phase, which runs from 1861 until the Giolitti period, we see that the curves of loans and deposits substantially overlap. The growth of deposits and loans was very intense until the eve of the First World War, with a slowdown during the banking crisis of 1887–1893 that led to the birth of the Bank of Italy. During the First World War, there was a reduction in both loans and deposits, but once the conflict ended, both started to grow rapidly again, reaching a peak in 1933. At that point, the Great Depression fully manifested its consequences, causing a sharp reduction in loans and deposits. The reduction continued during the Second World War, and in 1945 the ratio between deposits and GDP reached the minimum peak of 15%, thus returning to the levels of the mid-1880s. Differently, during the two decades 1950–1970, there was an exceptional growth in loans and deposits, and the ratio of loans to GDP reached the maximum peak of 73%, while the deposits-to-GDP ratio was equal to 71%.

From the mid-1970s until 1990, deposits exceeded loans due to a greater propensity of banks towards other investments, including the purchase of public securities, mainly due to monetary measures to reduce inflation. The end of the Bretton Wood system, the 1970′s oil crises, the increase of salaries, and public debt fuelled inflation. One of the measures adopted was the “divorce” in 1981 between the Treasury and the Bank of Italy, with which the autonomy of monetary policy with respect to fiscal policy was established. After the divorce, the Bank of Italy would no longer be forced to buy public debt securities. The Government was likewise constrained to pay higher interest rates on public debt, and one

[2] To test a structural stability of the model there are different tests based on recursive residuals. The two most important ones are the CUSUM and the CUSUM SQUARES, with the data ordered chronologically, rather than according to the value of an explanatory variable. The CUSUM test is based on a plot of the sum of the recursive residuals. If this sum goes outside a critical bound, it may be concluded that there was a structural break at the point at which the sum began its movement toward the bound. The CUSUM SQUARES test is similar to the CUSUM test, but plots the cumulative sum of squared recursive residuals, expressed as a fraction of these squared residuals summed over all observations.

[3] Annual report, years 1975-2010, available on www.bancaditalia.it We express our gratitude to Riccardo De Bonis (Bank of Italy) for the important suggestions about the source where to find the unit labour costs and we thank him also for the suggestions about the elaboration of data. Also, we want to thank the Study Office of the Italian Banking Association (ABI) for the important insights.

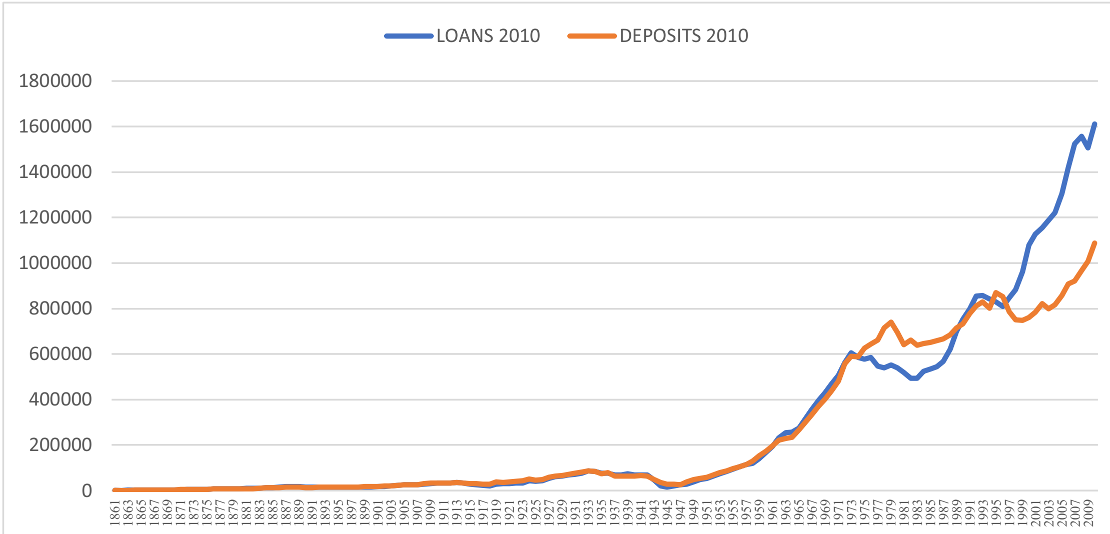

Fig. 1. Bank loans and deposits, 1861–2010 (millions euro 2010). *Source: our calculations on De Bonis et al. (2012); Baffigi (2017).*

of the effects was an increase in the amount of government debt securities in the balance sheets of banks, not only for compliance with reserve requirements but also because government debt securities had become a safe and profitable investment. After the privatisations of the early 1990s, the amount of loans exceeds that of deposits. Following the signing of the Maastricht Treaty, loans grew more than deposits, thanks to the abolition of the constraints, the reduction of interest rates, and the increase in banking competition. From 2010, loans had exceeded GDP, while the ratio of deposits to GDP was about 70%.

The long-term efficiency study requires to consider in the analysis factors that could have had effects on the dynamics of the efficiency of the Italian banking system. In this regard, we consider three dummies that we have identified by taking into account the various significant historical events that occurred in Italy during the period 1861–2010 (see Section 2). Furthermore, it is necessary to consider specific factors that have influenced the stability and solvency of the Italian banking system. In this regard, we identify and calculate two indicators: the non-core ratio (proxy for stability) and the capital ratio (proxy for solvency). The capital ratio corresponds to Basel III “leverage ratio”, given by Tier 1 capital divided by total assets (Jorda et al., 2017). Non-core ratio corresponds to the ratio of “Other liabilities” over the sum of deposits with other liabilities (Jorda et al., 2017). The intense growth of global financial markets, fuelled by the rapid development of information and communication technologies, resulted in a high degree of financial interdependence amongst countries. These developments highlighted the importance of the cooperation between central banks for promoting the adoption of minimum standards in banking supervision, with the aim to preserve global financial stability (Bordo and Toniolo, 2008). The so-called Basel process played a central role in international cooperation toward global standards in banking supervision (Kapstein, 1994). An important stimulus in this direction was given by the end of Bretton Woods system in 1971, the oil price shocks of 1973–1974, and the collapse of Bankhaus Herstatt and Franklin National Bank, which led the G10 Basel Committee on banking supervision, which gathered in Basel at the Bank for International Settlements (BIS) ,[4] to work on the definition of minimum capital requirements (Toniolo, 2005). With the 1988 Basel Capital Accord, a set of minimum capital standards for internationally active banks (Basel I) became globally accepted. In addition, the 1992 Maastricht Treaty, and the achievement of the European Monetary Union (EMU) played a central role for the development of an effective monetary and financial international cooperation (Clement, 2008). Furthermore, the 1994–1995 Mexican financial crisis and the 1997 Asian financial crises highlighted the need to extend the G10 system of financial supervision also to emerging countries and, at the same time, the need to further enhance international cooperation amongst financial supervisors (Kapstein, 2008). The minimum capital standards were revised in 2004 (Basel II), with the aim to adapt standards to advances in risk management techniques (Borio and Toniolo 2008). The 2007–2008 global financial crisis showed several weaknesses of the Basel II standards, amongst these, first and foremost, the quantity and quality of capital requirements. As a reaction, the Basel Committee promoted new regulatory reforms between 2010 and 2017 called the Basel III reforms (Signorini, 2021). The aforementioned reforms have led to a significant strengthening of the capital and liquidity of banks, increasing market confidence in their soundness and their ability to absorb large shocks.[5] Fig. 2 shows our reconstruction of the non-core ratio, which displays a cyclical pattern, with long waves of recovery and reduction. In all, four main phases may be distinguished. The first wave goes from the Unification of Italy to the end of World War I. We can see that the increase in the non-core ratio was particularly rapid from 1886, and after the peak of 29% in 1891, while the non-core ratio dropped to 3% in 1920. The second wave goes from the fascist period to the end of World War II. The third wave starts with the 1947 credit crunch promoted by president Einaudi, aiming to reduce the hyperinflation that soared during World War II. The fourth wave started in 1992, together with the signing of the Treaty of Maastricht, and represented a phase with the highest levels of non-core ratio. Considering a period of 150 years indeed, the highest level was reached in 2009,

[4] BIS was created in 1930 in Basel, with the aim to promote central bank cooperation. In addition, the institution of BIS as “international bank”, was seen as a guarantee for the management of future payments of the German reparations. Despite increasing international tensions during the 1930s, central bank governors regularly meet, every month, at the Bank for International Settlements in Basel (Toniolo, 2005, 2011).

[5] Over time, the Committee’s operational modalities and the forms of its interaction with the market have also changed, because it was decided to broaden the participatory base, including large emerging economies. The extension of the Basel Committee to the major emerging economies was inevitable. Today the Member States are about thirty, much more diverse than the group of the original countries (Signorini, 2021).

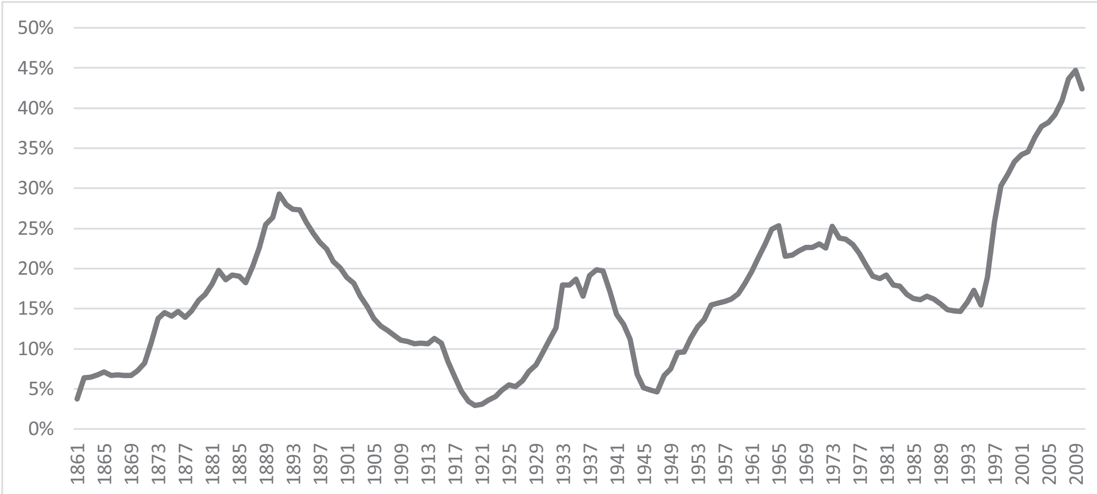

Fig. 2. Long-term pattern of the non-core ratio (1861–2010). *Source: our calculations on* De Bonis et al. *(2012).*

with a non-core ratio equal to 49%, which reflected the difficulties that the Italian economic and financial system was experiencing following the international crisis of 2007.

The first wave is particularly interesting, since it features a first jump in the non-core ratio, after the first reform of issuing banks in 1874, which established that only six banks could emit money, namely *Banca Nazionale, Banco di Napoli, Banco di Sicilia, Banca Romana, Banca Nazionale Toscana* and *Banca Toscana di Credito*. This is an important aspect to consider, because during this period, the loans granted by issuing banks were higher than those granted by commercial banks. To be more precise, in the first years after the unification of Italy, the support granted by issuing banks to the economy was very important, due to the backwardness of commercial banks. Issuing banks indeed operated non only with other banks but also with private companies (lending them money), and until the 1870s the loans of issuing banks were higher than those of commercial banks. In particular, the loans from issuing institutions represented 71% of the total in 1870, while commercial banks provided less than 30%. In addition, the main investment bank, *Credito Mobiliare* benefitted from the support of *Banca Nazionale*, which was the most important issuing bank. Starting from the new banking law of 1874, the loans granted by issuing banks, while remaining important, significantly decreased, also thanks to the development of the activity of investment banks, such as *Credito Mobiliare* and *Banca Generale*, and from 1894, thanks to German-style universal banks (mixed banks).

The second jump of non-core ratio corresponds to the years before the banking crises of 1893, mainly caused by the burst of an asset bubble, which fuelled a more rapid increase of the non-core ratio, until the peak of 29% in 1891. The crisis of the Italian banking sector was severe, and the issuing banks were particularly hit. After the scandal of the *Banca Romana*, which issued duplicates of banknotes already issued, a new banking law was approved in 1893, establishing the reduction of the issuing banks from six to three. Banking law n. 449 of 10 August 1893, authorised the creation of the Bank of Italy, through the merger of *Banca Nazionale degli Stati Sardi, Banca Nazionale Toscana* and *Banca Toscana di Credito*.

The issuing privilege, however, was not yet reserved to the Bank of Italy alone, because *Banco di Napoli* and *Banco di Sicilia* also retained the privilege of the issue. Another important novelty in the banking sector was the birth of mixed banks, such as *Banca Commerciale* founded in Milan in October 1894, whose initial capital was for the most part subscribed by German banks. *Credito Italiano* was established in February 1895, following the merger of some banking companies, including *Banca di Genova*, and thanks to the contribution of mainly Italian capital, while foreign capital (mostly German and Swiss) played a more marginal role (Confalonieri, 1974). In 1898, another mixed bank was founded, *Società Bancaria Italiana* (SBI), which was born only and exclusively with national capitals, thanks to the merger of pre-existing banking companies, and the participation of numerous private bankers. In 1898, another important mixed bank was established, i.e. *Banco di Roma* (Confalonieri, 1982, 1994). Mixed banks, also called universal banks, were unspecialised banks offering both short-term and medium-long term loans; they were very active in the stock exchange market, participating in the establishment and recapitalisation of industrial companies and carry overs shares (*riporti su azioni*). The 1893 banking reform contributed to the reduction of non-core ratio. Differently, the rapid increase and high levels of the non-core ratio from 1995 to 2010 show lower stability and strength of the banking system during this period.

5. Results of the stochastic frontier analysis

Table 2 reports the results of the empirical analysis. As anticipated in Section 2, we estimate two models and we implement four estimates for each model, each conditional on a given distribution of the inefficiency component (exponential, half-normal, truncated normal and gamma distribution). For both models we omit the estimate with the gamma distribution of the term inefficiency because the estimator features convergence problems. In general, parameter λ is always significant, indicating that deviations from the frontier do not depend entirely on random noise, but also on technical inefficiency. Model specification seems robust with respect to distributional assumptions: coefficients do not differ much, for any hypothesis on the error term. For both models, the t-normal specification of the inefficiency term minimises the AIC and BIC criteria and maximises the Log-likelihood. For this reason, we will comment only on the results of these models.

In both models, the parameters associated with the regressors of the frontier function show the expected positive sign, in line with the literature that studies banking efficiency (see Lucchetti et al., 2001). We observe the greater weight of loans and deposits compared to revenues from services. As regards the results of the inefficiency function, it is interesting to note that the parameters associated with the capital ratio and the non-core ratio present the expected signs and are both significant. In particular,

Table 2
stochastic cost frontier under several error distribution assumptions.

	First model				Second model	
	(exponential) TC b/se	(hnormal) TC b/se	(tnormal) TC b/se	(exponential) TC b/se	(hnormal) TC b/se	(tnormal) TC b/se
Frontier function						
q_1	0.394***	0.329***	0.648***	0.732***	0.735***	0.641***
	(0.09)	(0.01)	(0.06)	(0.11)	(0.08)	(0.06)
q_2	0.418***	0.577***	0.560***	0.051	0.050	0.175***
	(0.08)	(0.02)	(0.04)	(0.08)	(0.06)	(0.05)
p_1	−0.010	0.250***	0.243**	0.253**	0.197*	0.189***
	(0.14)	(0.04)	(0.12)	(0.10)	(0.10)	(0.03)
p_2	0.425*** (0.03)	0.294*** (0.005)	0.300** (0.02)	0.222** (0.03)	0.259** (0.03)	0.245*** (0.03)
p_{31}	−0.004	0.318***	0.302***	0.051	−0.018	0.110***
	(0.09)	(0.02)	(0.09)	(0.07)	(0.06)	(0.02)
p_{32}	−0.058	0.318***	0.489***	0.736***	0.657***	0.437***
	(0.15)	(0.02)	(0.15)	(0.10)	(0.09)	(0.09)
Constant	−4.963***	−5.400***	−5.470***	−7.154***	−7.072***	−6.616***
	(0.83)	(0.37)	(0.39)	(0.60)	(0.456)	(0.25)
Usigma- Inefficiency function						
Non-core ratio				7.762*	9.178***	10.442***
				(4.04)	(3.00)	(2.46)
Capital ratio				−9.005*	−9.287**	−6.157***
				(5.38)	(3.69)	(2.56)
1893-WWI				3.687***	2.908***	3.829***
				(1.13)	(0.662)	(0.49)
1929-WWII				0.226	0.048	0.253
				(0.703)	(0.49)	(0.521)
CBA_1993				4.681***	4.130***	3.961***
				(1.19)	(0.90)	(0.77)
Constant	−3.621***	−2.013***	4.454	−2.944***	−1.822***	−2.616***
	(0.38)	(0.12)	(3.10)	(0.93)	(0.67)	(0.54)
Vsigma						
Constant	−4.177***	15.676***	−6.397***	−5.233***	−6.038***	−6.430***
	(0.34)	(1.14)	(0.71)	(0.40)	(0.60)	(0.5)
Mu†						
Constant			0.204***			−1.154
			(0.06)			(1.94)
sigma_u	0.163***	0.363***	0.267***			
	(0.031)	(0.025)	(0.03)			
sigma_v	0.123***	0.028*	0.041***	0.073***	0.048***	0.04***
	(0.021)	(0.015)	(0.705)	(0.014)	(0.014)	(0.010)
Lambda	1.32***	12.889***	227.177***			
	(0.048)	(0.035)	(14.17)			
AIC	−39.915	−54.802	**−59.150**	−44.454	−59.076	**−71.740**
BIC	−14.388	−32.112	**−36.459**	−2.30	−16.927	**−32.602**
Log-likelihood	28.957	35.401	**37.575**	36.227	43.538	**48.870**

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$; (): standard errors; †: half-normal distribution has mean μ=0.

the variable that mainly influences the efficiency of the banking system, reducing its resource allocation capacity (i.e., the parameter has a positive sign), turns out to be the non-core ratio. The parameter associated with the capital ratio, instead, has an expected negative sign (an increase leads to a reduction in the inefficiency of the banking system). Finally, we verify that only the 1893-WWI and CBA1993 dummies are significant and show a positive sign: in the two sub-periods affected by the dummies, the Italian banking system experienced a reduction in performance. Furthermore, as regards the efficiency scores of the Italian banking system in the period 1861–2010, we note that the average score stands for the various estimates implemented around 0.80. Moreover, the minimum value of about 0.30 is reached in 2009; on the contrary, the maximum value is about 0.98 and is reached in 1922, probably as a result of the development of universal banks, as seen before (see Table 3) Fig. 3. shows the temporal evolution of the efficiency scores of the estimates of the two models under the hypothesis of t-normal distribution of the inefficiency component. In general, the two series show the same trend during the period of analysis. We can observe that the series of the efficiency scores of the second model dominates the series of scores of the first model in the 1861–1894-time interval, highlighting greater stability and strength of the banking system in this sub-period. On the contrary, we observe a dominance of the series of efficiency scores of the first model over the efficiency scores of the second model in the 1960–1973 and 1995–2010 intervals, unfolding lower stability and strength of the banking system in these two sub-periods.

In order to understand the greater instability of the banking system during the 1960–1973 period, we must consider the industrial development occurred during the 1950s and 1960s which determined a deep transformation of the Italian economy and the financial system. In particular, during the 1950s there was a strong growth in the stock exchange, favoured by the reduction in interest rates and the opening of international markets. The greatest growth in equity prices and exchanges occurred between 1959 and 1960 and was not limited to Italian economy; indeed, it was common to all the countries of the European Common Market created in 1958. Considerable capital flowed into the stock exchange and the rapid growth of carryovers increased speculative trends. Equity prices reached a maximum peak in 1961, and then strongly

Table 3
descriptive statistics for efficiency scores.

	First model			Second model		
	exponential	half-normal	t-normal	exponential	half-normal	t-normal
Mean	0.804	0.769	0.804	0.812	0.776	0.806
Std. Deviation	0.167	0.152	0.167	0.181	0.155	0.181
Min(year)	0.311 (2009)	0.385 (2009)	0.311(2009)	0.274 (2009)	0.274 (2009)	0.271 (2009)
Max(year)	0.984 (1922)	0.985 (1922)	0.984 (1922)	0.986 (1922)	0.995 (1922)	0.986 (1922)

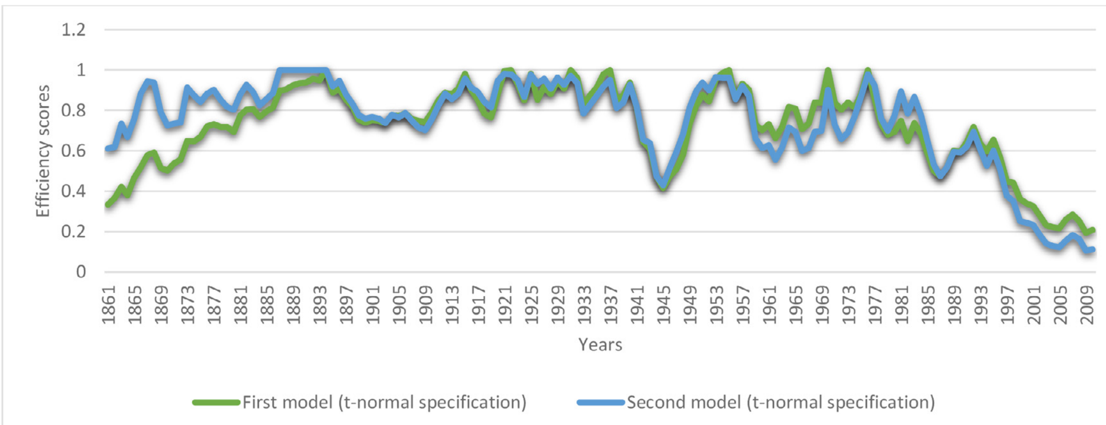

Fig. 3. Temporal path of efficiency scores, 1861–2010.

reduced, reaching a through in 1965. The crisis of stock market was due not only to the burst of speculative bubble, but also to other factors related to economic policy choices, such as the nationalization of electricity which led to the delisting from the stock exchange of electricity companies and fuelled a climate of uncertainty. Another important factor of the lower stability and strength of the banking system during the sub-period 1960–1973 was the 1963 credit crunch that was put in place to reduce inflation rates. Following the reduction of the compulsory reserve ratio of banks from 25 to 22.5 per cent in early 1962, there was a sharp increase in the monetary base and credit. Special credit institutions also had greater resources at their disposal because the purchases of their debt securities (obbligazioni) by other banks increased considerably. At the same time, the increase in wages contributed to the growth of inflation, which however was incompatible with the fixed exchange rate system envisaged by the Bretton Woods monetary regime. For this reason, in September 1963, a new credit squeeze took place, requiring banks to rapidly reduce their external indebtedness. Meanwhile, the growth of ICS continued, and it was particularly intense until the early 1970s. This growth was largely financed by an increase in ICS debt securities issues underwritten by other banks.

The lower stability and strength of the banking system during the 1995–2010 period corresponds to a delicate period for the Italian economy, owing to political instability and the creation of the Eurozone. The banking business model was revolutionized by the 1993 banking law, which reintroduced the model of universal banking, eliminating the distinction between short-term credit institutions and long-term credit institutions which had been introduced by the previous 1936 banking law. The banking system, which until then had been controlled by the State, was privatised, both because major credit institutions had reported significant losses in their balance sheets, and because compliance with the Maastricht criteria required the reduction of high public debt. Finally, the Italian banking system has been strongly affected by the international crisis of 2007 (Affinito et al., 2016). The sovereign debt crisis affected the Italian banks, which registered losses in their balance sheets for several reasons, such as the rapid increase of percentage of bad loans on the total loans, and the increasing cost that banks had to pay for financing in interbank, stock market and through di emissions of debt securities (Bartoletto et al., 2018; Bank of Italy, 2011, 2014).

The remaining years of the series are characterised by an apparent overlap. In fact, differences of minor entity between the series emerge more clearly from Fig. 4. In particular, Fig. 4 reports the series of the difference between the efficiency scores of the second model and those of the first model; in addition, we report the two series of the capital ratio and the non-core ratio to highlight the impact of these two factors on the allocative capacity of the Italian banking system in the hundred-fifty years of analysis Fig. 4. shows the relevance of the non-core ratio on the size of the difference between the two series. Specifically, with the growth of the non-core ratio, and therefore with the reduction of the stability of the banking system, the allocation capacity of the Italian banks decreases. It is important to highlight that, despite the growing trend of bank instability in the period 1861–1894, the difference between the two efficiency scores tends to decrease, proving the negative effect of the non-core ratio, which in this sub-period shows an increasing trend. On the contrary, only in the 1906–1914, 1920–1922 and 1929–1940 time intervals the difference between the two series takes on negative values, highlighting three-time windows in which bank instability has greatly reduced the allocation capacity of resources by the Italian banking system. An increase in the gap between the two efficiency scores with a growing and persistent trend over time emerges for the 1953–1973, and 1989–2010 time windows. In general, the capital ratio series confirms the empirical results: it slightly mitigates the stronger effect of the non-core ratio, which turns out to be a significant variable in the study of the efficiency of banks, at least in the Italian case.

6. ARDL results

In time series analysis, before running the ARDL cointegration procedure, the variables must be tested for stationarity. If the order

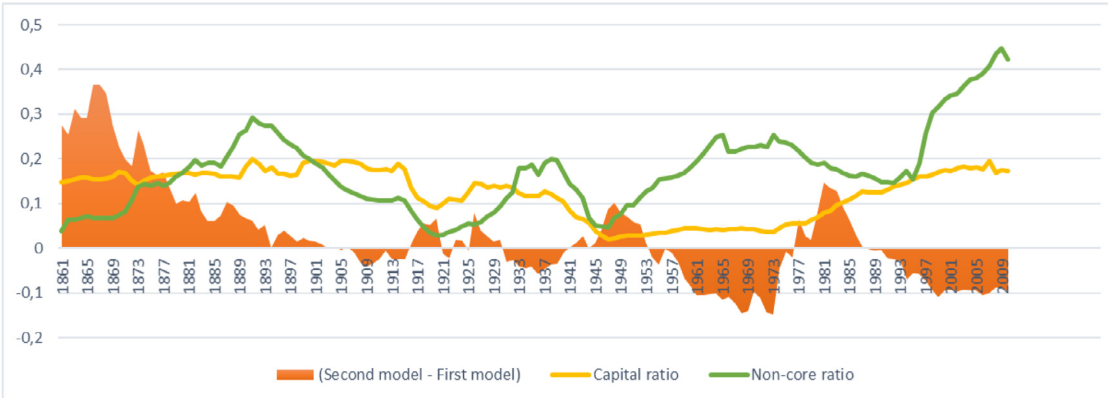

Fig. 4. Difference between the efficiency scores of the two models, capital ratio and non-core ratio series, 1861–2010.

Table 4
Unit root tests, structural break test and bound test.

	Unit root tests		
Unit root test	ADF test t-stat	PP test t-stat	Result
Variables at level			
Eff	−2.334	−2.074	Non-stationary
brecapital ratio	−1.158	−0.585	Non-stationary
non-core ratio	−1.821	−0.694	Non-stationary
Variables at first difference			
Eff	−6.503***	−10.542***	I(1)
capital ratio	−7.256***	−8.765***	I(1)
non-core ratio	−4.197***	−7.018***	I(1)
	Structural break test		
Variables at level	break years	ADF-test t-stat	Result
Eff	1977	−4.456	Non-stationary
	Bound test		
F-test 3.244*			

I(0) denotes the variable is stationary at the level; *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

of integration is beyond one, the ARDL method becomes invalid. There are plenty of unit root tests that sometimes yield conflicting results. In order to obtain robust results, we conduct different unit root tests. In particular, we implement the augmented Dickey-Fuller test (ADF, see Dickey and Fuller, 1979) and the Phillips and Perron test (PP, see Phillips and Perron, 1988). The results of the unit root tests are shown in Table 4 (first 11 lines). None of the variables is I(2) according to both tests. Therefore, the ARDL technique is appropriate to estimate the possible cointegration relationship amongst the variables included in the econometric models.

In addition, in order to control for a potential structural break in the efficiency score variable, we implement a breakpoint unit root test: a structural break in the time series can affect the results of the unit root tests. Perron (1989) argued that the ADF tests become biased towards the non-rejection of the null hypothesis when a structural break is present. Further, he claimed that most macroeconomic series do not actually exhibit unit roots. Rather, this characteristic has come from large and infrequent shocks which indicate that the economy is returning to a deterministic trend after small and frequent shocks.[6] The results of the endogenous breakpoint unit root test, following the third type of breakpoint (a change in the level and rate of growth) ,[7] are shown in Table 4 (from 12 to 15 lines). The break years are selected when the t-statistic related to the ADF test is at the minimum. We identify only one break (1968), but it is not significant and therefore we do not include it in the ARDL analysis.

To estimate the efficiency scores equation, the ARDL approach to cointegration is used Table 4. (from 16 to 18 lines) shows the F-statistics calculated for the two equations for each country. The appropriate lag length is selected based on AIC. The bounds test developed by Pesaran et al. (2001) is performed on Eq. (4). The values of the F-statistics are calculated by considering the null hypothesis where the parameters estimated with respect to the variables at a level equal to zero. If the calculated value of the F-stat exceeds the hyper appropriate critical values of the bounds test, the null hypothesis of no cointegration is rejected, and therefore a cointegration relationship between our variables is established Table 4. shows that the null hypothesis must be rejected at 10%, implying that there is cointegration relationship amongst the variables.

As the cointegration relationship has been established, the next step is to estimate the long-run coefficients and short-run coefficients of the efficiency scores equation by using the ARDL specification. The ARDL specification assumes that the errors are serially uncorrelated, and therefore we choose the maximum number of lags based on AIC, to prevent errors from being autocorrelated. The optimum ARDL order suggested by AIC is specified in Table 5 for both the long-run and the short-run relationship.

The results show that the estimated error correction coefficient ECM (−1) is negative and significant and it is equal to −0.248, indicating that the adjustment speed to restore the long-run equilibrium in the dynamic model will be corrected by 24.8% in one year.

As for the long-term relationship, we verify that the efficiency of the Italian banking system is statistically influenced only by the stability of the banking system (non-core ratio). In particular, the parameter associated with the non-core ratio is significant at 5% and has an expected negative sign: as bank instability increases,

[6] Many previous empirical studies do not consider structural breaks. One noticeable feature is that most of the macroeconomics time series with a long-span historical time are subject to the existence of structural breaks (Basher and Westerlund, 2008). If the unit root tests do not account for the existence of structural breaks that arise from any economic events which are wrongly specified (Arestis and Mariscal, 1999), they tend to produce inaccurate inferences (Chaudhuri and Wu, 2003) and might lead to bias and spurious rejection. Furthermore, structural breaks are normally associated with anomalous events (wars, oil crises, etc.). For this reason, these tests are important for our analysis.

[7] The Zivot and Andrews test (1992) considers three types of breakpoints: the first concerns changes in the level of the time series (a change in the intercept); the second is related to a change in the growth rate (change in the trend); the third is the result of both (change in the level and in the growth rate).

Table 5
Estimates of the ARDL model and error correction model.

Long-run relationship	coefficients ARDL(0,0)	t-stat
capital ratio	−0.963	−0.82
non-core ratio	−0.280**	−3.27
1893-WWI	−0.275***	−4.07
1929-WWII	0.039	0.58
CBA1993	−0.585***	−5.41
Short-run relationship	ARDL(1,1,4,3)	
Intercept	0.212***	5.65
Δcapital $ratio_{t-1}$	1.245**	1.99
Δnon-core $ratio_{t-1}$	−0.907**	2.29
Δnon-core $ratio_{t-2}$	0.477	1.13
Δnon-core $ratio_{t-3}$	0.473	1.11
Δnon-core $ratio_{t-4}$	1.03	0.34
$\Delta CBA1993_{t-1}$	0.068	0.98
$\Delta CBA1993_{t-2}$	0.076	1.15
$\Delta CBA1993_{t-3}$	−0.180**	2.61
EMC(−1)	−0.248***	−6.01
LM-test for ARCH	0.61	
Breusch-Pagan/Cook-Weisberg test	1.13	
Breusch-Godfrey LM-test for autocorrelation	1.34	
Ramsey RESET test	1.14	

Note: ***, **, * denotes significance at 1%, 5% and at 10% respectively. Also, the AIC is used to select the optimum number of lags in the ARDL models. LM-test for ARCH, Breusch-Pagan/Cook-Weisberg test for heteroskedasticity are, respectively, Lagrange multiplier statistics for autoregressive conditional heteroskedasticity, and for Breusch-Pagan/Cook-Weisberg test for heteroskedasticity. Breusch-Godfrey LM-test is Lagrange multiplier statistics for tests of residual serial correlation. Finally, Ramsey RESET test allows to verify if regression has any omitted variable bias.

the ability of the banking system to correctly allocate its resources decreases. The parameter associated with the solvency (capital ratio) of the banking system, on the contrary, shows an unexpected negative sign, but it is not statistically significant. Only in the short run, the allocative capacity of the Italian banking system is positively influenced by its degree of solvency. The parameter associated with the capital ratio is positive and statistically significant at 5%. Furthermore, again in the short term, a negative effect of the non-core ratio and of the changes introduced by the consolidated banking act in 1993 emerges on the efficiency of the Italian banking system. In summary, instability is a significant factor in both the short and long term in determining the efficiency of the Italian banking system; solvency, on the other hand, is only relevant in the short term.

Our results are consistent with previous studies, which demonstrate that there is empirical evidence that higher levels and faster growth of the non-core liabilities can destabilize the banking system (Schin, 2011; Hahm et al., 2013). Although a high capital ratio is a measure of a well-funded loss-absorbing buffer, on the other hand more capital could represent more risk-taking on the asset side of the bank balance sheet (Jorda et al., 2017). Moreover, a recent study of the European Central Bank has showed that increase in capital is often accompanied with a cost, because banks react by increasing the average risk weights of their portfolio to compensate their lower profitability (Dautović, 2020). As showed by Jorda et al. (2017), there is a reverse causality mechanism: "the more risks the banking sector takes, the more markets and regulators are going to demand banks to hold higher buffers". If we consider the dynamic of capital ratio in Italy in a historical perspective, we can observe a gradual increase from 1970, having been very low from WW2 to the 1960′s. From 1861 to WWI, the capital ratio was higher and rather stable because commercial banking – and especially universal banks – represented a new business model with high risks and informational frictions, so bank creditors required more guarantees and larger capital buffers. When the business model of banks became safer, as effect of the nationalisation of banks during the 1930s, through the creation of IRI, the need of capital buffers reduced (Grossman, 2010). In addition, the Bank of Italy consolidated its role of central bank from the banking law of 1926, allowing banks to manage short-term liquidity problems.

The last lines of Table 5 show the test results. The Breusch-Pagan/Cook-Weisberg test and LM-test for ARCH do not reject the null hypothesis and allow us to ascertain the absence of heteroskedasticity and the absence of autoregressive conditional heteroskedasticity effects. The Breusch-Godfrey LM-test for autocorrelation allows us to exclude the presence serial correlation in the error terms. The Ramsey RESET test does not reject the null hypothesis and allows to conclude that our regression does not suffer from omitted variable bias.

Finally, we examine the stability of short-run and long-run coefficients, performing the plots of the cumulative sum of the recursive residuals (CUSUM) and the cumulative sum of recursive residuals squared (CUSUM squared) test for both equations. It can be assumed that the estimated coefficients are stable when the plot of these statistics lies inside the critical bounds of 5% significance. These tests are usually implemented and interpreted thanks to a graphical representation and they also allow to evaluate stability over time. In Figs. 5a and 5b, we plot the cumulative sums together with the 5% critical lines. The movement inside the critical lines is suggestive of parameters stability. Finally, we can conclude that, except for an imperceptible instability in the years 1922–1925, the CUSUM squared (Fig. 5b) are within the 5% significance lines, suggesting that the variance of the residuals can be defined quite stable.

7. Conclusions

The aim of this paper was to investigate the performance of the Italian banking system for the period 1861–2010. First, we implement a stochastic frontier approach, modelling the inefficiency component with a measure of the financial strength (capital ratio) and a measure of the stability (non-core ratio) of the banking system, and considering dummies that allow us to check for historical and economic events, as well as institutional changes that occurred during the analysed period. The results of the empirical analysis turn out to be robust, since they find their justification in the historical events that took place in the course of the 150 years of analysis.

In addition, the ARDL analysis corroborates the validity of our results, highlighting the relevance of the long-term non-core ratio (a proxy for bank stability) on the allocative capacity of the Italian banking system. Once again, the period of instability that emerged from the ARDL analysis found its justification not only in the omission of relevant variables (a purely technical matter) but also in the historical events that affected the Italian banking system. We verified that only in the short run the allocative capacity of the banking system was influenced by the capital ratio. On the other hand, the non-core ratio influenced the allocative capacity in the long run. Our paper emerges as a seminal work to be extended to other economies in order to carry out a comparative analysis. In particular, the empirical relevance of the capital ratio and of the non-core ratio allows us to identify these two measures as indicators of the strength and stability of a banking system, allowing for a comparative analysis in a historical perspective amongst different banking systems.

Finally, methodological limits emerge linked to the dynamic efficiency analysis. This limitation led us to use two separate methods, stochastic frontier approach and ARDL analysis, and not just a method that would have made the analysis more computationally efficient. In this regard, we hope that this work will pique the interest of the scholars involved in the analysis of efficiency applied to time series. Furthermore, given the long-term nature of the data,

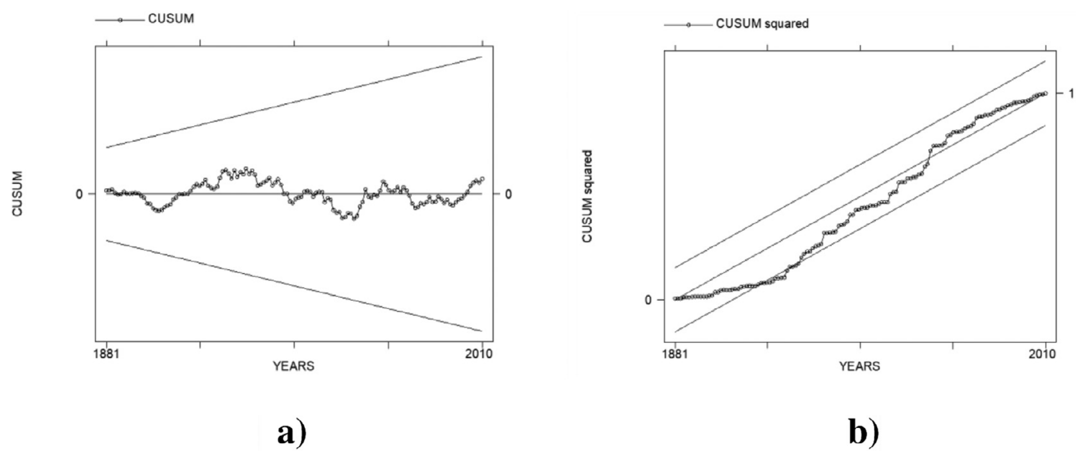

Fig. 5. Plots of CUSUM and CUSUM squared statistics for coefficient stability.

it would have been fair to assume potential regime changes occurring in the individual sub-periods of the historical series analysed. We could have used Markov-switching models that would have allowed us to identify potential changes in the effect of the regressors on the efficiency scores that occurred in the different time windows identified through the dummies variables of our analysis. This turns out to be a potential and natural continuation of this work.

Appendix. Estimation of missing values of the unit cost of labour

A problem addressed in the cost efficiency analysis was the lack of the unit cost of labour variable for the years 1861–1974. Unfortunately, the variable provided by the Bank of Italy is only available from 1975 onwards. After having reconstructed the series for the period 1975–2010, using the annual reports of the Bank of Italy, we proceeded to estimate the missing values for the period 1861–1974.

To proceed for the entire analysis period (1861–2010), we used the methods of imputing missing data. In particular, statistically principled methods for handling missing data exist. They include the maximum likelihood estimation via the expectation maximization algorithm (Dempster et al., 1977) and multiple imputation (Little and Rubin, 2002; Rubin,1976; Schafer and Graham, 2002). These methods produce estimates that are superior as compared to those of the older methods, but for many researchers, multiple imputation is the general solution to missing-data problems in statistics (Rubin, 1976; Schafer, 1997).

In our case, we use the ICE or MICE (multiple imputation chained equations) approach for its many advantages. In particular, MICE turns out to be a very flexible method: each variable can be modelled by using a model tailored to its distribution. In addition, MICE can manage imputation of variables defined only on a subset of the data. MICE can also incorporate variables that are functions of other variables, and it does not require monotone missing-data patterns.

MICE is a practical approach for imputing missing datasets based on a set of imputation models, given that there is one model for each variable with missing values. MICE approach imputes data on a variable-by-variable basis by specifying an imputation model per variable. Suppose we have a set of variables $X_1,\ X_2, \ldots, X_k$. Of this set of variables, some or all have missing values. If X_1 has missing values, it will be regressed on the other variables X_2 to X_k. The estimation is thus restricted to individuals with observed X_1. The missing values in X_1 are then replaced by the predictive

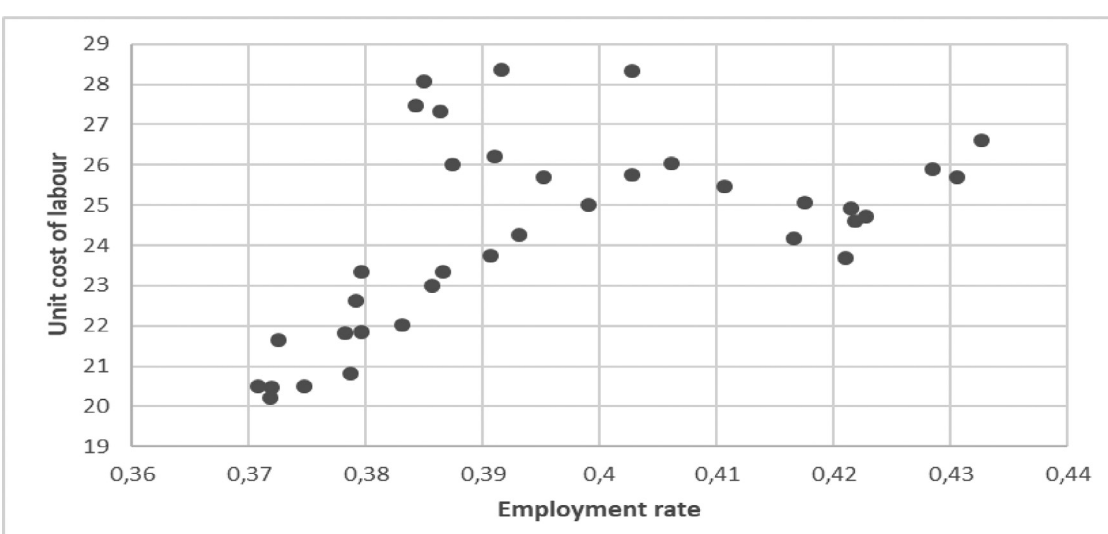

Fig. A1. Relationship between unit cost of labour and employment rate, 1975–2010.

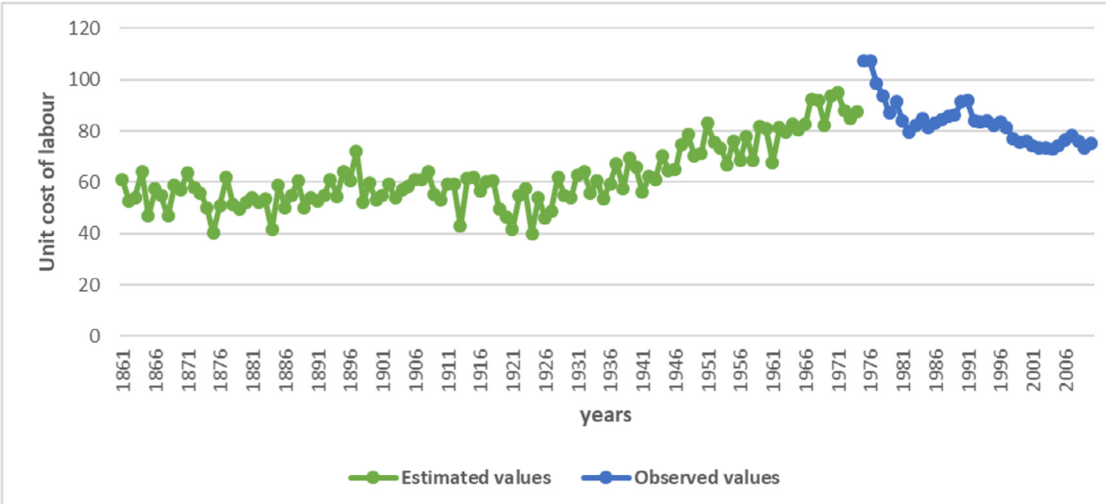

Fig. B1. Estimated and observed values of unit cost of labour, 1861–2010.

values, which are simulated draws from the posterior predictive distribution of X_1. The following variable with missing values, X_2, is regressed on all the other variables X_1, X_3 to X_k. Estimation is thus restricted to individuals with observed X_2 and uses the imputed values of X_1. Here again, the missing values in X_2 are replaced by simulated draws from the posterior predictive distribution of X_2. This process is repeated for all the other variables in turn for n cycles in order to stabilize the results and to produce single imputed datasets Royston and White (2011). and Van Buuren et al. (1999) have all suggested that more than 10 cycles are needed for the convergence of the sampling distribution of imputed values, whereas the entire procedure is repeated independently M times, yielding M imputed datasets. In our case, we consider 100 cycles.

In our case, in order to avoid multicollinearity problems that could arise by attributing the missing values of the unit cost of labour using the other regressors of the cost function, we prefer to identify a new variable different from the regressors used in the stochastic frontier analysis. In our case, the variable used for the imputation of missing data is chosen using the economic theory of the labour market. Since the real unit cost of labour represents a proxy of the real wage and recalls the negative relationship between the real wage and the unemployment rate, we use this relationship to estimate the missing values of the unit cost of labour. Specifically, we need the unemployment rate for the entire analysis period; Unfortunately, l'ISTAT[8] (Italian National Institute of Statistics) provides the data from 1975 to 2015 and this does not solve the problem. Having the employment rate from 1861 to 2010 (Broadberry et al., 2012) we can think of the employment rate as the opposite of the unemployment rate and expect a positive relationship between it and the unit cost of labour Fig. A1. shows the expected positive relationship between the employment rate and unit cost of labour, with a correlation of about 0.60. At this point, using the MICE approach, we proceed to estimate the missing values. The result of the analysis is shown in Fig. B1, where the observed values of the unit cost of labour are shown in blue, while the estimated values are in green. The series shows a constant trend in unit cost of labour up to 1926, it follows an increasing trend up to 1974 and a decreasing one from 1975 onwards, the latter due to a constant increase in inflation recorded from the 1970s onwards.

[8] http://seriestoriche.istat.it/, last accessed, December 4th 2021.

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