Are big banks too-big-to-fail? An investigation into the size premium and scale economies for European banks

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1. Introduction

Are large Systemically Important Banks (SIBs) such as the French BNP Paribas or Spain's Banco Santander Too-Big-To-Fail (TBTF) banks, more specifically are they perceived by investors to be TBTF? How about the much smaller size SIBs of Cyprus, Greece, or Portugal? In a recent paper, Gandhi and Lustig (2015) show that large banks in the U.S. have significantly lower risk-adjusted returns than small- and medium-sized banks, attributing this anomaly to implicit TBTF guarantees. In a follow up unpublished study Goyal (2017) challenges the main Gandhi and Lustig findings arguing that implicit government guarantees for large banks, if they do exist, are not perceived as such by investors. We shed further light on this contentious issue by analysing European bank stock returns. We depart from previous studies in some important respects noting the following:

First, previous studies use country-specific (US) samples ranging from very small to very large banks. In contrast all banks in our cross-country sample are large, some much larger than others, and most are SIBs at least in their home country. Second, we rank all bank stocks by market capitalisation as of January of each year rather than rebalancing the sample monthly, hence we are not subject to the Goyal (2017) one month return reversal critique. Third, we address the size effect more broadly by considering the moderating effects of scale economies in our analysis. Specifically, we ask whether investors perceive large banks as less risky because they exploit economies of scale rather than enjoying TBTF implicit safety net subsidies. Fourth, we use a new measure of returns to scale that benchmarks bank size relative to the most post productive scale size widely perceived as an optimal regulatory size. This is important as regulatory attempts to limit large bank size in the pursuit of enhancing systemic safety nets may prove socially counterproductive if the restrictions inhibit bank's ability to achieve potential scale economies that can be passed onto bank customers in the form of more efficient intermediation and therefore lower prices (Beccali et al., 2015)

Our approach offers several advantages. Using a sample of large predominantly SIBs means that we can carry out a cleaner test of the size factor in testing the TBTF hypothesis by avoiding potential confounding effects in assessing the role of size on expected bank stock returns. Second, we recognise that size may be associated with implicit TBTF guarantees but also may reflect investor perceptions regarding economies of scale, the quality of governance, and market power. For example, investors may perceive large banks operating under increasing returns to scale (IRS) as less risky. This is important, recognising that many large banks may pursue risky overambitious balance sheet expansions while operating under decreasing returns to scale (DRS). Investors may also value the quality governance inclusive of its social and environmental (ESG) performance as well as perceive banks with more market power to be less risky. While we control for ESG performance in characteristics regressions, the focus of this study is on bank size in relations to TBTF implicit government guarantees and scale economies. We leave questions about the nexus between TBTF, ESG and market power for future research.

Large financial institutions are highly complex and highly interconnected and have been known to enjoy too-big-to-fail (TBTF) implicit government guarantees such as government support to prevent their failure. Such implicit guarantees are likely to incentivise moral hazard, distorting scale (e.g., DRS banks getting too big) and risky choices (e.g., banks may care less about downside risk) as evident from overambitious expansion of balance sheets in the lead up to the global financial crisis (GFC).

In this study we revisit the TBTF issue for European banks by asking whether size may be considered to be an important risk factor in the cross-section of bank returns. We pay attention to post GFC regulatory changes, such as the UK Financial Services Act 2012 and the EU 2014 Banking Resolution and Restructuring Directive (BRRD) followed by the 2016 Single Resolution Mechanism (SRM), by asking whether they have been effective at reducing implicit TBTF guarantees in terms of investor perceptions. In addition, we ask whether scale economies provide further insights in assessing the TBTF issue. We control for increased investor awareness about environmental risks in characteristics regressions noting the environmental or more generally ESG question is only peripherally addressed since it is the subject of a follow up paper.

In a recent study Gandhi and Lustig (2015) show that if a bank is deemed too-big-to-fail, the expected return on its stock is lower than that of smaller banks even though large TBTF banks are significantly more levered. This size anomaly in bank stock returns is further shown to be different from the size factor documented in the literature for nonfinancial firms. Gandhi and Lustig interpret this finding as evidence of an implicit subsidy by government absorbing the tail risk of large banks but not small banks in disaster states.

Such findings provide further ammunition to long held views that implicit government guarantees incentivise TBTF banks to take excessive risks, hence posing serious threats to financial system stability. The situation has become critical again as ultra-low interest rates during the pandemic crisis squeezed bank margins, and more recently as monetary policy tightening, in response to rising inflation, is placing extra pressure on bank balance sheets as evident from bank failures or near-failures in the US and Europe.

While Gandhi and Lustig study US banks, our focus is on European banks. Specific interest on European banks and TBTF implicit guarantees stem from the special status many large banks in Europe enjoy across member states in the form of protection and by fostering national banking champions, notwithstanding that several EU states have much more concentrated banking systems than the US. European banks are also coming under closer scrutiny by investors and their regulators in relation to their environmental record.

Though smaller banks' business models may differ from those of larger banks, there are no firm a priori reasons to believe that such differences amount to systematic differences in expected risk-adjusted returns unless, as Gandhi and Lustig (2015) point out, there is bank-specific tail risk that is priced but not spanned by the traded returns on other risk factors. We take this issue further in this study.[1]

The question we ask is whether large banks are less risky because of their TBTF status or simply because of exploiting economies of scale. Previous studies have mainly focussed on the period around the Global Financial Crisis. What is notable here is that over the past decade most banks have reduced the scale and scope of their trading activities (including proprietary trading), in the interest of lessening exposure to risk. At the same time, they have come up under a lot of pressure to respond to the financial risks of climate change.

[1] Some may argue that large banks are less risky because they are better diversified, and hence have lower idiosyncratic risk. Yet large banks tend to have much larger systematic risk, because of their systemic importance, and asset pricing is about systematic risk.

Banks are also facing tighter regulatory requirements, which are even stricter for large systemic banks, as well as a new resolution regime that places explicitly the onus of a bank failure primarily on shareholders and creditors. This is all happening as banks are still in search of profitable new business models as well as ways to handle digital disruption stemming from increased competition in their retail business from financial technology and platform-based competitors.

Hence the issues at stake are whether (1) implicit TBTF guarantees still exist in the new environment, and more importantly (2) priced accordingly in bank stock returns. Changes in resolution regimes and stricter capital requirements may have altered investor perceptions, although it is not clear that by specifically identifying banks as TBTF in the regulation does indeed alleviate implicit guarantees or moral hazard concerns.

Yet investors may require higher stock returns for large banks that have reduced their scale by foregoing economies of scale, are less likely to actively manage environmental, social and governance risk exposures or lack market power. The economies of scale issue appears to have been largely neglected in much policy debate on bank size following the shift of regulatory policy after the GFC. One possible explanation is the difficulty policymakers face in measuring returns to scale in banking while remaining cognizant of the fact that large balance sheet expansions may be risky not only for the bank but also for the system at large.

Using an asset pricing model offers the advantage of capturing the market assessment of implicit government guarantees including investor perceptions about the credibility of bail-in resolution for large TBTF banks. We recognise that such an asset pricing model needs to capture the particular risk characteristics of financial institutions. The standard approach is to complement equity risk with debt risk factors (see Gandhi and Lustig, 2015) recognising the particular characteristics of banks as asset transformers in managing their interest rate and liquidity risk exposures. Yet pricing anomalies may still exist. As in Gandhi and Lustig, we incorporate an extra 'size' factor in the pricing model constructed from size sorted bank returns portfolios. In addition, we pay attention to returns to scale in the pricing model to avoid confounding effects that may arise in assessing the 'size' effect by simply relying on market capitalisation.

We start by forming portfolios of banks based on size. We obtain risk adjusted excess returns and compare the returns of small vis-à-vis large banks. We then proceed to construct a size factor that is intended to capture the size anomaly that may exist across small banks vs. large banks risk-adjusted returns. To shed further light into the 'size' anomaly we go one step further analysing the interaction between bank size and returns to scale by sorting portfolios first on size (small-medium-large) and then on returns to scale (increasing, decreasing, and constant returns to scale).

Returns to scale and their associated scale elasticity (SE) metrics are essential features of the production technology and play an important role in decision making, e.g., decisions regarding M&A targets or the premium an acquirer is willing to pay for a target. RTS is also an important input in competition policy since market power has traditionally been rooted in underling scale economies in an industry. In banking, there are extra regulatory concerns about increased industry concentration insofar it encourages excessive risk taking as a result of implicit government guarantees for very large 'too-big-to-fail' (TBTF) banks, in addition to moral hazard problems arising from the presence of explicit guarantees, e.g., deposit insurance.

Where the costs of achieving scale may be extensive, the losses of plurality arising from M&As[2] or more generally from large banks getting bigger, are likely to be significant and potentially irreplaceable. This is particularly true if expansion is driven by high leverage (debt to assets) which may not be sustainable, e.g., as a result of asset price run-ups, or from rapid expansion of loosely regulated off-balance-sheet activities involving complex financial instruments which may prove excessively risky as evident from the subprime crisis.

Deutsche Bank's daunting problems in 2016 resulting from an over ambitious off-balance-sheet expansion, a very costly gamble, at a time other European banks were retrenching in the face of slackening markets and tightening regulation also come to mind. But large banks may be getting bigger and historically have done so for reasons which may have more to do with potentially significant technological or cost advantages brought about by economies of scale. However, the potential benefits of operating at a large scale have been largely ignored in policy discussions. It is the intent of this paper to examine if indeed such benefits exist and whether they are more common amongst the largest banks.

While TBTF banks have been under regulatory scrutiny for a long time, the global financial crisis (GFC) widened the focus and importance attached to these institutions recognising that TBTF banks are likely to pose even greater risks to systemic stability in the event of a failure

[2] For example, Molyneaux, Schaeck and Zhou (2014) report that safety related implicit subsidies derived from bank M&A activity in Europe between 1997 and 2007 have a positive association with rescue probability, indicative of significant moral hazard problems. Davies and Tracey (2014) find no evidence of scale economies once they control for implicit subsidies associated with the reduction of funding costs for TBTF banks.

than previously thought. With concerns over large banks needing assistance looming, lawmakers have been debating proposals giving regulators extra powers to cap bank size or split-up banks, in addition to tighter regulations on capital, leverage and liquidity introduced as a response to the financial crisis.

Capping the size of banks may, of course, have a serious downside (see Wheelock and Wilson, 2018) if it prevents banks from exploiting economies of scale. Yet size is widely regarded as the main underlying cause of systemic risk, and it is the benchmark generally adopted for the purposes of identifying systemically important financial institutions.

We assess bank performance using a measure of bank efficiency constructed as the distance to the technological frontier and investigate whether larger banks are exploiting technologically driven scale economies using a new measure of RTS based on closeness to the most productive scale size (MPSS). Using an MPSS benchmark for estimating scale elasticity is highly desirable recognising that MPSS is considered to be an optimal scale size. We pay attention to the relationship between bank size and market performance and the relationship between bank size and scale elasticity.

Studies generally find evidence of scale economies for large US banks in the 1990s and 2000s (e.g., see Berger and Mester, 1997; Hughes, Mester and Moon, 2001; Feng and Serletis, 2010; Hughes and Mester, 2013; Wheelock and Wilson, 2012, 2018). We focus on approaches to RTS characterisation and SE measurement that are directly applicable to non-parametric multiple-output technologies (e.g., see Panzar and Willig, 1977; Färe, Grosskopf and Lovell, 1985; Banker and Thrall, 1992; Førsund, 1996; Sueyoshi, 1999; Fukuyama, 2000; Podinovski, Førsund and Krivonozhko, 2009; Balk, Färe and Karagiannis, 2015).

Scale elasticity is thus defined in terms of distance functions (a generalisation of the more familiar production function) and is computed from Farrell (1957) technical efficiency measures and the multiplier (shadow value) of the convexity constraint of the dual data envelopment analysis (DEA) model. While DEA has been extensively used in the measurement of efficiency and productivity in banking, RTS measures have generally been obtained from parametric cost functions offering the convenience of smooth differentiable functional forms.

One issue, however, with cost-based measures is that prices for bank inputs are not readily available which raises questions about the reliability of proxies used in empirical studies. Scale elasticity estimates can also be obtained from parametric production functions but the problem is that they are limited to a single output model which is not suitable for the multioutput specifications of production technologies in banking studies. Another issue is that RTS measures are meaningful for frontier points or for the projection of an inefficient point to the frontier but not for the inefficient point itself since there is confounding between inefficiency and economies of scale. This is a subtle point often not recognised in the literature where parametric stochastic frontier models lump together measures of economies of scale for both frontier and interior points.

Previous methods of calculating scale elasticity for frontier points based on non-parametric piecewise linear technologies suffer from inherent ambiguities in choosing a single candidate as the final SE value. SE may not be uniquely determined between an upper or lower bound or a particular value from the SE interval unambiguously chosen since the efficient point may lie on several efficient facets. Further complications arise as the chosen value may be unrealistic, very sensitive to even small changes in input or output values as well as sensitive to the orientation of the DEA model.

We construct a metric for SE as the minimum distance from the MPSS frontier. Calculating SE against MPSS gives a more intuitive economic meaning to the scale elasticity concept since MPSS corresponds to a production point on the efficient frontier with the maximum average productivity for the given input-output vectors (Banker, 1984).

Our approach has some quite attractive features: (i) offers a single linear programming (LP) model that provides a unique value for SE invariant to multiple optimal solutions; (ii) characterises RTS directly; and (iii) does not depend on the choice of orientation whether input, output or directional. Furthermore, we demonstrate that it provides a non-ambiguous measure of SE that allows regulators and managers to clearly see whether firms (and their sector) are operating at an efficient scale level.

There are also approaches that measure SE for production points inside the frontier making use of directional projection points (Førsund and Hjalmarsson, 2004), and using reference points as projections (Banker et al., 2004) or adjusting SE (Podinovski et al., 2009). These methods relate to our approach since the reference for calculating SE for inefficient units is the frontier. The choice of targets for projections to the frontier has been the topic of much discussion. In a related study Petersen (2018) defines the relevant part of the frontier as corresponding to the vector of prices that maximises the profit efficiency of DMUs.

A natural choice for the projection is then defined as the profit maximising virtual price normal for the supporting hyperplane of the production possibility set with the minimal Euclidean distance to the DMU. In a similar fashion, we choose projections to a point in the direction of an MPSS hyperplane supporting the technology set. Since the MPSS frontier may not be unique we take advantage of the prices that we have, and we select the closest MPSS hyperplane to the existing price facet. For missing prices, we use the average MPSS shadow prices. Similar to previous studies, our focus is in utilising a variable return to scale (VRS) technology, specifically its dual representation, which can be characterised by its supporting hyperplanes.

Some of the questions we set out to assess empirically are as follows:

- Are differences in bank returns due to differences in RTS rather than TBTF subsidies?
- Do banks under pressure to downsize experience a change in RTS, thereby forgoing advantages offered by economies of scale?
- What are the implications of RTS for the bank cost of equity?
- Are there size distortions in the bank cost of capital?
- How do returns to scale interact with ESG performance in relation to the bank's cost of capital?

2. Empirical section

2.1 Size Effect in Bank Stock Returns

We collect and merge monthly data for 165 European/UK commercial banks for the period from 2000:1 to 2023:3 from Refinitiv, Euro Interbank Offered Rate database, and FRED economic database. The majority of the banks are considered as systemically important in their home country. We build our bank portfolios employing the standard portfolio formation strategy of Fama and French (1993). We first rank all bank stocks by market capitalisation. The stocks are then allocated to 10 portfolios and equally- as well as value-weighted returns are calculated using the January market capitalisation for each portfolio each year.

We use the Fama and French (1993) three-factor model augmented by extra factors reflecting the risk profile of the banking industry to estimate risk-adjusted returns. A bank manages a portfolio of bonds of varying maturities and credit risk. Therefore, we also include two bond risk factors in addition to three stock risk factors.

$$\boldsymbol{f_t} = [Mkt \quad SMB \quad HML \quad EBR \quad HY], \tag{1}$$

Mkt, SMB, and HML represent the returns on the Fama-French European 3 factors, namely, market, firm size, and value factors, respectively. EBR is the Euribor 12-months to 1-month spread, and HY is the Option-Adjusted Spread (OAS) of the ICE BofA Euro High Yield Index that tracks the performance of Euro denominated below investment grade corporate debt publicly issued in the euro domestic or eurobond markets. Funds with maturity less than 30 days are fully covered by the liquidity coverage ration, hence the 12-month to 1-month Euribor spread indicates the bank's willingness to lend funds rather than engage in transactions.

We regress monthly excess portfolio returns for each size-sorted portfolio on the three Fama-French stock factors and the two bond factors.[3] For each decile portfolio i we run the following time-series regression to estimate the vector of betas, β_i:

$$R_{t+1}^{i} - R_{t+1}^{f} = \alpha^{i} + \beta^{i,'}\boldsymbol{f}_{t+1} + \epsilon_{t+1}^{i}, \tag{2}$$

where R_{t+1}^{i} is the monthly return on the ith size-sorted portfolio.

Table 1 provides the results of the regression specified in equation (2). The table reports the regression coefficients for each size-sorted portfolio, along with their statistical significance. Panel A reports the results for the entire (2000-2023) sample period while Panel B reports the results for the post GFC/Euro Sovereign Crisis (2012-2023) period. The portfolios are ranked from smallest (1) to largest (10).

The estimated intercepts (portfolio alphas) decline nearly monotonically with bank size from 1.13% in the first decile to −1.06% in the tenth decile (Panel A). A long-short position loses 2.32% per month over the entire sample period which is significant at 1% level. We obtain similar results for the post GFC period as shown in Panel B. A long-short position that goes long on the largest and short on the smallest banks loses about 2% per month in the post GFC/Sovereign Crisis period.

The first row of Table 1 (Panel A) shows the coefficient on excess market return, for each size-sorted portfolio. The market beta increases monotonically with bank size. Over the entire

[3] We have carried out several unreported robustness checks. We have re-estimated (2) with (a) two extra Fama-French factors, robust minus weak (RMW) operating profitability and conservative minus aggressive (CMA) investment portfolios average returns, (b) without the bond market factors, (c) with value-weighted instead of equally weighted decile returns, and (d) using a sub sample covering the period 2000 to 2012. We have obtained similar results in terms of both patterns across deciles and long-short positions. The 10-1 alphas for (a), (b), (c) and (d) are -2.37, -1.08, -2.33, and -2.81, respectively, and are all statistically significant at the 1% level.

sample, a portfolio of large banks has a market beta of 1.026, as compared to a beta of 0.232 for a portfolio of the smallest banks. The largest banks were more than fourfold exposed to market risk as compared to the smallest banks. This difference can be attributed largely to differences in leverage. Some may argue that larger banks are less risky. This may be true as they may have lower idiosyncratic risk because they may be better diversified than smaller banks, yet they have larger systematic risk, and asset pricing is about systematic risk. TBTF implicit subsidies is part of systematic risk so large banks which are TBTF may enjoy subsidies that lessen their systematic risk exposures hence justifying an artificially lower cost of capital. They may also benefit from size-related diversification. The latter is an interesting question, and we provide some evidence based on estimates of economies of scale.

Table 1. Risk-Adjusted Returns of Size-Sorted Portfolios of European Commercial Banks

This table presents estimates from OLS regression of monthly equally-weighted excess returns on each size-sorted portfolio of European commercial banks on the three Fama-French European equities factors, Mkt, SMB, and HML, and two bond risk factors, $EURB\_SP$ is the Euribor 12 months to 1 month spread and $EURO\_HY$ is the Option-Adjusted Spread of the Euro High Yield Index. $*$, $**$, and $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) with three lags. The sample is 2000:2 to 2023:3 in Panel A and 2012:1 to 2023:3 in Panel B.

Panel A: Market Cap Deciles 2000:1-2023:3											
	Small	2	3	4	5	6	7	8	9	Large	10-1
MKT_RF	0.232***	0.328***	0.41***	0.321***	0.405***	0.517***	0.644***	0.778***	0.975***	1.026***	0.797***
SMB	0.605***	0.65***	0.638***	0.543***	0.37***	0.476***	0.257**	0.212	0.048	-0.215	-0.809***
HML	0.21***	0.329***	0.396***	0.286***	0.319***	0.384***	0.518***	0.986***	0.849***	1.035***	0.814***
EURB_SP	-0.642	-1.261**	0.027	-0.5	-0.269	0.139	0.255	0.86	1.435**	1.069	1.733**
EURO_HY	-1.731***	-1.786***	-0.755	-1.222**	-0.059	-0.695	-1.088	-1.796**	-1.029	-0.608	1.152
C	1.113***	1.439***	0.321	0.753*	0.15	0.451	0.522	0.16	-0.551	-1.058*	-2.318***
Adj-Rsq	0.304	0.429	0.487	0.399	0.537	0.605	0.591	0.620	0.712	0.708	0.550
Panel B; Market Cap Deciles 2012:1—2023:3											
	Small	2	3	4	5	6	7	8	9	Large	10-1
MKT_RF	0.295***	0.372***	0.454***	0.377***	0.451***	0.516***	0.699***	0.692***	0.938***	1.025***	0.731***
SMB	0.463***	0.385***	0.686***	0.583***	0.37***	0.623***	0.266*	0.073	0.198	0.084	-0.37
HML	0.231**	0.377***	0.461***	0.305***	0.346***	0.421***	0.612***	1.455***	0.971***	1.287***	1.06***
EURB_SP	-0.477	-2.015**	-0.146	0.595	-0.119	0.498	0.564	0.106	0.306	1.005	1.325
EURO_HY	-2.834	-0.652	-1.759	-7.789***	-2.617	-3.585	-6.32**	0.023	1.319	-1.602	1.628
C	1.732*	1.290*	1.036	2.789***	1.156	1.458*	2.338***	0.41	-0.678	-0.158	-2.037***
Adj-Rsq	0.292	0.454	0.561	0.464	0.570	0.658	0.732	0.672	0.755	0.780	0.593

The loadings on SMB and HML also depend systematically on size. We first look at the exposure to the size factor. Over the entire sample the loadings on SMB decrease from 0.605 in the first size decile to -0.215 in the tenth decile. The loadings on HML increase from 0.21 in the first decile portfolio to 1.035 in the tenth portfolio.

2.2. Size Factor in Bank Stock Returns

There is evidence (e.g., Acharya and Yorulmazer 2007, Farhi and Tirole 2012) suggesting that banks seek exposure to similar risk factors. The risk factor we have in mind based on the evidence in Table 1 is a size factor. We use principal component analysis (PCA) to construct a bank-specific size factor.[4] The main interest here is to see if this factor is able to address the size anomaly, we observed in the results of Table 1. Following Gandhi and Lustig (2015) we construct the size factor based on the residuals of the time-series decile regressions.

The first two principal components of the idiosyncratic (residual) decile portfolio risk explain 63 percent of the total return residual variation. The first principal component (PC1) is a banking industry level factor exhibiting little loadings variation. However, it is the second principal component (PC2) which has loadings that generally depict a bank size related pattern commensurate with the risk-adjusted returns pattern we observe in Table 1. Thus, PC2 is a candidate for a size factor since it loads positively on small banks and negatively on large banks.

A size factor can be constructed by multiplying the ($T \times 10$) matrix of residuals for each of the size-sorted portfolio of banks obtained from the estimation of (2) times the (10×1) vector of loadings on the normalised second principal component ($\widehat{PC}2$) in each period The factor loadings on PC1, PC2 and its normalised version $\widehat{PC}2$ with loadings adding up to one are shown below:

Table 2. Principal Components

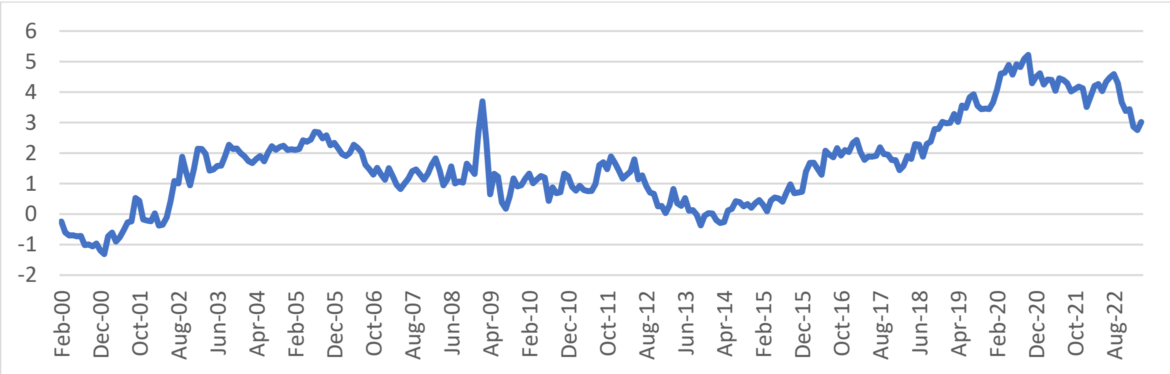
$PC1$	0.227	0.262	0.315	0.345	0.350	0.341	0.337	0.306	0.333	0.324
$PC2$	0.392	0.448	0.303	0.307	0.160	-0.135	-0.297	-0.282	-0.376	-0.327
$\widehat{PC}2$	2.022	2.314	1.565	1.584	0.829	-0.696	-1.534	-1.454	-1.940	-1.691

The normalised PC2 loadings indicate that a highly levered portfolio can be formed with a long position of €202 in small banks and a short position of €169 in large banks. The return on this portfolio has a monthly standard deviation of 7.30%.

[4] The advantage of PCA in factor analysis with observed and latent factors is that it spans the entire factor space of returns, within which all potential factors may reside. By identifying the spanning vectors, or factors, of this space, ensures that any factor required for inclusion in the model is either one of these spanning factors or a rotation thereof (see Giglio and Xiu, 2021).

We turn next to investigate whether the size factor reconciles the anomaly in risk-adjusted bank returns. We proceed as follows. We construct the priced 'size' factor R[PC2] by multiplying the ($T \times 10$) matrix of returns for each of the size-sorted portfolio of banks times the (10×1) vector of loadings on the normalised second principal component in each period. This portfolio is long in small banks and short in large banks. The cumulated returns on this portfolio are shown in figure 1. There are sharp declines in Sept 2001 as well as in the period leading to the sub-prime crisis in 2007, the aftermath of both the GFC in 2009 and sovereign crisis in 2012, and during the pandemic and its aftermath. However, a highly levered long-short position although hitting bottom by 2014, appears to be quite profitable over the entire sample period.

Figure 1. The cumulated returns on the priced bank size factor (Cum_R[PC])



Figures 2-4 plot the bank 'size' factor (PC) against the Fama-French size and value factors. The bank 'size' factor exhibits more volatility as to expected than the size and value equity market factors which is more notable during the GFC period and its aftermath (2008-2013).

Figure 2. The bank size factor against Mkt

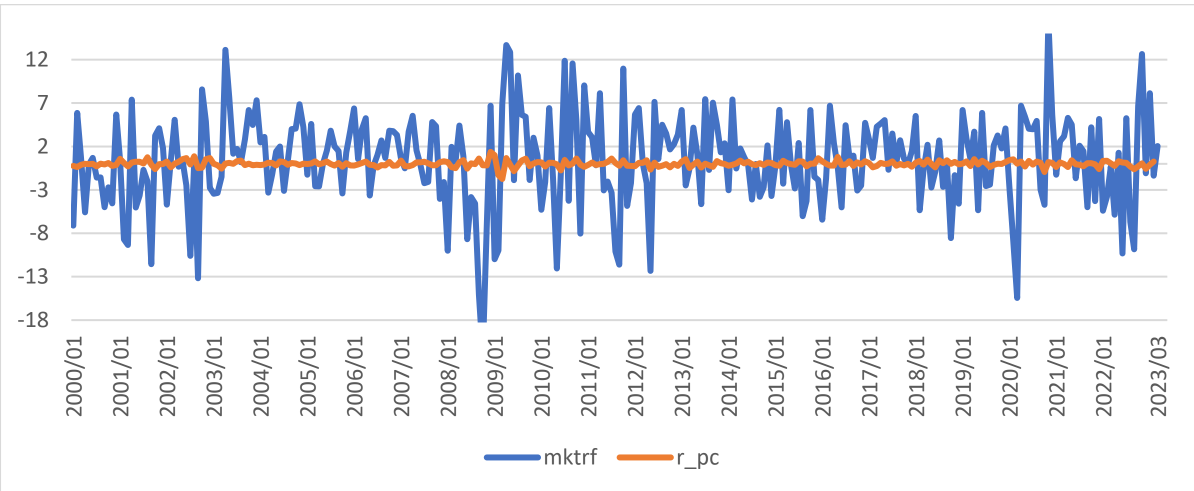


Figure 3. The bank size factor against SMB

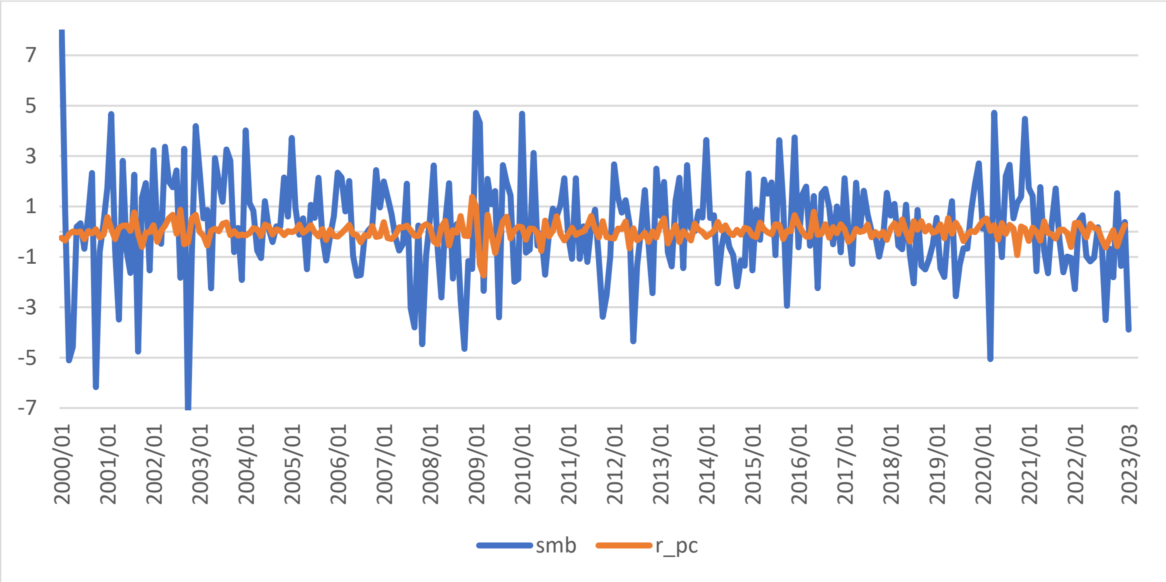
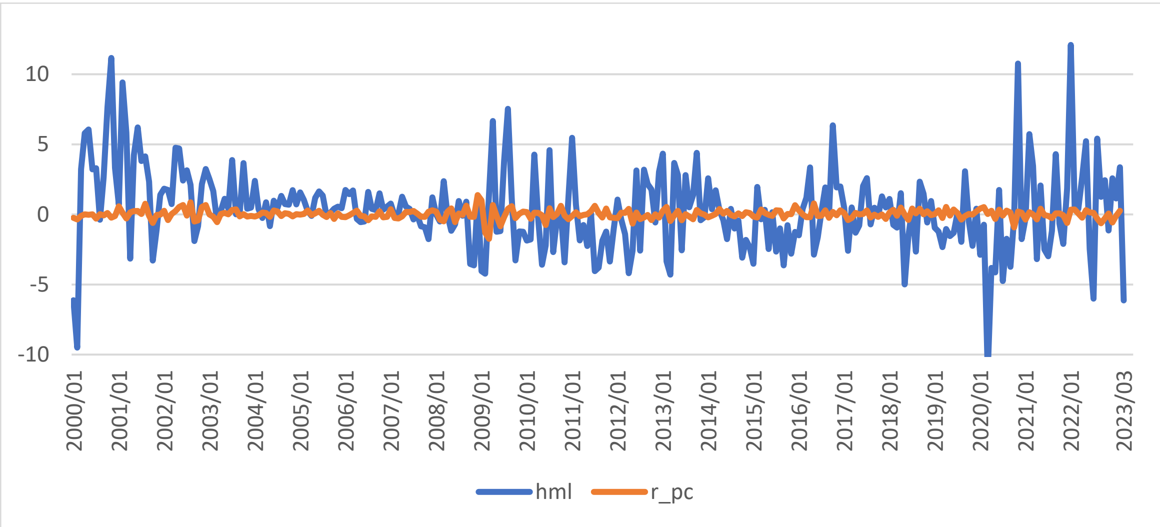


Figure 4. The bank size factor against HML



We turn next to estimate time-series regressions of the size-sorted bank portfolios on the equity and bond factors, as well as the priced size factor (*R[PC2]*):

$$R_{t+1}^{i} - R_{t+1}^{f} = \alpha^{i} + \beta^{i,\prime} f_{t+1} + \beta_{PC2}^{i} R[PC2]_{t+1} + \epsilon_{t+1}^{i}. \qquad (3)$$

Table 3. Size-Factor Risk-Adjusted Returns on Size-Sorted Portfolios of Commercial Banks
This table presents estimates from OLS regression of monthly equally-weighted excess returns on each size-sorted portfolio of commercial banks on the three Fama and French (1993) European equities factors, Mkt, SMB, and HML, two bond risk factors, EBR is the Euribor 12 months to 1 month spread and HY is the Option-Adjusted Spread of the Euro High Yield Index, and the bank size gactor (R[PC]). $*$, $**$, and $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey-West (1987) with three lags. The sample is 2000:1 to 2023:3 (Panel A) and 2012:1 to 2023:3 (Panel B).

	Market Cap 2000:1-2023:3										
	Small	2	3	4	5	6	7	8	9	Large	10-1
MKT_RF	0.41***	0.538***	0.528***	0.431***	0.428***	0.409***	0.398***	0.462***	0.618***	0.67***	0.262***
SMB	0.388***	0.394***	0.495***	0.409***	0.343***	0.607***	0.557***	0.597***	0.484***	0.219*	-0.158
HML	0.382***	0.532***	0.509***	0.393***	0.341***	0.28***	0.28***	0.682***	0.504***	0.692***	0.298***
EBR	-0.056	-0.571	0.412	-0.139	-0.196	-0.214	-0.553	-0.176	0.26	-0.101	-0.024
HY	-1.545***	-1.567***	-0.633	-1.107*	-0.036	-0.807	-1.345**	-2.125***	-1.402**	-0.979	0.595
R[PC]	0.052***	0.061***	0.034***	0.032***	0.007	-0.031***	-0.072***	-0.092***	-0.104***	-0.104***	-0.156***
C	0.633*	0.874**	0.006	0.457	0.09	0.74**	1.184***	1.009**	0.411	-0.1	-0.88**
Adj-Rsq	0.412	0.552	0.522	0.437	0.537	0.634	0.692	0.716	0.825	0.802	0.806
	Market Cap 2012:1-2023:3										
	Small	2	3	4	5	6	7	8	9	Large	10-1
MKT_RF	0.484***	0.586***	0.55***	0.52***	0.484***	0.504***	0.572***	0.451***	0.656***	0.746***	0.263***
SMB	0.283*	0.181	0.595***	0.448***	0.339***	0.635***	0.387***	0.303	0.467***	0.349**	0.075
HML	0.532***	0.718***	0.614***	0.532***	0.397***	0.4***	0.41***	1.071***	0.521***	0.844***	0.315***
EBR	0.048	-1.419*	0.121	0.991	-0.029	0.462	0.211	-0.565	-0.478	0.231	0.025
HY	-1.959	0.34	-1.315	-7.131**	-2.467	-3.644	-6.909***	-1.095	0.013	-2.891	-0.538
R[PC]	0.066***	0.075***	0.034**	0.05***	0.011	-0.004	-0.045***	-0.085***	-0.099***	-0.098***	-0.164***
C	1.059	0.526	0.694	2.282**	1.041	1.503*	2.792***	1.271	0.328	0.834	-0.369
Adj-Rsq	0.401	0.587	0.580	0.515	0.570	0.656	0.757	0.715	0.828	0.831	0.796

The results reported in Table 3 show remaining evidence of risk-adjusted excess returns (portfolio alphas) across deciles in both Panel A for the entire sample and Panel B for the post GFC/Sovereign Crisis sample. A long-short position that goes long on large banks in decile 10 and short on small banks in decile 1 loses 0.88% on average each period over the entire sample. While this spread is statistically significant, it is much smaller than the return spread reported in Table 1. We do not find evidence that the spread is significant in Panel B. We turn next to examine the importance of returns to scale in the pricing relationship.

2.3. Scale Elasticity and size interactions

In order to calculate scale elasticity, we follow the intermediation approach (see Sealey and Lindley 1977) to select the inputs and outputs to construct the banks' production technology. There are four inputs and three outputs in this study. Inputs comprise total employees (full-time equivalent), bank premises and fixed assets, deposits and other borrowed funds, and bank equity capital. The outputs are total securities, net loans and leases, and non-interest income. The summary statistics for scale elasticity are shown in Table 4 below exhibiting little variation around unity on average across different periods. This is not surprising since our SE measure is defined in terms of closeness to the most-productive-scale-size.

Table 4. Scale Elasticity (SE) Descriptive Statistics

	Obs.	Mean	Std.Dev.	Min	Max
2000-2007	935	1.12	0.37	0.36	4.01
2008-2011	514	1.11	0.37	0.20	4.04
2012-2023	1,672	1.03	0.49	0.49	3.50

We next sort banks into quantiles using their SE values. Table 5 reports total assets, market capitalisation ROE, ROA and bank efficiency statistics for each SE quantile. Table 5 as well as Figure 5 sorted on market cap, and Figure 6 sorted on total assets, demonstrate a clear pattern of economies of scale inversely related to bank size across all periods.

Table 5. Total assets, market cap, ROE, ROA, Efficiency score by SE quantiles

SE Q.	Total Assets			Market Cap			ROE			ROA			DEA Efficiency		
	Mean	p50	std	mean	p50	std	mean	p50	std	mean	p50	std	mean	p50	std
2000-2007															
1	253,095,809	52,610,426	385,229,335	23,830,855	8,600,451	38,099,635	14.70	14.11	6.66	1.07	0.85	0.98	0.56	1.00	0.49
2	180,570,660	23,437,811	335,061,454	11,578,321	3,093,536	18,125,319	12.88	11.73	6.86	1.07	0.79	1.23	0.56	1.00	0.48
3	19,114,852	11,293,392	28,286,341	4,935,989	589,431	23,997,665	11.59	9.11	9.31	0.87	0.70	0.57	0.06	0.03	0.15
4	6,603,359	4,924,206	12,344,300	2,191,552	173,653	21,945,471	10.96	9.74	5.78	0.93	0.84	0.56	0.11	0.05	0.17
5	446,962	297,711	425,550	47,778	26,440	66,067	11.87	10.99	5.87	1.53	1.15	1.28	0.56	0.53	0.31
2008-2011															
	Total Assets			Market Cap			ROE			ROA			DEA Efficiency		
1	337,358,750	51,150,966	511,946,080	15,229,245	3,153,563	30,646,126	8.33	7.42	4.79	0.66	0.65	0.44	0.21	0.02	0.38
2	372,550,929	40,296,000	630,439,573	12,018,461	2,963,727	21,373,518	10.59	8.07	10.22	1.03	0.50	2.04	0.53	1.00	0.49
3	28,252,548	15,321,732	45,001,194	2,039,481	607,045	3,022,044	9.20	7.53	5.20	0.86	0.76	0.50	0.07	0.02	0.22
4	9,406,702	8,274,011	7,492,429	514,530	255,526	621,619	9.51	7.86	5.95	0.79	0.71	0.48	0.08	0.04	0.14
5	20,455,631	594,855	196,349,984	1,135,279	20,702	10,656,237	7.61	5.06	8.95	0.82	0.54	1.06	0.53	0.49	0.34
2012-2023															
	Total Assets			Market Cap			ROE			ROA			DEA Efficiency		
1	352,538,846	33,299,419	611,742,840	15,978,475	2,427,480	29,622,023	7.25	6.73	4.38	0.72	0.61	0.50	0.24	0.03	0.39
2	208,832,766	29,059,414	404,669,161	8,891,784	1,967,307	14,006,393	8.04	6.70	6.76	0.77	0.60	0.67	0.51	0.29	0.48
3	203,603,914	26,893,144	424,632,119	8,579,397	1,645,213	15,867,009	9.45	7.12	10.04	0.82	0.63	0.71	0.53	1.00	0.48
4	18,191,954	11,906,911	21,515,665	1,447,122	580,210	3,472,892	8.07	6.73	6.21	0.90	0.76	0.64	0.12	0.02	0.23
5	1,392,791	650,960	2,475,302	108,125	46,457	202,098	8.65	6.79	10.00	1.37	0.93	2.76	0.49	0.45	0.35

Figure 5. SE Quantile 1 vs Quantile 5 sorted on Market Cap

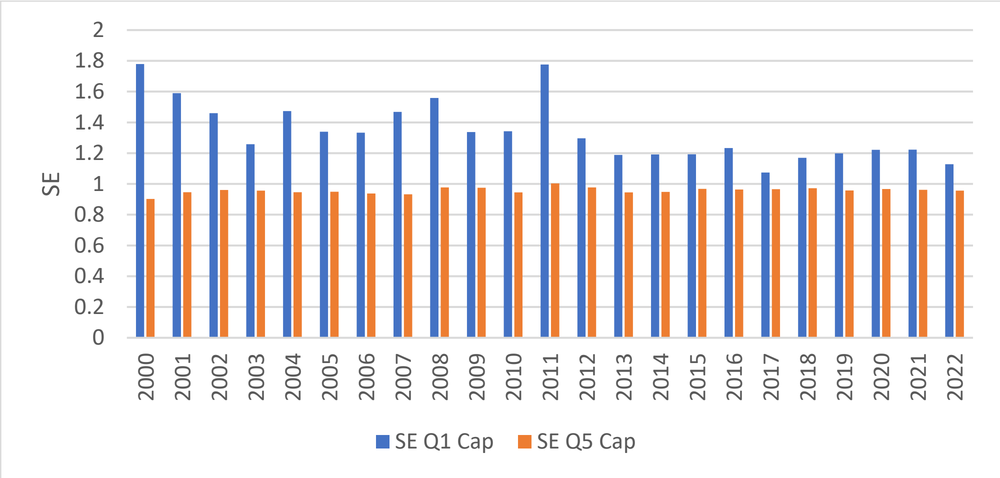


Figure 6. SE Quantile 1 vs Quantile 5 sorted on Total Assets

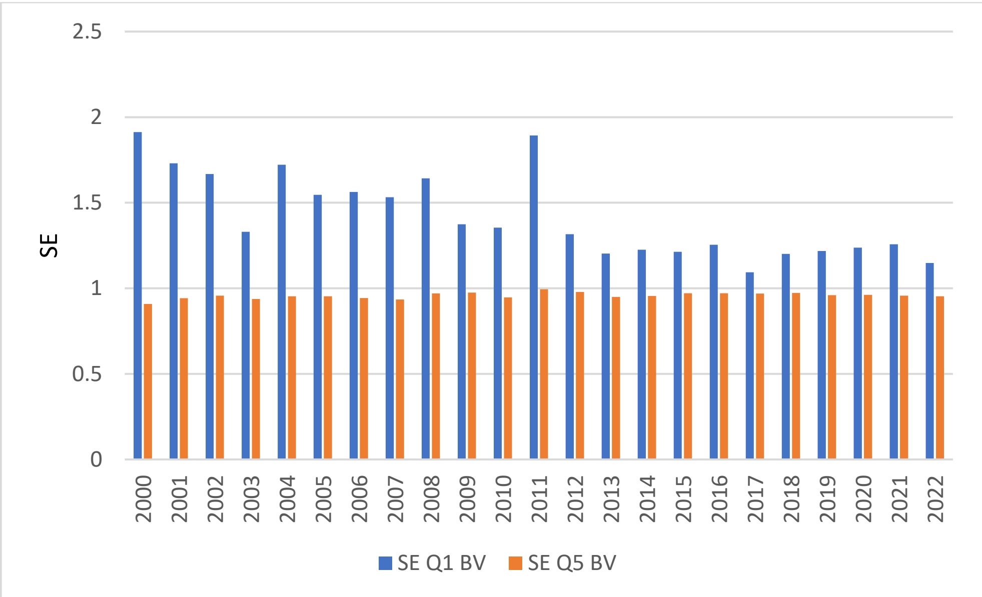


Table 6 presents SE statistics across quantile sorts of total assets and market cap, respectively. The patterns we observe in Tables 5 and 6 are quite consistent, namely the order by which we sort either based on size or scale elasticity does not matter in the sense that we observe larger banks to have smaller SEs.

Table 6. SE across Total Assets and Market Cap Quantiles

2000-2007							
Total Assets Q.				Market cap Q.			
BV Q.	mean	median	stdev	MC Q.	Mean	median	stdev
1	1.620	1.446	0.617	1	1.466	1.364	0.491
2	1.057	1.027	0.105	2	1.071	1.016	0.172
3	1.002	1.006	0.024	3	1.032	1.007	0.191
4	0.990	1.000	0.035	4	0.989	1.000	0.052
5	0.942	1.000	0.112	5	0.942	1.000	0.112
2008-2011							
1	1.566	1.366	0.632	1	1.51	1.276	0.637
2	1.037	1.021	0.115	2	1.098	1.010	0.275
3	0.999	1.006	0.025	3	0.987	1.003	0.098
4	0.983	1	0.084	4	0.99	1.000	0.030
5	0.972	0.999	0.154	5	0.975	1.000	0.160
2012-2023							
1	1.208	1.084	0.389	1	1.191	1.058	0.396
2	1.001	1.001	0.041	2	1.007	1.000	0.048
3	0.995	1	0.015	3	0.995	1.000	0.031
4	0.99	1	0.022	4	0.99	1.000	0.025
5	0.963	0.999	0.072	5	0.963	0.999	0.074

Next we want to see how SE may interact with size in determining excess risk-adjusted returns. Recall that in the decile regressions we observed an anomaly, namely small banks had higher excess returns than larger banks afer controlling for systematic risk factors. In other words, investors appear to require a higher return for smaller banks, presumably considering them as riskier in view of the TBTF implicit subsidy that large banks are perceived to grasp.

We use market cap at the end of year t to allocate banks into (S)mall (25%) (M)edium (50%) and (L)arge (25%) and intersect this with the three RTS portfolios (D)ecreasing, (C)onstant, (I)ncreasing RTS using the SE estimates for each year. Hence we have 9 Size-SE portfolio sorts -- S/D, S/C, S/I, M/D, M/C, M/I, L/D, L/C, L/I.

We calculate equally-weighted returns for each Size-SE sort and estimate nine monthly time series regressions. We regress the returns on the FF3 European factors plus the two bond factors (Panel A) and with the extra size factor (Panel B). We find significant alphas, positive for small banks and negative for large banks operating under IRS in Panel A. The risk-adjusted excess return for large IRS banks is no longer significant after we control for the size factor in Panel B. Panel B also confirms that small banks have positive and significant exposures to the size factor whereas large banks have negative and significant exposures. There is no evidence that large and small DRS and CRS banks exhibit positive and significant risk-adjusted returns.

The notable finding in Table 7 is that the large minus small portfolio (9-1 alpha) risk premium shown in the last column of Table 7 is no longer significant after we control for the size factor. Overall our findings suggest that excess returns differences between small and large banks reflect TBTF subsidies mainly associated with banks operating under IRS.

Table 7. Risk-Adjusted Returns for Size-Sorted Portfolios of Commercial Banks
This table presents estimates from OLS regression of monthly equally-weighted excess returns on each Size-SE sorted portfolio of commercial banks on the three Fama and French (1993) European equities factors, Mkt, SMB, and HML, two bond risk factors, EBR the Euribor 12 months to 1 month spread, and HY the Option-Adjusted Spread of the Euro High Yield Index (Panel A) along with the extra size factor R[PC] (Panel B). $*$, $**$, and $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey-West (1987). The sample period is 2000:1 to 2023:3.

Panel A Market Cap-SE Portfolio Sorts (25 50 25)										
	Small			Medium			Large			
	DRS	CRS	IRS	DRS	CRS	IRS	DRS	CRS	IRS	9-1
MKT_RF	0.459***	0.425***	0.335***	0.602***	0.54***	0.455***	0.9***	0.908***	0.851***	0.562***
SMB	0.407**	0.498***	0.602***	0.459***	0.412***	0.467***	-0.013	0.077	-0.409*	-1.266***
HML	0.304**	0.104	0.224***	0.547***	0.62***	0.433***	1.321***	1.071***	1.268***	0.766***
EBR	-0.170	-0.434	-0.596	0.496	-0.074	-0.336	0.84	-0.046	0.873	1.887
HY	-0.096	-0.061	-0.123***	-0.138**	-0.072	-0.009	-0.021	0.058	0.298**	0.375*
C	0.404	0.29	1.036***	0.266	0.557	0.348	-0.81	-0.624	-1.896**	-2.589***
Adj-Rsq	0.188	0.231	0.454	0.706	0.668	0.647	0.766	0.739	0.547	0.222
Panel B Market Cap-SE Portfolio Sorts (25 50 25)										
	Small			Medium			Large			
	DRS	CRS	IRS	DRS	CRS	IRS	DRS	CRS	IRS	9-1
MKT_RF	0.583***	0.596***	0.507***	0.556***	0.463***	0.464***	0.66***	0.663***	0.569***	0.022
SMB	0.248	0.286*	0.388***	0.534***	0.536***	0.451***	0.378***	0.475***	0.051	-0.345
HML	0.414***	0.256**	0.386***	0.456***	0.47***	0.451***	0.848***	0.589***	0.712***	-0.233
EBR	0.243	0.138	-0.014	0.36	-0.301	-0.308	0.126	-0.774	0.033	0.48
HY	-0.084	-0.046	-0.109***	-0.151**	-0.093	-0.006	-0.089	-0.011	0.218*	0.226
R_PC	0.035**	0.048***	0.05***	-0.017**	-0.028***	0.003	-0.088***	-0.089***	-0.103***	-0.187***
C	0.075	-0.157	0.576*	0.414	0.804**	0.317	-0.032	0.169	-0.98	-0.996
Adj-Rsq	0.201	0.276	0.558	0.710	0.683	0.645	0.828	0.811	0.618	0.414

We obtain similar results using total assets instead of market cap to allocate banks into (S)mall (25%) (M)edium (50%) and (L)arge (25%) and intersect this with the three RTS portfolios (DRS, CRS, IRS). We regress equally-weighted returns for each portfolio in each month on the FF3 European factors plus the two bond factors (Panel A), and with the addition of the bank 'size' factor (Panel B). We report these results in Table 8.

We find significant alphas, positive for small banks and negative for large banks operating under IRS. Panel B shows that small banks have positive and significant loadings on the size factor whereas large banks have negative and significant loadings. We find that the large minus small portfolio, 9-1 alpha, risk premium shown in the last column of Table 8 is no longer significant after we control for the size factor.

Table 8.

Panel A Total Assets-SE Portfolio Sorts (25 50 25)										
	Small			Medium			Large			
	DRS	CRS	IRS	DRS	CRS	IRS	DRS	CRS	IRS	9-1
MKT_RF	0.857***	0.328***	0.299***	0.626***	0.594***	0.483***	1***	1.018***	0.935***	-0.081
SMB	1.502***	0.479***	0.607***	0.36***	0.48***	0.443***	-0.191	-0.066	-0.266	-2.211***
HML	0.191	0.358***	0.251***	0.402***	0.26***	0.375***	1.054***	0.981***	1.752***	2.292***
EURB_SP	3.206	-0.532	-0.831*	-0.025	0.086	0.271	1.237	0.897	2.198	-3.156
EURO_HY	0.074	-0.242***	-0.156***	-0.122**	-0.055	-0.006	-0.097	-0.066	0.285*	0.262
C	-3.023	1.659**	1.384***	0.601	0.132	-0.038	-0.687	-0.557	-3.515***	1.647**
Adj-Rsq	0.330	0.184	0.480	0.569	0.586	0.612	0.711	0.706	0.503	0.293
Panel B Total Assets-SE Portfolio Sorts (25 50 25)										
	Small			Medium			Large			
	DRS	CRS	IRS	DRS	CRS	IRS	DRS	CRS	IRS	9-1
MKT_RF	0.994***	0.473***	0.458***	0.567***	0.522***	0.469***	0.635***	0.671***	0.608***	-0.389
SMB	1.129**	0.296	0.409***	0.433***	0.568***	0.46***	0.262**	0.366***	0.336	-1.385**
HML	0.542	0.491***	0.399***	0.347***	0.193***	0.362***	0.712***	0.655***	1.197***	1.549***
EURB_SP	3.325	-0.048	-0.295	-0.226	-0.155	0.226	0.005	-0.279	0.862	-3.768
EURO_HY	0.114	-0.229**	-0.143***	-0.127**	-0.061	-0.007	-0.128**	-0.095	0.224	0.168
100*R_PC	0.055	0.042***	0.046***	-0.017**	-0.021***	-0.004	-0.106***	-0.101***	-0.108***	-0.116**
C	-3.172	1.263*	0.961***	0.76*	0.322	-0.002	0.285	0.37	-2.303**	2.337
AdjRsq	0.340	0.208	0.578	0.574	0.596	0.611	0.812	0.799	0.550	0.333

2.4. Characteristics Regressions

We turn next to provide further evidence by running characteristics regressions. The portfolio sorts have shown that the actual size of a bank measured by its assets value appears to be a key determinant of bank stock returns: larger banks have lower returns. Table 9 reports the results of predictive cross-sectional regressions of average annual returns on firm characteristics – (log) market capitalisation, (log) assets, (log) book value of equity, NIM, ESG, RTS scores -- along with the interactions of RTS with (log) assets, book value, market cap and ESG.

The characteristics regressions findings corroborate the importance of the size factor in bank returns. Larger banks measured by their (log) assets value have lower expected returns. A 100% increase in value above the sample average lowers annual returns by more than 600 bps for an average bank, holding other variables, including market capitalisation constant. The coeeficient estimate for (log) book value is similar to that of (log) assets which is not surprising since we do not expect much variability in the equity multiplier for banks. Similarly, (log) market and (log) book have about the same albeit opposite sign coefficient estimates consistent with the interpretation of the (log) book to market equity ratio as a risk measure.

Table 9. Characteristics Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log_assets	-0.064***	-0.066***			-0.057***	-0.103***		-0.085***	-0.084***
Log_assets*IRS		0.007***							
Log_assets*DRS		-0.006**							
Log_market	0.062***	0.063***	0.056***	0.058***	0.063***	0.090***	0.111***	0.090***	0.090***
Log_market*IRS	0.004*		0.011***		0.005**	0.007*	-0.047***	-0.043***	-0.042***
Log_market*DRS	-0.006**		-0.006**		-0.006**	0.015***	0.025***	0.025***	0.023***
Log_book			-0.067***	-0.072***	-0.009		-0.122***		
Log_book*IRS				0.014***					
Log_book*DRS				0.001					
ESG							-0.001***	-0.001**	-0.001*
ESG*IRS							-0.001**		-0.001
ESG*DRS							0.001**		0.001
ESG*CRS									
IRS	-0.090*	-0.154***	-0.206***	-0.286***	-0.103**	-0.168**	1.057***	0.906***	0.896***
DRS	0.066	0.078	0.072	-0.064	0.072	-0.423***	-0.683***	-0.667***	-0.641***
NIM						-0.010***			
Constant	0.316***	0.341***	0.334***	0.401***	0.325***	0.695***	0.372***	0.218**	0.211**
Adj. R-sq	0.036	0.036	0.033	0.032	0.036	0.037	0.071	0.061	0.061

Table 9 also shows that the effects of (log) assets, market cap and book value vary across and within the RTS groups of banks. The negative and significant ESG coefficients show that better governance attributes are also associated with lower expected returns.

3. Conclusion

This paper investigates the size premium within the European banking sector. One question we address is whether regulatory adjustments implemented in the European Union post GFC, specifically those designed to diminish implicit TBTF guarantees, have impacted the risk-adjusted returns of large banks relative to their smaller counterparts.

The empirical analysis provides robust evidence, corroborating similar evidence observed for US banks, indicating that large European banks exhibit lower risk-adjusted returns compared to their smaller peers. The introduction of a banking sector-specific size factor can in part (fully) address the observed size anomaly in bank returns across the entire sample period (post crisis period).

Our results show that larger banks exhibit higher market beta values, indicating greater exposure to systematic risk. This finding suggests that investors may perceive larger banks as riskier due to their systemic importance, even though they may have lower idiosyncratic risk. Additional findings suggest that differences in returns may in part be attributed to differences in RTS rather than TBTF subsidies. Specifically, we find what is perceived as TBTF implicit subsidy may in part be explained by RTS for large banks operating under increasing returns to scale. Overall our findings suggest a size anomaly in risk adjusted bank returns associated with implicit TBTF subsidies unless they are exploiting significant IRS

Evidence from characteristics regressions corroborates the importance of the size factor in bank returns. We find a significant negative associations of (log) assets and (log) book value with expected stock returns. Further evidence shows that the effects of (log) asstes, (log) market cap and (log) book value vary across RTS groups of banks. The negative effect of ESG suggests that better governance attributes towards sustainable environmental investing are also associated with lower expected returns.

Our findings contribute to the ongoing discourse surrounding the implications of bank size while highlighting the importance of factoring in economies of scale within policy discussions. They also shed further light on the interplay between bank size and other bank characteristics, providing valuable insights for regulatory authorities, investors, and financial institutions.

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