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A test for the too-big-to-fail hypothesis for European banks during the financial crisis

Paolo Mattana*, Filippo Petroni and Stefania Patrizia Sonia Rossi

Department of Economics and Business, University of Cagliari, 09123 Cagliari, Italy

Motivated by the theoretical prediction of the opportunistic behaviour of large banks that face expected public intervention, we test a *full* and a *partial* form of the too-big-to-fail (TBTF) hypothesis. The full form of the hypothesis implies the increase in the risk undertakings *and* profitability of banks that exceed a certain dimension; the partial form of the hypothesis implies only an augmented risk appetite of large banks compared to their smaller counterparts. The examined area is the European banking industry, whose behaviour is observed over the first wave of the present financial crisis (2007/09). The estimation of a quadratic fit that links change in a bank's credit risk profile and profitability retention rates with a bank's size suggests the existence of a *partial* form of the TBTF hypothesis. However, a more precise, local rolling windows estimation of the size sensitivities reveals that large banks – those whose liabilities exceed approximately 2% of the country of origin's GDP (15% of our sample) – show an increase in credit risk profile and a superior capability of retaining higher ROA scores, *vis-à-vis* their smaller counterparts. With the caveats of our investigation, we interpret these results as evidence of a *full* form of the TBTF hypothesis.

Keywords: financial crises; bailout policy; banking risk; moral hazard; TBTF

JEL Classification: G21; G28

I. Introduction

The extent and depth of the 2007/09 financial crisis has urged a dramatic policy intervention in both the US and European countries to counter bank defaults and to avoid a disastrous financial instability. The government bailouts of a large number of banks and the interventionist efforts of governments to stabilize economies have generated a wealth of controversy regarding the short- and long-term effects of the policy. In particular, it is alleged that, by insulating partial financial institutions from the full

*Corresponding author. E-mail: mattana@unica.it
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consequences of a negative outcome, the anticipation of further bailouts may result in a misallocation of resources, which would inspire risky behaviour and leave the economy more vulnerable to future crises.

A widespread literature has targeted large banks as the most likely to be involved in this type of morally hazardous behaviour: in presence of a bailout policy, it is expected that only a fraction of small- to medium-sized banks find it optimal to increase their exposure to risk but that all large banks (those exceeding a certain size) find it convenient to expand (cf., *inter alia* Freixas, 1999; Chang, 2010).[1] This is known as the 'too-big-to-fail' (TBTF) hypothesis, which is a colloquial term that denotes a particular situation in which there are financial institutions that are so large and/or so widely interconnected to the rest of the economy that their failure would generate a disastrous domino effect for the whole economy. The hypothesis implies that the larger the bank, the higher the probability of public intervention in case of default. The TBTF hypothesis has been analysed in great detail by the literature, both from theoretical and the empirical viewpoints (cf., *inter alia* Stern and Feldman, 2004, 2009; Morgan and Stiroh, 2005; Mishkin, 2006; Stern, 2009). Although the link between bank size and the safety net policy appears to be more complex than is generally believed (cf. Hetzel, 2009; De Nicolò *et al.*, 2010; Ioannidou and Penas, 2010; Molyneux *et al.*, 2011; Beltratti and Stulz, 2012; Brewer and Jagtiani, 2013), the literature is in near agreement that government bailout guarantees affect the risk exposure of banks by reducing their market discipline, which in turn tempts banks towards an increase in risk-taking and morally hazardous behaviour (Sironi, 2003; Gropp *et al.*, 2006; Völz and Wedow, 2011).[2] Consistency with this evidence, Gropp *et al.* (2011, 2014) and Hakenes and Schnabel (2010) show that, in addition to the substantial increases in the risk-taking of banks, bailout policies also induce distortions in competition.

This article aims to deliver fresh evidence on the propensity of the banking industry to take advantage of implicit bailout guarantees. Some novelties in our approach are worth noting. First, we take into account the impact of banks' strategic choices regarding the effect that an inefficient increase in risk appetite may have on the profit side. This element, despite the availability of many theoretical predictions (cf., *inter alia* Freixas, 1999; Chang, 2010; Hakenes and Schnabel, 2010; Gropp *et al.*, 2011), remains a largely overlooked feature of empirical investigations. As a consequence, we refer to the concomitant existence of a link between risk and size and between profitability and size as a *full* form of the TBTF hypothesis, and the *partial* form remains confined to the traditional simple relationship between risk undertakings and bank size.

Moreover, our investigation also departs from the extant literature in the empirical approach used to capture the assumed nonlinearity between banks' strategic choices and banks' dimensions. We first propose a robust estimation of a quadratic fit. Then, to have more precise local details on the size-induced strategic choices of the financial industry, we also proceed to estimate a piecewise linear approximation of the quadratic relationship by means of a rolling window procedure: essentially, bank size is divided into several overlapping windows (of dimension 1), and a linear fit is performed for each of these.

Our investigation is based on a large panel of European banks (1366 units). To avoid spurious elements linked to the dangerous build-up of public budget deficits and debt, we limit the time span of observation to 2007–2009.

The article is structured as follows. In Section II, we illustrate the stylized theoretical framework in which our major hypotheses are discussed. In Section III, we present the empirical model and describe the construction of the variables used in the empirical analysis and the data sources. Section IV contains the empirical analysis and the results from both the baseline quadratic estimations and the rolling window estimates. Section V concludes the article.

II. A stylized Theoretical Framework

There are several theoretical frameworks that describe the potential emergence of opportunistic behaviour in the financial industry as an unintended

[1] Additional sources on the link between optimal risk undertaking and bank size in the context of bailout policy include Barrell *et al.* (2011), Fungáčová and Solanko (2009) and Hakenes and Schnabel (2011) and Dam and Koetter (2012).
[2] Indeed, public guarantees may generate an opposite effect on the banks' risk-taking for banks' margins and charter values. Throughout this channel, higher charter values decrease the incentives for excessive risk-taking. Therefore, the net effect of these bailout policies may result in ambiguous outcomes (Cordella and Yeyati, 2003; Hakenes and Schnabel, 2010).

effect of overly ‘soft’ access to implicit bailouts guarantees.

For the purposes of this article, a particularly useful framework of reference is represented by Freixas (1999), where the *ex ante* distortive effect of a Regulator’s policy (both in a noncommitment and commitment cases) is discussed.[3] It is found that, depending on the negative externalities of bank failures, the optimal policy may be either a systematic bailout or a mixed strategy and that the latter provides a theoretical foundation for the ‘constructive ambiguity’ (discretion) doctrine. For the scope of this article, it is worth noting that, when the risk appetite is endogenized, banks above a certain dimension (beyond the threshold at which the marginal cost of rescuing equals the marginal social benefit of avoiding the failure) strategically react *ex ante* by inefficiently expanding their risk appetite as a way of increasing their expected profit. For the illustrative scopes of this section, we discuss only a simplified variant of the noncommitment case. A similar cut-down-to-size of the Freixas model has also been discussed by Chang (2010).

We consider the simple case in which a bank’s debt consists of only noncore uninsured liabilities, B. Let p denote the probability that a bank with cash flow $x(B)$ is solvent. The complement $(1-p)$ denotes the probability that a bank is in financial distress. Moreover, it is assumed that debt holders are promised $B(1+R_L)$ if the bank remains solvent or is bailed out (although the assets’ value reduces to V_C in the latter case; conversely, the assets’ expected value reduces to V_L if the bank is liquidated).

The difference $V_C - V_L = G > 0$ represents the goodwill of the bank. It is further assumed that V_C and V_L and also their difference G depend positively on the assets size B.

Now, consider the returns required by creditors to lend uninsured funds B to the bank. As shown in Freixas (1999), the market requires

$$B(1+R_L) = \frac{B(1+r) - (1-p)\,V_L}{p} \tag{1}$$

where in case of $p = 1$ (certainty of solvency), $B(1+R_L) = B(1+r)$.

The cost incurred by filing bankruptcy is $C(B)$, with $C'(B) > 0$. This expresses the implicit cost that bankruptcy imposes on the overall financial system. The Regulator weighs two lines of action

- liquidation, with a cost equal to $C(B)$, where $\frac{\partial C}{\partial B} > 0$;
- continuation, with a cost equal to $B(1+R_L) - V_L - G = S - G$, where $S = B(1+R_L) - V_L$ represents the subsidy, which the bank’s uninsured holders receive in case of a bailout.

Further, assuming that there are no efficiency discrepancies between the public/private uses of resources and considering the case in which the Regulator does not attribute different weights to the two lines of action, the decision to rescue the bank occurs, if

$$\begin{aligned}\Delta &= B(1+R_L) - V_L - G - C(B)\\ &= S - G - C(B) < 0\end{aligned} \tag{2}$$

This apparently innocuous decision rule has several pervasive implications. For instance, consider Fig. 1, where the difference $S - G$ is a simple linear function of size and where $C(B)$ is strictly convex.

It is clear that, in this example, there is a threshold $\hat{B}$ beyond which Δ changes its sign from positive to negative. This also implies that it is optimal for the Regulator to rescue any bank larger than $\hat{B}$.

In this setting, to what extent and under what conditions does the Regulator’s approach induce an inefficient size increase and moral hazard in the form

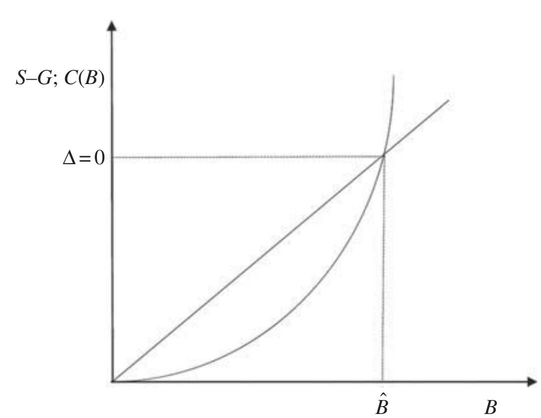

Fig. 1. The threshold at which the Regulator chooses to rescue a financial institution

[3] Multi-period extensions of this framework can be found in Hakenes and Schnabel (2010) and Gropp *et al.* (2011). Other variants introduce stochastic returns (cf., *inter alia*, Cordella and Yeyati, 2003).

of a higher risk appetite?[4] Consider the way Equation 1 is modified by in the noncommitment case where the Regulator plays a mixed strategy (constructive ambiguity = discretion), assigning a probability z to continuation and the complementary probability $(1 - z)$ to liquidation of a bank $pB(1 + R_L) = B(1 + r) - (1 - p)\,[zB(1 + R_L) + (1 - z)\,V_L]$, which implies[5]

$$B(1 + R_L) = \frac{B(1 + r) - (1 - p)\,(1 - z)\,V_L}{p + (1 - p)\,z} \tag{3}$$

We are now ready to show that large banks react *ex ante* to the probability of intervention by inefficiently increasing their size and risk appetite. As for the incentives to expand, consider the following argument. *Ex ante* (expected) profit for a bank that anticipates the probability of a public intervention will be:

$$\begin{aligned}\Pi &= p[x(B) - B(1 + R_L)] + (1 - p)\,V_L \\ &= p[x(B) - \tfrac{B(1+r)-(1-p)\,(1-z)\,V_L}{p+(1-p)\,z}] + (1 - p)\,V_L\end{aligned}$$

where it is assumed that the profit function is concave with regard to probability $(1 - p)$. Notice that, when $z = 0$, the profit equation reduces to

$$\Pi_0 = p[x(B) - B(1 + R_L)] + (1 - p)\,V_L \tag{4}$$

Let us now compute the extra profit in the general case in which $z \neq 0$. Simple algebra shows that by taking into account Equation 3

$$\begin{aligned}\Pi_z - \Pi_0 &= pB[R_L(z) - R_L(0)] \\ &= (1 - p)\,z\frac{B(1 + r) - V_L}{p + (1 - p)\,z} \\ &= \frac{(1 - p)\,zS}{p + (1 - p)\,z} > 0\end{aligned}$$

from which it is clear that

Remark 1: *The expectation of public intervention incentivizes banks to incur more debt to increase their expected profits.*

Note that, for banks with size $B > \hat{B}$, $z = 1$, and the above expression becomes the simple

$$\Pi_z = \Pi_0 + (1 - p)\,S \tag{5}$$

where excess profit is a direct function of risk appetite $(1 - p)$ and the level of the subsidy.

Showing how a lenient Regulator provides incentives towards higher risk-taking is also straightforward. Assume that the degree of riskiness of a bank's portfolio $(1 - p)$ results from the banks' own strategic decision and that this occurs at no extra cost. Furthermore, assume that this probability is not observable by the market. The market expects the bank to choose the optimal level of $p = \hat{p}$ such that

$$\begin{aligned}\frac{\partial \Pi}{\partial p} &= 0 \equiv \Psi(p, z, B) \\ &= x(B) - B(1 + \bar{R}_L(z)) - pV_L = 0\end{aligned}$$

where $\bar{R}_L(z)$ is the market-required return-adjusted for the rationally expected banks' choice of probability $\hat{p}$. The effect of the bailout policy on the endogenous probability p can then be calculated by implicitly deriving the function $\Psi(p, z, B)$ with regard to z. We obtain the following:

$$\begin{aligned}\frac{dp}{dz} &= \frac{\partial \Psi(p, z, B)}{\partial z} = -\frac{\frac{\partial^2 \Pi}{\partial p \partial z}}{\frac{\partial^2 \Pi}{\partial p^2}} = -\frac{B\frac{\partial R_L}{\partial p}}{\frac{\partial^2 \Pi}{\partial p^2}} \\ &= -\frac{\frac{-S(1 - z)}{[p + (1 - p)\,z]^2}}{\frac{\partial^2 \Pi}{\partial p^2}} < 0\end{aligned} \tag{6}$$

where the negative sign depends on $\frac{\partial^2 \Pi}{\partial p^2}$ being negative because of the concavity of the profit function with regard to risk appetite $(1 - p)$. Therefore,

Remark 2: *The expectation of public intervention incentivizes banks to increase their risk appetite.*

[4] Note that the model also supports moral hazard in the form of a loosened monitoring effort by creditors. For the sake of a simple discussion, we do not provide a derivation of this result.
[5] Note that, if $z = 0$, we are back to the simple case in Equation 2, where the formula that links risky/riskless asset returns depends on only p. Conversely, if $z \neq 0$, a more general formula applies.

III. The Framework for the Empirical Analysis

In this section, we construct an empirical test of the predictions derived above. We first discuss the empirical ambience of reference. Then, we give details on the formation of the sample of banks. Finally, we account for the choice of the proxy variables.

The empirical model

There are several possibilities of empirically capturing a size-induced nonlinearity in the strategic behaviour of financial institutions. We consider the following quadratic specification:

$$Credit\_risk = \alpha_0 + \alpha_1 Size + \alpha_2 Size^2 + \sum \varphi_1 Z + e_1 \tag{7}$$

$$Profit = \beta_0 + \beta_1 Size + \beta_2 Size^2 + \sum \varphi_2 Z + e_2 \tag{8}$$

where *Credit_risk* and *Profit* represent some suitable measures of risk undertakings and profits, *Size* is a proxy for bank dimension and *Z* is a vector of control variables. In this context, α_0 and β_0 measure the 'autonomous' fraction of the variation in credit risk undertakings and profit. α_1, β_1, α_2 and β_2 are the parameters of interest, which measure the effect of bank dimension on the changes in credit risk and profitability variables. φ_1 and ϕ_2 are the vectors of the parameters associated with the control variables, and e_1 and e_2 are Gaussian error terms. From our perspective, the presence of a full form of the TBTF hypothesis in banks' behaviour can be expressed by significant and positive coefficients of the nonlinear part in Equations (7) and (8), namely α_2 and β_2.

Furthermore, to gain a more comprehensive understanding of the nonlinear interplay between the *Credit_risk*/*Profit* variables and *Size*, we complement the analysis with an estimation of a piecewise (local) linear approximation of the quadratic relationship. Essentially, the distribution of the *Size* variable is divided into *p* overlapping windows for each of which a linear fit is applied. The model becomes as follows:

$$Credit\_risk = \alpha_{0,p} + \alpha_{1,p} Size + \sum \varphi_{1,p} Z + u_1 \tag{9}$$

$$Profit = \beta_{0,p} + \beta_{1,p} Size + \sum \varphi_{2p} Z + u_2 \tag{10}$$

We believe this approach to be particularly useful in our case because a number of critical details of the nonlinear risk/profitability relationship can be obtained. In particular, we can detect more precise information regarding the way size sensitivities change at various regions of the *Size* distribution. The critical threshold at which the parameters become statistically significant can also be derived.

The sample of banks

Our data set is composed of single bank records for the European countries and consists of the annual accounting data made available through the BankScope database of Bureau van Dijk and Fitch/Ibca. To limit heterogeneity in the composition of the sample, we have considered several exclusion criteria. In particular, with regard to stratification, the exclusion criteria are as follows:

(i) Country of origin – We do not consider banks that belong to East European countries. This accounts for the fact that the banking industry of these countries, despite the intensive internationalization and progressive foreign bank penetration, still appears to be not fully comparable to the western banking system according to several dimensions (market orientation, diversification strategies, monitoring strategies, levels of capitalization, etc.). For reasons that depend mainly on their 'tax haven' status, banks that belong to very small countries (Andorra, Cyprus, Luxemburg, Liechtenstein, Malta and Monaco) are excluded.[6] Therefore, our sample is composed of 16 Western European countries;

(ii) Bank specialization – We do not consider investment banks, securities firms, finance companies, central banks, investment and

[6] As is made clear below, another good reason for the exclusion of banks that belong to very small countries is linked to the construction of our proxy for *Size*, where the GDP of the country of origin is used to normalize the variable.

trust corporations, Islamic banks, micro-financing institutions, clearing institutions or custody. Therefore, we take into account only institutions for which credit risk is an appropriate indicator of risk-taking (commercial banks, cooperative banks, savings banks, real estate and mortgage banks, and specialized governmental credit institutions);

(iii) Type of ownership – Finally, we exclude banks with outright public ownership. This choice is strictly linked to the very nature of our investigation because, as discussed in the literature, banks of this type may be assumed to have an explicit bailout guarantee (cf., on the issue, Gropp *et al.*, 2011).

Table 1 reports the details of the resulting sample according to nationality and the specialization of the banks. The total number of banks is 1366.

Further, crucial information about the criteria for the construction of the sample concerns the decision to limit the observation period to the first wave of the present financial crisis (2007/09). This prevents the spurious elements linked to the dangerous build-up of public budget deficits and debt from interfering in our investigation.

Table 1. Country and specialization distribution of banks

Country	Banks	% of the sample
Austria	51	3.73
Belgium	12	0.88
Denmark	46	3.37
Finland	8	0.59
France	87	6.37
Germany	500	36.6
Greece	14	10.2
Ireland	11	8.1
Italy	184	13.47
Netherlands	18	1.32
Norway	76	5.56
Portugal	12	0.88
Spain	57	4.17
Sweden	13	9.5
Switzerland	219	16.03
UK	58	4.25
Total	**1366**	**100.00**
Bank specialization		
Commercial	427	32.76
Cooperative	488	33.65
Real estate mortgage	64	4.90
Saving	357	25.41
Specialized government credit institutions	30	3.27
Total	**1366**	**100.00**

The risk/profitability indicators, Size measure and control variables

A typical proxy used in the literature for measuring credit risk in financial institutions is the ratio of loan loss provisions (LLP) over a proper measure of overall bank activity (cf., *inter alia* Berger and DeYoung, 1997).[7] Following in the footsteps of this literature, we compute the ratios of LLP over Total Loans (LLP_TL) and LLP over Total Capital (LLP_TC). Moreover, we also compute the difference of the variables between the recorded values at the end of the period of interest (2009) and the beginning of the global financial crises (2007) to obtain ΔLLP_TL and ΔLLP_TC. Our proxies imply that the higher ΔLLP_TL and ΔLLP_TC, the higher the *change* in the credit risk profile displayed, *ceteris paribus*, by the *i*th bank over the crisis.

With regard to the profit-side variables, we consider ROA and ROE indicators. As for the credit risk variables, we proceed to calculate the 2009–2007 differences in the profitability indicators to obtain ΔROA and ΔROE. Therefore, the higher the ΔROA and ΔROE for the generic *i*th bank, the higher the capability of the bank, *ceteris paribus*, to retain profitability over the crises.

It is important to remark that the use of the difference operator is crucial for our analysis. First, its use is an effective method to exclude heterogeneity at the single unit level because spurious differential elements such as economies of scale, diversification strategies, monitoring strategies, levels of capitalization, etc. are all likely to be offset (at least in the short-run horizon

[7] An alternative proxy makes use of the impaired loans (cf., *inter alia*, Sironi, 2003; Gropp and Vesala, 2004). Note that our choice of considering only LLP depends on two elements: (a) loan loss provisioning appears to be, *ceteris paribus*, less reliant on pre-crisis banks' strategic choices, as it is deemed to be more an indication for expected risk compared to the impaired loans which are more an ex-post risk measure (cf., also Bushman and Williams, 2012); (b) data on impaired loans are provided for only a largely reduced number of banks.

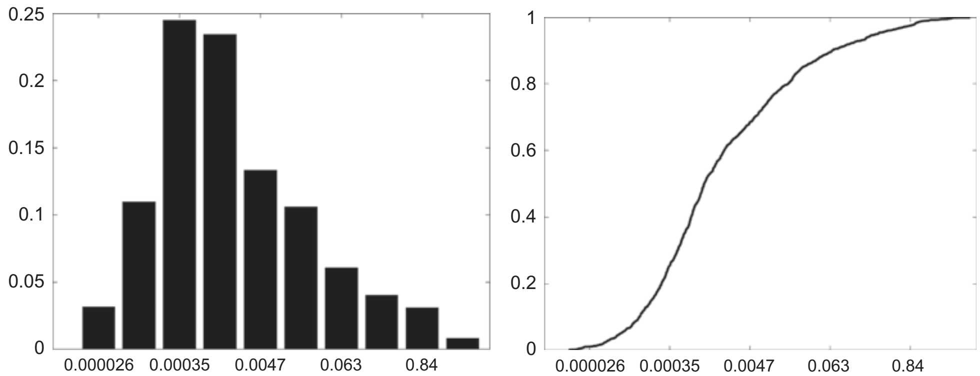

Fig. 2. Frequency distributions of the *Size* variable

of our analysis).[8] Therefore, under a null hypothesis of no opportunistic behaviour, we expect the size sensitivities of our risk/profit proxies to be zero. Conversely, the presence of significant coefficients would imply a size-induced reduction in market discipline and banks' strategic moves towards opportunistic behaviour. Moreover, from a more technical econometric point of view, our choice of the difference operator reduces the risk that endogeneity intrudes in the results of the estimation.

We have considered the ratio between bank *i*th's liabilities and its country of origin's GDP as a proxy for bank dimension (*Size*). The ratio, which is expressed in log terms, is calculated for 2007, which is the initial period of our analysis. The data on country GDP come from the OECD statistics. As is widely discussed in the literature (see among others Völz and Wedow, 2011; Bertay *et al.*, 2013), this ratio offers a better signal of the potential fiscal costs associated with a bailout than do other indicators. In other words, this ratio corresponds to a country's maximum expenditure in a bank bailout relative to its GDP if all of a bank's assets go completely sour.[9] The left panel of Fig. 2 reports the frequency distributions of the *Size* variable. The cumulative frequency distribution is depicted in the right panel.

Note that, in creating the variables, we have concentrated on choosing the most appropriate accounting standards. In this regard, we prefer financial statements that use IAS over those that use national standards; we also use consolidated balance sheets whenever available to avoid double counting institutions. All of the values are finally converted into a single currency (US$).

Concerning the control variables (vector Z in the Equations 7–10), we employ only strictly exogenous variables without accounting for the balance-sheet indicators.[10] Therefore, our set of controls includes country dummies, bank specialization dummies and a

[8] We are aware that there may be other sources of heterogeneity regarding risk and profit changes over the crisis that are not necessarily linked to opportunistic behaviour. For instance, a bad/good luck argument (cf., *inter alia*, Beltratti and Stulz, 2012) could be used to justify time heterogeneous risk profiles across banks. However, in our analysis, we assume that external shocks symmetrically hit large and small banks. Another potential source of bias concerns the effects of various degrees of exposure to systematic risk. In this regard, a strand of the literature (see, for instance, Acharya *et al.*, 2006; Altunbas *et al.*, 2007; Rossi *et al.*, 2009) argues that this does not necessarily imply different risk/profit combinations.

[9] In our empirical investigation, we have also tried alternative proxies for the variable *Size*. In particular, we have considered measuring banks' size as (a) total assets and (b) the ratio of total assets to the assets of the whole banking system in the country of origin. Interestingly, estimates are qualitatively comparable, except when ΔROA is used in Equation (10) as a proxy for profit retention over the crisis. Results are available upon request. We also acknowledge that some recent studies have questioned the use of a size variable and employed, albeit in a different ambience, alternative proxies of systemic risk such as CoVar measures (see Barth and Schnabel, 2013).

[10] In this regard, it is worth noting that, in contrast to other comparable settings, we did not control for the amount of total capital. There are several reasons for this. First, total capital is highly correlated with our measure for bank dimension (the sample correlation is 0.49). Second, total capital also serves as a divisor for the credit risk indicator. In any case, any residual misspecification bias is (at least partially) neutralized in our econometric approach because we also estimate the model over various class sizes. Therefore, by assuming that (average) bank total capital does not vary within class size, the effect of total capital on the dependent variable will be captured by the constant term.

Table 2. Descriptive statistics of the main variables

Variable	Year	Mean	SD	Min.	Max.
Liabilities (billions of US$)	2007	56.99	260.54	0.04	3624.71
	2008	57.58	272.05	0.04	3383.75
	2009	54.59	239.24	0.04	2848.56
Liabilities/GDP	2007	0.06	0.31	0.00	5.87
ΔLLP_TL (%)	2009–2007	0.44	1.85	−11.41	40.32
ΔLLP_TC (%)	2009–2007	5.22	18.37	−306.22	344.36
ΔROA (%)	2009–2007	−0.35	1.22	−24.12	6.25
ΔROE (%)	2009–2007	−4.46	14.71	−200.34	77.07

Notes: LLP_TL is the ratio (loan loss provisions)/(total loans).
LLP_TC is the ratio (loan loss provisions)/(total capital).
ROA is Returns on Assets.
ROE is Returns on Equity.
The symbol **Δ** represents 2009–2007 differences.

dummy variable for listed and nonlisted banks. Although we have excluded from the sample banks with outright public ownership, we additionally control for potential ownership heterogeneity by using a public ownership dummy that accounts for banks partially owned by public sector shareholders.[11]

The descriptive statistics of the relevant variables are presented in Table 2. To better appreciate the overall trends in the European banking sector, we also display data regarding (level) Liabilities (distinguishing the 3 years of sample coverage). As expected, both credit risk variables have a positive mean, which signifies that credit risk has increased across the crisis on average. Conversely, the average values of the change in the profit measures are negative (–0.35% and −4.46% for ΔROA and ΔROE, respectively).

To complete the information on the characteristics of the sample, we report the correlations matrix of our risk/profitability variables in Table 3. All of the correlations appear to be high and significant. As expected, changes in credit risk appear to be negatively correlated with profit retention rates.

Table 3. Correlation matrix across credit risk and profitability indicators

	ΔLLP_TL	ΔLLP_TC	ΔROA	ΔROE
ΔLLP_TL	1.00			
ΔLLP_TC	0.43	1.00		
ΔROA	−0.31	−0.22	1.00	
ΔROE	−0.31	−0.33	0.70	1.00

Notes: LLP_TL is the ratio (loan loss provisions)/(total loans).
LLP_TC is the ratio (loan loss provisions)/(total capital).
ROA is Returns on Assets.
ROE is Returns on Equity.
The symbol **Δ** represents 2009–2007 differences.

IV. Econometric Methodology and Results

In this section, we present the results of the estimation of the quadratic fits in Equations 7 and 8 and of the local rolling window procedure (Equations 9 and 10).

Our econometric strategy is based on the 2009–2007 cross-section estimates. We are aware that the risk/profit interplay with the *Size* variable could also have been studied in a repeated cross-section setting (2009–2008 and 2008–2007). However, motivated by the fact that the shifts in the banks' strategic behaviour that we are looking for might emerge in balance sheets measures well after one year's horizon, we make the choice of not exploiting the efficiency gain due to the panel dimension of the data set.

Quadratic fits

Linear least squares estimates can behave badly when the error distribution is not normal and particularly when the errors are heavy-tailed. Therefore,

[11] In our analysis, we have also used the ownership dummy in interaction with the *Size* variable. The results do not qualitatively change.

to estimate the quadratic equations in Equations 7 and 8, we employ the Robust Least Squares M-Estimation (RLS) with Bisquare weights (Tukey Estimator). The method minimizes a weighted sum of squares, where the weight given to each data point depends on how far the observation is from the fitted line such that points near the line are assigned a full weight, points further from the line are assigned a reduced weight, and points that are further from the line than would be expected by random chance are assigned a zero weight.

The results of the application of the RLS estimator to Equation 7 are reported in Table 4.

Note that because the method excludes the extreme tails of the distribution of the dependent variable (less than 2.5% and higher than 97.5%), the number of observations changes according to the dependent variable.

Table 4. RLS estimations of Equation 7

Coefficients and statistics	ΔLLP_TL	ΔLLP_TC
α_2	0.0039**	0.0373**
	(0.0017)	(0.0196)
α_1	0.0616***	0.6382***
	(0.0201)	(0.2237)
α_0	0.5491***	4.7075***
	(0.1439)	(1.6318)
R^2	0.18	0.21
No. of obs.	1310	1312

Notes: We report the coefficient of the quadratic fit and, in parentheses, the SE.
*** and ** mean significance at 1% and 5% levels, respectively.

As implied by the signs and significance levels of the coefficients, the evidence supports a nonlinear shape of the relationship between a bank's credit risk and a bank's *Size*. This suggests that larger banks have shown a more than proportional change (testified by the positive and significant α_2) in credit risk over the crises *vis-à-vis* smaller banks. The representation in Fig. 3 of the estimated quadratic fits, along with the *Risk/Size* scatterplots, is very informative on this point. In more detail, panels (a) and (b) report the scatterplot and quadratic fit of the ΔLLP_TL and ΔLLP_TC versus *Size*, respectively. In addition to being highly dispersed, the row data show a clear quadratic relationship between credit risk and *Size*. As is testified by the convexity of the slope in both case, the larger the bank, the higher the credit risk appetite appears to be over 2007–2009.

The estimation of the quadratic links between the profit retention rates (ΔROA and ΔROE) and the *Size* variable leads towards an unexpected direction.

As implied by the estimated coefficients reported in Table 5, our profit variables are linked to *Size* in a concave relationship. β_1 and β_2 are both significant and negative, which suggests that the larger the bank, the higher the contraction in its profit margins.

A representation of the estimated fits is reported in Fig. 4, where panels (a) and (b) report the scatterplot and the quadratic fit of ΔROA and ΔROE versus bank *Size*, respectively.

All in all, the results obtained through the estimation of a quadratic relationship are deceiving from the perspective of the validation of the full working of the TBTF hypothesis. Although large banks appear to have increased their risk appetite during the first wave of the present

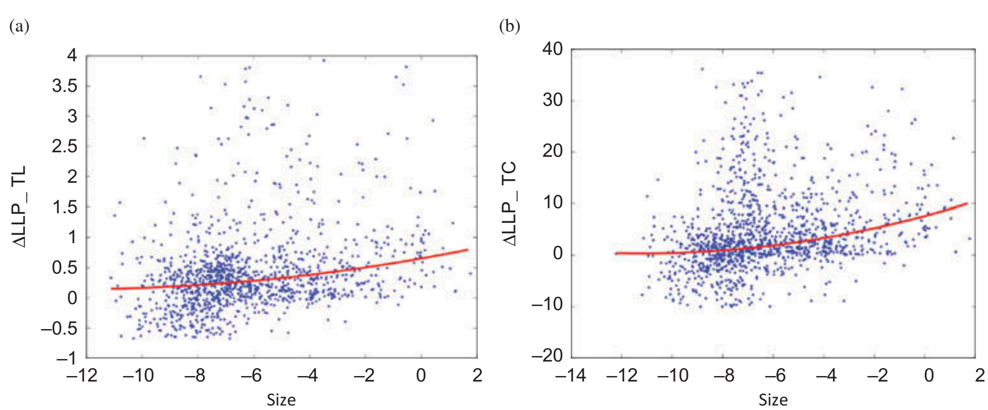

Fig. 3. Size–risk scatterplot and estimated quadratic fit

Table 5. RLS estimations of Equation 8

Coefficients and statistics	ΔROA	ΔROE
β_2	−0.0023***	−0.0517***
	(0.0008)	(0.0193)
β_1	−0.0373***	−1.0408***
	(0.0101)	(0.2267)
β_0	−0.2887***	−9.0567***
	(0.0748)	(1.8144)
R^2	0.57	0.38
No. of obs.	1304	1311

Notes: We report the coefficient of the quadratic fit and, in parentheses, the SE.
*** means significance at 1% level.

financial crisis, there are no signs that this has translated, *ceteris paribus*, into larger profit. Therefore, according to our definition, the results imply the prevalence of a *partial* form of the TBTF hypothesis.

Rolling window estimates

As discussed above, to gain more details on the features of the quadratic fits, we proceed to estimate the piecewise linear approximations in Equations 9 and 10. The rolling window approach appears quite appropriate because, observing the quadratic fits above, it seems well possible that the coefficients become significantly different from zero at only a certain value of the size variable. Essentially, with the rolling window procedure, bank *Size* distribution is divided into several overlapping windows (of dimension 1) and a linear fit is performed for each of these windows. Because the number of banks is not uniformly distributed with respect to *Size*, we use

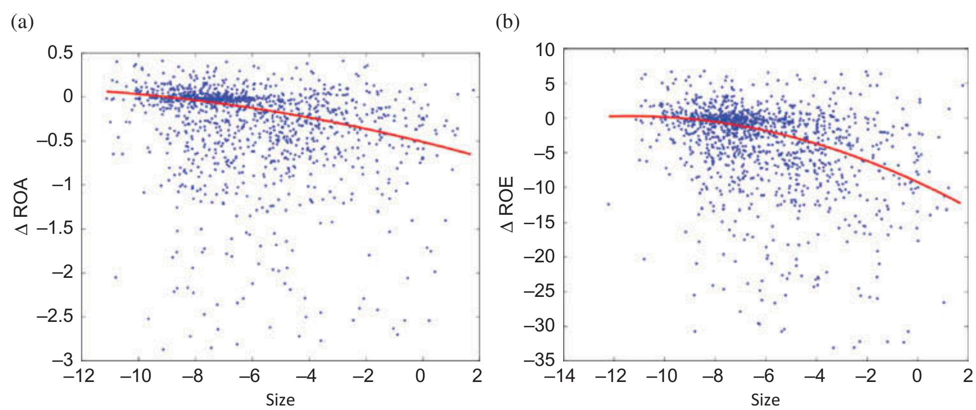

Fig. 4. Size–profit scatterplot and estimated quadratic fit

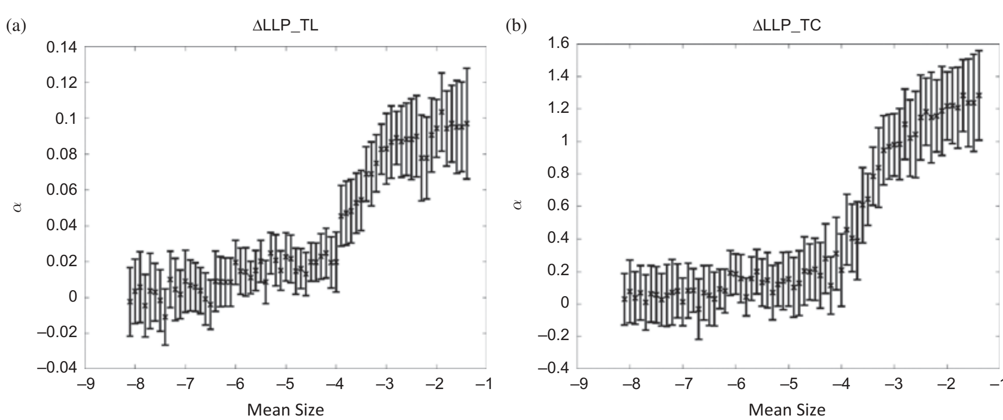

Fig. 5. Rolling estimations of the *Size* elasticities of the credit risk variables

a bootstrap procedure to construct confidence intervals that allow us to compare the coefficients.

We start our discussion with the credit risk measures. The results are displayed in Fig. 5, where panels (a) and (b) depict the sequence of the estimated values of the size sensitivities in Equation 9 for the two measures of credit risk (ΔLLP_TL and ΔLLP_TC).[12] A number of interesting details emerge. First, as is also predicted by the model in Section II, the size sensitivities of ΔLLP_TL and ΔLLP_TC are virtually zero for a large part of the left tail of the distribution of *Size*: there is no appreciable size-induced change in our proxy of risk appetite over the first wave of the present financial crisis. Then, approximately at a value of −4, the coefficients soar and become highly significant. Note that the value of −4 of the log of the ratio liabilities/GDP corresponds to approximately 0.02. Therefore, two cases can be stated: (i) for banks with *Size* < 0.02, the alpha coefficients are not appreciably different than zero when either ΔLLP_TL or ΔLLP_TC are used as measures of the variations in credit risk appetite over the period 2007–2009; (ii) for banks with *Size* above this critical value, a size-induced increase in credit risk emerges. Note that banks that lie on the right of the critical size of 0.02 constitute 15% of the sample (cf., in this regard, the Cumulative Frequency Distribution in Fig. 2).

We now proceed to study the behaviour of the size sensitivities of the profit variables in Equation 10 at various points of the distribution for *Size*. The results are presented in Fig. 6, panels (a) and (b).

The interpretation of the findings is now much less straightforward. The point estimates of the β coefficients appear to be significant and negative at (almost) all points of the distribution of *Size* in the case of both ΔROA and ΔROE. Furthermore, a decreasing magnitude of the size elasticities is observed, which is more intense for the case of ΔROE, until the class *Size* approximately centred at −4 is reached; then, the size sensitivities of ΔROA begin to show an upward trend, but we observe a lateral development (with greatly enlarged bands of uncertainty) in the case of ΔROE.

What can be inferred from the observed behaviour of the size elasticities of profit retention over the first wave of the present financial crisis? Leaving ΔROE aside for the moment, the ΔROA case suggests that, similarly to what was found for the credit risk variables, there is a critical threshold in the liabilities/GDP ratio (2%) beyond which financial institutions appear able to improve their profit retention rates over the crisis on average. Therefore, according to our definition, this is evident that the European banking industry has indulged in a *full* form of TBTF activity over the first wave of the present financial crisis.

In concluding this section, we acknowledge the existence of various unsettled points in our results. For instance, the reasons behind the negative size sensitivities of the profit retention rates are unclear and difficult to accommodate in the present setting. There are several possible explanations, each of which requires further investigation: there could be size heterogeneous restructuring processes and/or in-

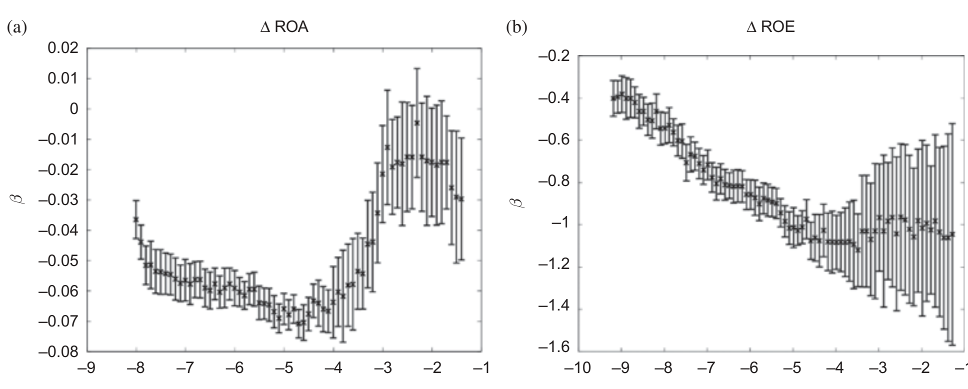

Fig. 6. Rolling estimations of the *Size* elasticities of the profit variables

[12] Note that Fig. 5 reports the mean of *Size* for each of the shifting window.

sample size-dependent strategic changes not neutralized by the 'difference' approach used in constructing the proxies for profitability retention rates. Various levels of diversification could also operate so that large banks are more exposed to systematic risk, which has a consequent higher profitability dip in times of crises.[13]

Furthermore, what is the explanation behind the various patterns shown by the beta coefficients in our measures of the profit retention rates? We think that the crisis has imposed heterogeneous adjustment paths to Assets versus Capital variables, ROA and ROE's denominators, respectively.[14] However, more coherent to our view of the banking industry, whose behaviour derives from planned strategic choices, there could also be more subtle arguments concerning the actors behind the dangerous build-up of the morally hazardous behaviour.[15] We leave the exploration of these issues to future work.

V. Conclusions

Based on the theoretical models of the strategic behaviour of financial institutions in the presence of implicit guarantees of a bailout, we provide an empirical test of a *full* and a *partial* form of the TBTF hypothesis. For the full form to apply, we require both risk appetite *and* profitability to grow for banks that exceed a certain dimension *vis-à-vis* smaller banks; for the partial form to apply, only a size-induced increased risk appetite needs to be observed. The investigated domain is the European banking industry over the first wave of the present financial crisis (2007/09).

We primarily discuss the results of a quadratic fit estimation that links banks' variations in risk appetite and profit retention rates to a measure of banks' dimension. The results are deceiving from the perspective of the validation of the full working of the TBTF hypothesis. Although large banks have increased their risk appetite during the first wave of the present financial crisis, there are no signs that this has translated, *ceteris paribus*, into larger profits. Therefore, according to our definitions, the results suggest the prevalence of a *partial* form of the TBTF hypothesis.

However, a more accurate, local rolling window investigation of the interplay between the risk/profit variables and bank dimension allows us to partially update these findings. It emerges that sensitivities significantly differ across various regions of the distribution of *Size* for both our risk and profit measures. In more detail, large banks, whose liabilities exceed approximately 2% of the country of origin's GDP (15% of the sample), have, on average, increased their risk profile over the first wave of the present financial crisis *vis-à-vis* their smaller counterparts. Furthermore, because there is evidence that approximately the same group of banks have also shown a better capability of retaining profits (when measured by the ROA indicator) over the crisis, we thus conclude, with all of the caveats of our investigation, that the European banking industry has indulged in a full form of TBTF activity. We also underline the need for further research on the issue.

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[13] Note that the point is largely controversial in the literature (see, for instance, Acharya *et al.*, 2006; Altunbas *et al.*, 2007; Rossi *et al.*, 2009). In banking, diversification *per se* is no guarantee for better profit scores. On the one hand, the classical theory of finance suggests that a higher diversification in a bank's loan portfolio should reduce its realized risk as measured by the amount of provisions for bad loans, and this in turn may increase the bank's profit (*classical diversification hypothesis*). On the other hand, if the management lacks the time/expertise to monitor the loan granting process to new customer segments or new industries effectively, more diversification may not necessarily imply less provisioning (*lack of expertise hypothesis*) (cf., also Acharya *et al.*, 2006).

[14] Interestingly, we observe that although Capital and Liabilities have shown a comparable reduction over the crisis (−14% and −17%, respectively) in our sample, the SD of the reduction is much higher for Capital than for Liabilities (233% versus 46%). This also justifies the much higher variability of the ΔROE compared to the ΔROA in our sample (cf., Table 2).

[15] In this regard, as is clear in the literature, managers may not act in the firm's best interest and may have an incentive to expropriate owners of the increased profitability linked to opportunistic credit expansion. Our rolling window estimations are consistent with a scenario where managers of large banks have inefficiently expanded the bank's dimension. Returns have increased more than proportionally, following the market relation with higher risk. On the capital side, keeping the capital adequacy ratios might have put a pressure on equity, which explains the lateral development of the size sensitivity of the ΔROE.

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