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What Explains the Difference in Leverage between Banks and Nonbanks?

Tobias Berg and Jasmin Gider*

Abstract

Banks have much more leverage than nonbanks. In this article, we use a joint sample of banks and nonbanks between 1965 and 2013 to analyze the determinants of this leverage difference. We find that a single factor, asset risk, is able to explain up to 90% of this difference. Banks' assets consist of a diversified portfolio of nonbank debt. Therefore, banks have much lower asset risk than do nonbanks. Because asset risk is a major determinant of capital structure choice, this factor is able to explain a large fraction of the difference between bank and nonbank leverage.

I. Introduction

There is a large difference in leverage between banks and nonbanks: Whereas banks in the U.S. had a median book-equity-to-asset ratio of 9% over 1965–2013, the comparable figure for nonbanks is 50%. In the wake of the recent financial crisis, many people point to bank leverage as a problem, arguing that banks are artificially allowed to have more leverage than nonbanks because of government guarantees.[1] These arguments are usually made without recognition of what drives the difference in leverage between banks and nonbanks.[2] In this article, we try to fill this gap. We use a joint sample of banks and nonbanks to analyze the determinants of the difference in leverage between banks and nonbanks using standard

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[1]For this line of argument, see Admati, DeMarzo, Hellwig, and Pfleiderer (2013) and Admati and Hellwig (2014), as well as the sources cited therein.

[2]In this article, what we refer to as *banks* are usually bank holding companies and what we refer to as *nonbanks* are all firms with a Standard Industrial Classification (SIC) code that does not start with 6. Details are provided in the data section.

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leverage regression techniques (Rajan and Zingales (1995), Titman and Wessels (1988), and Frank and Goyal (2009)).

We find that a single factor, asset risk, is able to explain up to 90% of the difference in leverage ratios between banks and nonbanks over 1965–2013. This result is based on 2 simple facts. First, asset risk is a major determinant of leverage ratios the samples of both nonbanks and banks: A doubling in asset risk is associated with a 15–20 percentage point increase in the equity-to-asset ratio. The importance of asset risk in explaining capital structure decisions has been recognized both by the theoretical (Leland and Toft (1996), Gornall and Strebulaev (2017)) and the empirical (Frank and Goyal (2009), Chen, Wang, and Zhou (2016)) literature. Second the asset risk of banks is a factor of 7 smaller than the asset risk of nonbanks. These differences in asset risk are not surprising given that bank assets typically consist of a diversified portfolio of nonbank debt, which makes banks senior creditors.

We provide a battery of robustness tests for our main result. First, accounting for other well-established determinants of capital structure decisions beyond asset risk (Rajan and Zingales (1995), Titman and Wessels (1988), Berger, DeYoung, Flannery, Lee, and Öztekin (2008), Frank and Goyal (2009), and Gropp and Heider (2010)) does not help explain differences in leverage between banks and nonbanks. Second, our results are robust to using various econometric designs (linear regression, propensity score matching, Tobit regression), as well as various measures for asset risk (unlevered equity volatility, value at risk (VAR) measure, standard deviation of return on assets), and leverage (book leverage, market leverage). Third, we analyze the impact of off-balance-sheet (OBS) activities. In particular, our results are robust to controlling for various measures for OBS activities. It is important to note that although leverage is understated in the presence of OBS activities, the risk of OBS activities itself is likely reflected in our measures for asset risk.[3] This implies that any effect of OBS activities on our results is likely to be muted.

In the next step, we investigate the role of bank size. Bank size matters because large financial institutions may be "too big to fail" and hence may have more leverage than their level of asset risk predicts. We do not find any evidence that large banks have more leverage than small banks after controlling for asset risk. Although equity-to-asset ratios of banks are indeed negatively correlated with bank size, asset risk itself also decreases with bank size. We find that the difference between bank and nonbank leverage is most pronounced during banking crises. Interestingly, this effect is most pronounced for large banks: Although the leverage of small banks relative to their nonbank peers does not differ significantly during normal times and financial crises, large banks appear to be undercapitalized in particular during financial crises. This finding offers one explanation why capital is important for small bank performance during all times, whereas it is

[3]This is because gains and losses induced by OBS activities are reflected in our measures of asset risk to a certain extent. As a purely illustrative example, a bank with only zero-risk cash on the balance sheet and a risky derivatives portfolio will exhibit a positive equity volatility and a positive return on assets (ROA) volatility.

particularly important for large bank performance during financial crises (Berger and Bouwman (2013)).

Government safety nets extend beyond too big to fail, for example, in the form of deposit insurance or access to the discount window. Thus, the lack of evidence for a size effect should not be misinterpreted as evidence against the argument that the government safety net reduces bank risk. To estimate bank asset risk in the absence of government safety nets, we estimate the volatility of a "synthetic" bank balance sheet. We thereby use the composition of banks' balance sheets derived from call report data and match each of the positions to a publicly traded index. For example, we match cash to cash (0% risk), banks' securities holdings to Barclays U.S. Government Bond Index, and loans to an average of investment-grade and non-investment-grade bond and loan indices. We then determine the volatility of the resulting "synthetic" bank assets based on the volatility and covariance of the underlying indices and determine the leverage implied by our leverage regressions. This synthetic portfolio results in a bank asset risk and bank leverage comparable to our baseline regression. Although this comparison is of course not exact, it conveys the gist of our argument: Bank assets consist of primarily nonbank debt, and nonbank debt is much less risky than nonbank assets. Even the volatility of the Loan Syndications and Trading Association (LSTA)/S&P U.S. Leveraged Loan Index, which consists of BB/B-rated syndicated loans, is a factor of 5 smaller than the average volatility of nonbank assets. As lower asset risk is associated with higher leverage, a large difference between bank and nonbank leverage can thus be explained by differences in asset risk.

Our results have several important implications. First, although determinants of leverage decisions at banks and nonbanks are similar (Gropp and Heider (2010)), banks and nonbanks differ significantly in the magnitude of the characteristics that are used to explain leverage. Thus, even though bank and nonbank leverage regressions provide similar coefficients, these regressions can still explain a large part of the leverage differences between banks and nonbanks. Second, our results have important implications for capital regulation. The common narrative that differences in leverage between banks and nonbanks are entirely due to implicit and explicit government guarantees is not correct. Furthermore, our results provide a rationale for the use of risk-based capital regulation: The strong correlation between asset risk and leverage we observe suggests that the equity-to-asset ratios that market participants tolerate in the absence of explicit or implicit guarantees likely depend on the riskiness of the assets that need to be financed.

The article adds to the growing literature that revisits the standard corporate finance and asset pricing literature for banks. Financial institutions are typically excluded from almost all key corporate finance studies (see, e.g., Rajan and Zingales (1995), Titman and Wessels (1988), and Frank and Goyal (2009) for the determinants of corporate leverage). A common explanation is that capital structure decisions at financial institutions are primarily driven by features that are unique to financial institutions, such as capital regulation. However, empirical evidence documents that banks have significantly more capital than regulatory standards predict (e.g., Berger et al. (2008)). This evidence lends support to the view that capital constraints are not necessarily binding (Allen, Carletti, and

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Marquez (2011), Flannery (1994)). Furthermore, standard factors shown to govern capital structure at nonfinancial firms seem to be first-order determinants of bank capital structure decisions as well. Gropp and Heider (2010) show that standard determinants of leverage for nonfinancial firms apply to banks as well; moreover, these determinants have a similar impact for banks as they have for nonfinancial firms. Using the methodology developed by Heider and Ljungqvist (2015), Schandlbauer (2017) documents that the effect of tax changes on leverage is similar for banks as compared to nonbanks. Baker and Wurgler (2015) provide evidence that the low-risk anomaly, an asset pricing anomaly previously documented only for samples of nonfinancial firms, also holds for banks. Panier, Péréz-Gonzáles, and Villanueva (2015) find that nonfinancial firms increase equity capital after the introduction of tax shields for equity in Belgium. Using the same natural experiment, Schepens (2016) confirms that this tax change affects banks similarly. Finally, Dinger and Vallascas (2016) show that decisions to issue equity at banks are determined by the same factors as for nonfinancials.

We contribute to this literature by analyzing leverage in a joint sample of banks and nonbanks. Our results provide a simple message: Although the raw difference in debt-to-asset ratios is large, up to 90% of this difference can be explained by differences in asset risk.

The remainder of the article is organized as follows: Section II describes our data source and provides descriptive statistics. Section III provides empirical results and Section IV concludes.

II. Data and Descriptive Statistics

We start with the universe of U.S.-listed Compustat firms between 1965 and 2013. We restrict the sample to firms that meet the following requirements: strictly positive value of book equity, not involved in major mergers,[4] and at least 12 months of return history available. We classify the firms into industries according to their SIC code. Firms with a SIC code that does not start with 6 are classified as *nonbanks*. Firms with a SIC code that starts with 60 and 61 are referred to as *banks*. From a legal definition, these firms are mostly bank holding companies. We nevertheless use the word *banks* throughout the article for ease of exposition. The remaining set of SIC code 6 firms is excluded from the samples of both banks and nonbanks. More specifically, we exclude 62 (investment banks and securities brokers), 63 (insurance), 64 (insurance agents, brokers, and services), 65 (real estate), and 67 (holding and other investment offices) as these firms clearly follow different business models.[5]

BOOK_LEVERAGE is our main variable of interest. We follow Gropp and Heider (2010) and construct our measure of leverage as follows:

[4]We define firms as involved in major mergers if the additional revenue stemming from an acquisition accounts for more than 50% of total revenues. The firms are excluded only for the affected accounting period.

[5]This classification of banks is, for example, consistent with Ghandi and Lustig (2015), the only difference being that their analysis includes SIC 62 firms, which are excluded from our sample.

BOOK_LEVERAGE = 1 − BOOK_EQUITY/TOTAL_ASSETS.[6] In a robustness test, we also report results using market leverage, defined as MARKET_LEVERAGE = 1 − MARKET_VALUE_EQUITY/(MARKET_VALUE_EQUITY + TOTAL_LIABILITIES).

With respect to the explanatory variables, we include all firm-level variables as well as macro variables used in the studies by Frank and Goyal (2009), Berger et al. (2008), and Gropp and Heider (2010) with the following exceptions: First, we exclude rating variables from the list of controls because these variables may contain investor bailout expectations for banks. Second, we use only variables that are available for banks and nonbanks; that is, we exclude all bank-specific items used in the studies by Berger et al. (2008) and Gropp and Heider (2010). Third, we exclude country-specific variables that are used in the cross-country study by Gropp and Heider (2010) as our study focuses on the U.S. Finally, we exclude industry dummies (used in the study by Frank and Goyal (2009)) as these are fully collinear with our bank dummy. Table 1 provides a list of variables and their definitions. We follow Frank and Goyal (2009), Berger et al. (2008), and Gropp and Heider (2010) and lag all control variables by 1 period. All variables are

TABLE 1
Definition of Variables

Table 1 provides definitions of the variables used in this article.

Variable	Definition
Panel A. Main Variables	
BOOK_LEVERAGE	1 minus (book value of equity/total assets)
MARKET_LEVERAGE	1 minus (market value of equity/((end-of-year price close multiplied by shares outstanding) plus total liabilities))
EQUITY_RISK	Standard deviation of monthly stock return in the past 12 months.
ASSET_RISK	Standard deviation of monthly stock return in the past 12 months/(book leverage)
VAR_95%	Lowest 5% quantile of the daily stock returns in the past 12 months/(book leverage)
ROA_VOLATILITY	Standard deviation of return on assets (net income/total assets) in the previous 5 years
Panel B. Additional Firm-Specific Variables	
TOTAL_ASSETS	Book value of total assets in USD million deflated to 2009
MARKET_TO_BOOK	(Total assets plus (end-of-year price close multiplied by shares outstanding) minus book value of equity)/total assets
ASSET_GROWTH	(Book value of total assets minus previous-year book value of total assets)/book value of total assets
ROA	Net income scaled by total assets
CAPEX	Capital expenditures scaled by total assets
TANGIBILITY	Net property, plant, and equipment scaled by total assets
RD	Research and development expenditures scaled by revenue
SGA	Sales general and administrative expenditures scaled by revenue

(continued on next page)

[6]We prefer this measure to the measure used in Frank and Goyal (2009) for the following reasons: Frank and Goyal's measure is based on the sum of debt in current liabilities and long-term debt. This measure is not appropriate for comparing banks and nonbanks, as it does not account for deposits, which represent a major source of debt financing for banks.

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TABLE 1 (continued)
Definition of Variables

Variable	Definition
Panel B. Additional Firm-Specific Variables (continued)	
ADVERTISING	Adverstising expenditures scaled by revenue
LOSS_CARRYFORWARDS	Tax loss carryforwards scaled by total assets
DEPRECIATION	Depreciation scaled by total assets
INVESTMENT_TAX_CREDIT	Investment tax credit scaled by total assets
TAX_RATE	Top statutory tax rate
12M_STOCK_RETURN	Stock return over the past 12 months
MATURE (d)	Dummy variable equal to 1 if the firm has been listed on the Compustat database for more than 5 years
DIVIDEND (d)	Dummy variable equal to 1 if the firm pays dividends
MERGER_INDICATOR (d)	Dummy variable equal to 1 if the sales contribution from acquisitions in a given year are greater than half of total sales.
HIGH_OBS_BANK_DERIVATIVES (d)	Dummy variable equal to 1 for banks if the notional value of off-balance-sheet (OBS) derivatives as reported in Schedule HC-L of the Consolidated Financial Statements for Holding Companies FR Y-9C (bank holding companies) and Schedule RC-L of the Consolidated Reports of Condition and Income for a Bank with Domestic and Foreign Offices FFIEC 031 (commercial banks) exceeds the value of total assets by at least 10 times
HIGH_OBS_BANK_ALL (d)	Dummy variable equal to 1 for banks if the notional value of all OBS items exceeds the book value of total assets by at least 10 times
LOG_OBS_DERIVATIVES	Natural logarithm of 1 plus the notional value of OBS derivatives scaled by the book value of total assets
LOG_OBS_ALL	Natural logarithm of 1 plus the notional value of all OBS items scaled by the book value of total assets
Panel C. Macro Variables	
12M_MARKET_RETURN	Value-weighted 12-month returns of all Center for Research in Security Prices (CRSP) firms incorporated in the United States and listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), or National Association of Securities Dealers Automatic Quotation System (NASDAQ) stock exchange
EXPECTED_INFLATION	Expected change in the Consumer Price Index over the coming year using data from the Livingston Survey
MACRO_PROFITS	Differences in log of aggregate annual corporate profits after tax for nonfinancial firms
MACRO_GROWTH	Differences in log of real gross domestic product (deflated)
INDUSTRY_LEVERAGE	Median leverage by Standard Industrial Classification (SIC) code and by year
INDUSTRY_GROWTH	Median change in assets by SIC code and by year
TERM_SPREAD	Difference between the 10-year interest series and the 1-year interest series based on Federal Reserve filings
RECESSION (d)	Dummy variable equal to 1 if at least 1 month in the respective year falls in a recession period, and 0 otherwise (according to the National Bureau of Economic Research (NBER) definition)

winsorized at 0.05% on the right and left tails. Our key explanatory variable, ASSET_RISK, is constructed by unleveraging equity volatility using monthly stock returns over the past 12 months (i.e., we use exactly the same definition as in Frank and Goyal (2009) and Gropp and Heider (2010)). We construct 2 additional proxies for asset risk (a VAR measure and ROA_VOLATILITY) that we discuss in more detail later in this section.

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TABLE 2
Summary Statistics

Table 2 provides summary statistics for the main leverage and risk variables and additional control variables for the bank and nonbank samples. Variable definitions are provided in Table 1.

	Banks			Nonbanks		
Variable	Median	Mean	Std. Dev.	Median	Mean	Std. Dev.
Panel A. Main Variables						
BOOK_LEVERAGE	0.913	0.886	0.11	0.498	0.487	0.22
MARKET_LEVERAGE	0.888	0.857	0.14	0.368	0.391	0.25
ASSET_RISK	0.021	0.035	0.06	0.196	0.251	0.20
VAR_95%	−0.003	−0.004	0.01	−0.020	−0.025	0.02
ROA_VOLATILITY	0.002	0.015	0.09	0.041	0.110	0.23
Panel B. Additional Variables						
TOTAL_ASSETS (USD million)	1,345.9	7,633.4	17,140.0	168.5	1,725.9	6,379.6
MARKET_TO_BOOK	1.019	1.065	0.36	1.272	1.841	1.82
ASSET_GROWTH	0.091	0.154	0.41	0.084	0.241	0.79
CAPEX	0.000	0.003	0.02	0.049	0.071	0.08
TANGIBILITY	0.015	0.022	0.05	0.265	0.326	0.24
RD	0.000	0.001	0.09	0.000	0.162	1.06
SGA	0.250	0.252	0.24	0.193	0.330	0.81
ADVERTISING	0.000	0.007	0.01	0.000	0.011	0.03
LOSS_CARRYFORWARDS	0.000	0.010	0.16	0.000	0.187	0.79
DEPRECIATION	0.002	0.003	0.01	0.037	0.045	0.03
INVESTMENT_TAX_CREDIT	0.000	0.000	0.00	0.000	0.001	0.01
MATURE (d)	1.000	0.660	0.47	1.000	0.753	0.43
DIVIDEND (d)	1.000	0.778	0.42	0.000	0.406	0.49
MERGER_INDICATOR (d)	0.000	0.102	0.30	0.000	0.148	0.36
TAX_RATE	0.350	0.372	0.04	0.350	0.394	0.05
12M_STOCK_RETURN	0.114	0.148	0.41	0.059	0.167	0.65
12M_MARKET_RETURN	0.143	0.088	0.18	0.140	0.098	0.17
EXPECTED_INFLATION	2.470	3.027	1.64	3.320	3.774	1.96
MACRO_PROFITS	0.077	0.087	0.12	0.074	0.077	0.12
MACRO_GROWTH	2.800	2.835	1.90	3.500	3.007	2.05
INDUSTRY_LEVERAGE	0.874	0.863	0.03	0.516	0.526	0.06
INDUSTRY_GROWTH	0.079	0.076	0.03	0.076	0.074	0.05
TERM_SPREAD	0.010	0.012	0.01	0.009	0.010	0.01
No. of obs.	21,996			188,692		

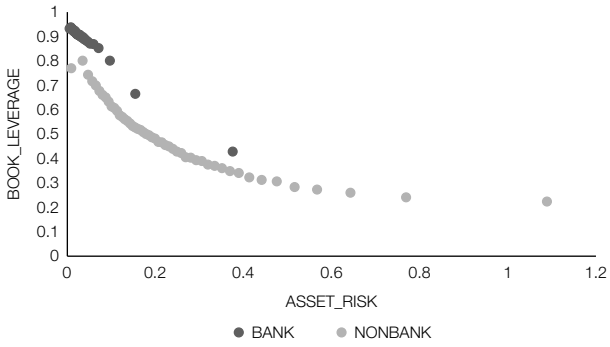
Table 2 provides summary statistics. The reported mean values, median values, and standard deviations are in line with statistics reported in Gropp and Heider (2010) and Frank and Goyal (2009). In particular, banks have much more leverage than nonbanks (median of 91% vs. 50% for nonbanks), banks are larger than nonbanks (median total assets deflated to 2009 of US$1,346 million vs. US$169 million for nonbanks), and banks have lower asset risk than nonbanks (median of 2.1% vs. 19.6% for nonbanks).

Figure 1 provides descriptive evidence of the relation between leverage and asset risk. We plot ASSET_RISK and BOOK_LEVERAGE separately for banks and nonbanks. For both banks and nonbanks, we sort the firm-year observations into 50 asset risk percentiles. Each dot represents the mean values of asset risk and book leverage in the respective percentile. The figure provides 2 key insights: First, leverage is negatively correlated with asset risk. Low-asset-risk firms have more leverage and high-asset-risk firms have less leverage (see also Flannery and Rangan (2008), Gropp and Heider (2010)). Second, consistent with Table 2, banks have much lower asset risk than nonbanks. Both findings together imply a strong message: Although the raw difference in leverage between banks and nonbanks is large, a significant part of this difference can be explained by differences in asset risk. As asset risk is the key explanatory variable in our set up, we provide

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FIGURE 1
Risk and Leverage for Banks and Nonbanks

Figure 1 illustrates asset risk on the *x*-axis and book leverage on the *y*-axis for banks and nonbanks. For both the bank and nonbank samples, the firm-year observations are sorted into 50 asset risk quantiles each. Each dot represents the mean values of asset risk and book leverage in the given quantile. Variable definitions are provided in Table 1.



further details on the difference between asset risk for banks and for nonbanks in the following paragraphs.

Conceptually, it is not surprising that banks have less asset risk than nonbanks: Banks hold debt claims of nonbanks on their asset side. Therefore, even a bank whose assets consist of only one large loan of a single firm will have less asset risk than this particular firm. This is because debt is paid first, and therefore the debt of a particular firm is always safer than the assets of the same firm. As banks hold diversified portfolios of debt claims on their asset side, this further reduces risk.

To ameliorate concerns about our empirical proxy for asset risk (i.e., asset volatility), we construct 2 alternative measures for asset risk. First, we construct a measure for downside risk, VAR_95%. Our main measure of risk above does not account for potential differences in the deviation from symmetric return distributions. Banks' assets consist mainly of loans. This characteristic might generate return distributions that are capped at the upside, skewed, and carry substantial downside risk. As a result, one might object that asset risk does not appropriately account for these characteristics. Our measure of downside risk, VAR_95%, is calculated as the 5% worst daily returns during the past 12 months. As for asset volatility, we unlever VAR_95% to have a downside measure for the asset value. The mean (asset) VAR_95% of banks is −0.4%, which is approximately one-sixth of the nonbank value (−2.5%).

As a second alternative measure for asset risk, we propose an accounting-based measure of asset risk, ROA_VOLATILITY, which is calculated as the realized standard deviation of ROA over the preceding 5 years for all firms in the same 4-digit SIC code industry.[7] We calculate ROA_VOLATILITY on the industry level to reduce noise associated with measurement on the single-firm level. The assumption is that dispersion in ROA across firms in the same 4-digit

[7]We calculate ROA as net income scaled by total assets. An alternative definition of earnings before interest and tax scaled by total assets provides similar results.

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SIC code industry is representative of the asset risk that firms in this industry face. This ROA volatility measure is based on accounting numbers as opposed to market expectations. As a result, this measure cannot be criticized on the grounds that market expectations are not correct, nor does the concern apply that this measure already incorporates investor bailout expectations. Moreover, this measure is constructed independently of any leverage measures, which does not raise any spurious correlation concerns.

The mean value of ROA_VOLATILITY is depicted in Table 2 for the samples of both banks and nonbanks. This ROA-based risk measure confirms the observation from the market-based measure of asset volatility: Whereas banks have a mean ROA_VOLATILITY of 1.5%, the corresponding value for nonbanks is 11.0%. Market-based and accounting-based measures thus point in the same direction: Banks have significantly lower asset risk than nonbanks.

Finally, we provide a list of the worst ROAs during our sample period in Table 3. This list provides us with a fundamental proxy for downside risk. To make the analysis meaningful, we restrict the sample to the largest 20 banks and the largest 20 nonbanks by total assets each year. Our sample thus contains the same number of banks and nonbanks. Confirming our conjecture, this list is dominated by nonbanks. There is not a single bank that makes it to the worst 10 firms by ROA. On top of the list are Time Warner (2002, 2008), Texaco (1987), General Motors (1992), Conoco Phillips (2008), and Du Pont (1992), all of them posting losses in excess of 10% of their assets. The first banks on the list are Regions Financial (2008) and Continental Bank Corp (1984) with losses of 3.83% and 3.57% of total assets, respectively. Only 12 of the worst 40 ROAs ever reported are banks, with 28 stemming from nonbank firms. Therefore, although losses at

TABLE 3
Worst Return on Assets

Table 3 provides a list of the lowest return on assets during the sample period. The sample is restricted to the largest 20 banks and the largest 20 nonbanks according to total assets in each year.

Ranking	Company	Type	Year	NET_ INCOME	TOTAL_ ASSETS	ROA
1	Time Warner	Non bank	2002	−98,696	115,450	−85.49%
2	Texaco	Non bank	1987	−4,407	34,388	−12.82%
3	General Motors	Non bank	1992	−23,498	191,013	−12.30%
4	Conoco Phillips	Non bank	2008	−16,998	142,865	−11.90%
5	Time Warner	Non bank	2008	−13,402	113,896	−11.77%
6	Du Pont	Non bank	1992	−3,927	38,870	−10.10%
7	IBM	Non bank	1993	−8,101	81,113	−9.99%
8	USX Corp.	Non bank	1986	−1,833	21,823	−8.40%
9	Ford	Non bank	1980	−1,543	24,348	−6.34%
10	AT&T	Non bank	1993	−3,794	60,766	−6.24%
...						
Banks among Worst 40 by ROA						
18	Regions Financial	Bank	2008	−5,596	146,248	−3.83%
19	Continental Bank Corp.	Bank	1984	−1,087	30,413	−3.57%
20	CIT Group	Bank	2008	−2,800	80,449	−3.48%
22	Santander USA	Bank	2008	−2,357	77,094	−3.06%
25	Mellon Financial	Bank	1987	−844	30,525	−2.76%
26	Freddie Mac	Bank	2009	−21,553	841,784	−2.56%
31	First Republic Bank	Bank	1987	−657	33,211	−1.98%
33	Continental Bank Corp	Bank	1987	−610	32,391	−1.88%
36	Fifth Third Bancorp	Bank	2008	−2,113	119,764	−1.76%
37	Bankers Trust	Bank	1989	−980	55,658	−1.76%
38	Manufacturers Hanover	Bank	1987	−1,140	73,348	−1.55%
40	Crocker National Bank	Bank	1984	−324	22,322	−1.45%

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banks can certainly be high, they are not high relative to the large balance sheets that are prevalent in the banking sector. This list therefore supports our stylized fact: Banks have significantly less asset risk than nonbanks.

III. Empirical Results

A. Baseline Regression

Our baseline regression is

$$(1)\quad \text{BOOK_LEVERAGE}_{i,t} = \beta_0 + \beta_1 \text{BANK} + \beta_2 \text{LOG_ASSET_RISK}_{i,t} + \beta_3 X_{i,t},$$

where i and t indicate firm and year, BANK is a dummy variable that is equal to 1 if firm i is a bank, LOG_ASSET_RISK denotes the natural logarithm of asset risk, and $X_{i,t}$ denotes a set of firm-specific variables, macro variables, and fixed effects that are discussed in more detail below. As a key innovation to prior papers, we apply regression (1) to a joint sample of banks and nonbanks. The coefficient of BANK thus provides us with the difference in leverage of banks and nonbanks that cannot be explained by standard capital structure determinants.

The results of regression (1) are reported in Table 4. The main variable of interest is the dummy variable BANK, which measures the difference in leverage between banks and nonbanks conditional on included covariates. Column 1 compares the mean leverage of banks and nonbanks and finds that banks have 39.9% more leverage than nonbanks. Once we control for LOG_ASSET_RISK, this difference decreases dramatically to 4.0% (column 2), consistent with the descriptive evidence from Figure 1. Accounting for the fact that the average bank is larger than the average nonbank and that size is positively related to leverage, we include the natural logarithm of the value of total assets (LOG_TOTAL_ASSETS) in the regression (column 3). The coefficient of BANK increases slightly to 4.1%.

Next, we include a large battery of additional potential leverage determinants taken from Frank and Goyal (2009), Berger et al. (2008), and Gropp and Heider

TABLE 4
Regression of Leverage on Log Risk and Controls

Table 4 provides the results of a linear regression of BOOK_LEVERAGE on ASSET_RISK, TOTAL_ASSETS, and control variables. Standard errors are clustered at the firm and year levels. The table reports point estimates and t-statistics in parentheses. * and *** indicate statistical significance at the 10% and 1% levels, respectively. Variable definitions are provided in Table 1.

	Dependent Variable: BOOK_LEVERAGE				
Variable	1	2	3	4	5
BANK (d)	0.399***	0.040***	0.041***	0.056***	0.045***
	(102.48)	(5.03)	(4.77)	(6.23)	(5.16)
LOG_ASSET_RISK		−0.177***	−0.180***	−0.187***	−0.193***
		(−73.73)	(−49.31)	(−70.59)	(−87.45)
LOG_TOTAL_ASSETS			−0.003*	0.006***	0.006***
			(−1.74)	(5.04)	(5.05)
Constant	0.487***	0.193***	0.201***	0.208***	0.132***
	(147.27)	(28.24)	(31.20)	(8.15)	(11.39)
Controls	No	No	No	Yes	Yes
Year fixed effects	No	No	No	No	Yes
No. of obs.	210,688	156,156	149,318	138,461	138,461
R^2	0.255	0.619	0.620	0.659	0.669

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(2010): market-to-book ratio; asset growth; research and development expenditures; industry growth; investment tax credits; selling, general, and administrative expenses; firm maturity; dividend status; asset tangibility; depreciation; capital expenditures; tax rates; 12-month prior stock and market returns; term spread; advertising expenditures; expected inflation; macroeconomic growth; net operating loss carryforwards; and macroeconomic profits (see variable definitions in Table 1). Controlling for these factors slightly increases the coefficient of BANK further to 5.6%.[8] Adding year fixed effects to the regression reduces the bank coefficient further to 4.5% (column 5 of Table 4).[9] In summary, the difference in leverage between banks and nonbanks decreases substantially once we control for asset risk. Although the raw difference in leverage ratios between banks and nonbanks is almost 40%, this difference shrinks by approximately 90% once we control for asset risk.

Tables 5 and 6 provide details on the impact of each of the explanatory variables. Table 5 sheds light on the difference in leverage between banks and nonbanks that can be explained by each of the control variables. In the first step, we

TABLE 5

Comparison of Implied Leverage Difference

Table 5 compares the implied leverage difference between banks and nonbanks. For each capital structure determinant in column 1, a regression of BOOK_LEVERAGE on this variable is estimated for nonbanks. The product of the difference in means (column 3) and the nonbank coefficient (column 4) is the implied leverage difference (column 5). Variable definitions are provided in Table 1.

	Mean				
	Nonbank	Bank	Diff.	Coef.	Leverage Diff.
Variable	1	2	3	4	5
LOG_ASSET_RISK	−1.654	−3.737	−2.083	−0.186	38.7%
LOG_TOTAL_ASSETS	5.273	7.402	2.129	0.028	6.0%
MARKET_TO_BOOK	1.841	1.065	−0.776	−0.025	2.0%
DIVIDEND (d)	0.406	0.778	0.371	0.027	1.0%
RD	0.162	0.001	−0.161	−0.024	0.4%
SGA	0.330	0.252	−0.078	−0.034	0.3%
LOSS_CARRYFORWARDS	0.187	0.010	−0.177	−0.012	0.2%
ASSET_GROWTH	0.200	0.123	−0.077	−0.026	0.2%
ADVERTISING	0.011	0.007	−0.005	−0.246	0.1%
MERGER_INDICATOR (d)	0.148	0.102	−0.046	−0.009	0.0%
12M_STOCK_RETURN	0.167	0.148	−0.019	−0.020	0.0%
INDUSTRY_GROWTH	0.074	0.076	0.002	0.084	0.0%
LOG_MACRO_PROFITS	0.077	0.087	0.009	−0.004	0.0%
12M_MARKET_RETURN	0.098	0.088	−0.010	0.011	0.0%
MACRO_GROWTH	3.007	2.835	−0.172	0.002	0.0%
TERM_SPREAD	0.010	0.012	0.002	−0.513	−0.1%
TAX_RATE	0.394	0.372	−0.022	0.195	−0.4%
MATURE (d)	0.753	0.660	−0.093	0.050	−0.5%
INVESTMENT_TAX_CREDIT	0.001	0.000	−0.001	4.509	−0.5%
EXPECTED_INFLATION	3.774	3.027	−0.746	0.007	−0.5%
CAPEX	0.071	0.003	−0.067	0.167	−1.1%
DEPRECIATION	0.045	0.003	−0.041	0.316	−1.3%
TANGIBILITY	0.326	0.022	−0.304	0.201	−6.1%

[8]Results for column 2 of Table 4 are similar if we restrict column 2 to those observations where all additional covariates from column 3 are available.

[9]Limited data coverage of interest expenses on deposits in Compustat makes it difficult to obtain a measure of operating profits for banks that is comparable to that of nonbanks. In the baseline regressions above, we do not control for profitability. When we additionally control for operating income before depreciation scaled by total assets or net income scaled by total assets, the coefficient of the bank dummy decreases further to 2.6% and 3.3%, respectively. Hence, omitting operating profitability from the list of controls is conservative.

TABLE 6
R^2 Contribution

Table 6 compares the contribution of R^2 in a regression of BOOK_LEVERAGE on LOG_ASSET_RISK, and control variables. Column 1 shows the R^2 from a regression of leverage on all independent variables in the baseline regression except for the listed variable. Column 2 shows the adjusted R^2 when the respective variable is added to the regression model, that is, the difference between an R^2 of 66.93% (when all control variables are included) and the R^2 from column 1. Variable definitions are provided in Table 1.

	Adjusted R^2		
	Baseline	Excl. Variable	Contribution
Variable	1	2	3
LOG_ASSET_RISK	66.93%	41.40%	25.52%
DIVIDEND (d)	66.93%	64.79%	2.14%
MARKET_TO_BOOK	66.93%	66.34%	0.58%
LOSS_CARRYFORWARDS	66.93%	66.65%	0.28%
LOG_TOTAL_ASSETS	66.93%	66.79%	0.14%
DEPRECIATION	66.93%	66.80%	0.12%
INDUSTRY_GROWTH	66.93%	66.85%	0.08%
INVESTMENT_TAX_CREDIT	66.93%	66.85%	0.07%
TANGIBILITY	66.93%	66.87%	0.05%
MATURE (d)	66.93%	66.88%	0.04%
RD	66.93%	66.91%	0.01%
ASSET_GROWTH	66.93%	66.92%	0.01%
12M_MARKET_RETURN	66.93%	66.92%	0.01%
ADVERTISING	66.93%	66.92%	0.00%
MERGER_INDICATOR (d)	66.93%	66.92%	0.00%
EXPECTED_INFLATION	66.93%	66.93%	0.00%
TAX_RATE	66.93%	66.93%	0.00%
MACRO_GROWTH	66.93%	66.93%	0.00%
MACRO_PROFITS	66.93%	66.93%	0.00%
SGA	66.93%	66.93%	0.00%
12M_STOCK_RETURN	66.93%	66.93%	0.00%
TERM_SPREAD	66.93%	66.93%	0.00%
CAPEX	66.93%	66.93%	0.00%

estimate, for each capital structure determinant separately, the coefficient from a regression of leverage on each capital structure determinant. We then calculate the implied leverage difference as the product of the differences in means between banks and nonbanks and the nonbank coefficient. The results in Table 5 clearly show that asset risk implies the largest difference of approximately 39%.

Table 6 determines the incremental increase in adjusted R^2 by adding a particular control variable. To do this, we include all control variables except one in the leverage regression to see how much the adjusted R^2 increases by adding this variable. Again, we observe that the incremental increase in adjusted R^2 for asset risk is 26%, thereby the largest by far among all control variables.

B. Alternative Econometric Designs

As shown in Figure 1, the distribution of ASSET_RISK for banks and nonbanks is substantially different. The results might thus be sensitive to the exact specification of the functional form linking leverage to asset risk. We thus report the following econometric robustness tests in Table 7. First, we run a regression over a sample that has common support with respect to ASSET_RISK by restricting observations to the overlap in distributions of ASSET_RISK. The lower bound of the interval represents the maximum of the 1% quantiles of the bank and nonbank samples, and the upper bound represents the minimum of the 99% quantiles of the bank and the nonbank samples. We estimate a coefficient of 4.1% (column 1 of Panel A) for the dummy variable BANK, which is comparable to our baseline regression. This result suggests that the difference in leverage holds for the region

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TABLE 7
Alternative Econometric Designs

Table 7 provides alternative econometric designs for the results of a linear regression of BOOK_LEVERAGE on ASSET_RISK, TOTAL_ASSETS, and control variables. Column 1 of Panel A provides the regression results for a subsample where ASSET_RISK is required to be larger than the 1% quintile of nonbanks and smaller than the 99% quintile of banks. Columns 2 and 3 report the average treatment effect for the treated based on propensity score matching by conditioning on ASSET_RISK and ASSET_RISK and size as given by TOTAL_ASSETS, respectively, and using the nearest neighbor. Panel B reports the results from Tobit regressions. Standard errors are clustered at the firm and year levels. The table reports point estimates and *t*-statistics in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are provided in Table 1.

Panel A. Propensity Score Matching

	Dependent Variable BOOK_LEVERAGE		
	None	Risk	Risk, Size
Matching	1	2	3
BANK (d)	0.041***	0.048***	0.048***
	(4.41)	(10.12)	(10.41)
LOG_ASSET_RISK	−0.179***		
	(−64.79)		
No. of obs.	126,822	126,822	126,822
R^2	0.582		

Panel B. Tobit Regression

	Dependent Variable: BOOK_LEVERAGE				
Variable	1	2	3	4	5
BANK (d)	0.399***	0.040***	0.041***	0.056***	0.048***
	(102.48)	(5.03)	(4.77)	(6.23)	(5.28)
LOG_ASSET_RISK		−0.177***	−0.180***	−0.187***	−0.191***
		(−73.73)	(−49.31)	(−70.60)	(−207.29)
LOG_TOTAL_ASSETS			−0.003*	0.006***	0.006***
			(−1.74)	(5.04)	(9.82)
Constant	0.487***	0.193***	0.201***	0.208***	−1.403**
	(147.27)	(28.24)	(31.20)	(8.15)	(−2.26)
Controls	No	No	No	Yes	Yes
Year fixed effects	No	No	No	No	Yes
No. of obs.	210,688	156,156	149,318	138,461	138,461
χ^2	62,136.88	150,870.05	144,479.91	149,102.79	152,372.45
p-value	0.000	0.000	0.000	0.000	0.000

of ASSET_RISK where there is common support. We then implement propensity score matching by conditioning on ASSET_RISK (column 2 of Panel A) as well as on ASSET_RISK and TOTAL_ASSETS (column 3 of Panel A).[10] The average coefficient of BANK is 4.8% (columns 2 and 3), thus comparable to the results from the baseline regression (Table 4).

BOOK_LEVERAGE is a censored dependent variable as it is bound to the interval [0, 1]. In this case, parameter estimates using conventional regression methods such as ordinary least squares regression may yield biased and inconsistent estimates. Therefore, we account for the censored nature of the dependent variable and rerun our main analysis using a Tobit regression, where we choose 0 as the lower limit and 1 as the upper limit. According to the results in Panel B of Table 7, our main finding is robust to this alternative specification.

[10] We use nearest neighbor matching with one neighbor. Using 5 or 10 nearest neighbors, kernel matching (either Gaussian or Epanechnikov), or Mahalanobis distance matching gives similar results.

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We provide a battery of further robustness tests in Table A1 in the Appendix. In particular, our results remain robust to using daily instead of monthly returns to determine asset risk (column 1 in Table A1) and using market leverage (MARKET_LEVERAGE $= 1 - $MARKET_VALUE_EQUITY/(MARKET_VALUE_EQUITY + TOTAL_LIABILITIES)) instead of book leverage (columns 2 and 3 in Table A1). The difference in raw MARKET_LEVERAGE of 47% is decreased drastically by approximately 80% once we control for ASSET_RISK.

C. Alternative Measures for Asset Risk

In all specifications used so far, we determine asset risk using unlevered equity volatility. This definition is the standard definition used in the prior literature (Gropp and Heider (2010), Frank and Goyal (2009)). It carries several implicit assumptions: First, this definition uses a symmetric concept of risk. It might be plausible that leverage decisions are influenced by downside measures of risk, as well. We thus repeat our main test using VAR_95% as an alternative measure for asset risk. The results, presented in Panel A of Table 8, are comparable to our earlier findings using asset volatility. Downside risk has high explanatory

TABLE 8
Alternative Measures of Risk

Panel A of Table 8 provides the results of a linear regression of BOOK_LEVERAGE on VAR_95%, TOTAL_ASSETS, and control variables. Panel B provides the results of a linear regression of BOOK_LEVERAGE on ROA_VOLATILITY, TOTAL_ASSETS, and control variables. Mean ROA_VOLATILITY is the average return on asset volatility over the corresponding 4-digit Standard Industrial Classification (SIC) code. Standard errors are clustered at the firm and year levels. The table reports point estimates and t-statistics in parentheses. ** and *** indicate statistical significance at the 5% and 1% levels, respectively. Variable definitions are provided in Table 1.

	Dependent Variable: BOOK_LEVERAGE				
Variable	1	2	3	4	5
Panel A. Value at Risk 95%					
BANK (d)	0.399***	0.077***	0.072***	0.075***	0.059***
	(102.48)	(7.63)	(6.50)	(6.59)	(5.57)
LOG_VAR_95%		−0.173***	−0.183***	−0.195***	−0.205***
		(−57.00)	(−35.70)	(−52.43)	(−61.07)
LOG_TOTAL_ASSETS			−0.008***	−0.002	−0.003**
			(−3.36)	(−0.91)	(−2.15)
Constant	0.487***	−0.193***	−0.195***	−0.079**	−0.281***
	(147.27)	(−13.98)	(−13.34)	(−2.38)	(−16.18)
Controls	No	No	No	Yes	Yes
Year fixed effects	No	No	No	No	Yes
No. of obs.	210,688	153,062	147,404	137,129	137,129
R^2	0.255	0.617	0.620	0.668	0.684
Panel B. ROA Volatility					
BANK (d)	0.399***	0.154***	0.175***	0.195***	0.193***
	(102.48)	(11.61)	(15.20)	(18.10)	(17.76)
Mean ROA_VOLATILITY		−0.090***	−0.068***	−0.073***	−0.073***
		(−21.62)	(−17.27)	(−21.47)	(−21.49)
LOG_TOTAL_ASSETS			0.018***	0.027***	0.028***
			(17.97)	(22.74)	(23.28)
Constant	0.487***	0.211***	0.181***	0.172***	0.059***
	(147.27)	(16.60)	(12.19)	(8.07)	(2.81)
Controls	No	No	No	Yes	Yes
Year fixed effects	No	No	No	No	Yes
No. of obs.	210,688	210,683	187,041	139,928	139,928
R^2	0.255	0.327	0.362	0.433	0.436

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power and reduces the coefficient of BANK to 7.7% (see column 2). Once we add further control variables and year fixed effects, the coefficient shrinks to 5.9% (column 5).[11]

Second, both asset volatility and the VAR measure are market-based measures of risk. It is not obvious whether leverage decisions should be primarily correlated with market measures of risk or whether fundamental measures of risk are also important. Therefore, we use ROA volatility as an alternative proxy for asset risk. Furthermore, using ROA_VOLATILITY ameliorates concerns that asset volatility might be affected by implicit government guarantees or that unlevering equity volatility might induce a spurious correlation between asset volatility and leverage.

Reassuringly, the relation between average bank ROA_VOLATILITY and average nonbank ROA_VOLATILITY closely resembles the respective relation for asset volatilities (see our discussion in Section II). The basic fact that banks' asset risk is significantly lower than nonbanks' asset risk is thus confirmed by accounting-based measures. Panel B of Table 8 reports the results of the multivariate regression of leverage on asset risk, with asset risk measured using ROA volatility. Similar to the results for asset volatility, ROA_VOLATILITY explains a significant part of the difference between banks and nonbanks. ROA_VOLATILITY explains approximately 50%–60% of the leverage difference between banks and nonbanks, which is clearly large in economic terms but smaller than the corresponding number for asset volatility (approximately 90%).[12]

D. OBS Activities

Banks' OBS activities can be an important source of risk (Demsetz and Strahan (1997), Berger et al. (2008)). Thus, banks need to have equity to cover losses from these OBS activities. In Table 9, we add a control variable for OBS activities to our baseline regression. Following Berger et al. (2008), in column 1, we define a bank as a *high-OBS bank* if the notional of its derivatives positions exceeds 10 times the value of total assets.[13] Controlling for ASSET_RISK and other control variables, the leverage of high-OBS banks is not different from other banks as suggested by the small and insignificant coefficient of high-OBS banks. The BANK dummy coefficient of 4.3% is close to the value from our baseline regression. Furthermore, using slightly different measures of OBS activities yields similar results. In column 2, we define high-OBS banks based on whether the notional of all OBS items exceeds 10 times the value of total assets. In columns 3 and 4, we use continuous measures and scale the notional of OBS derivatives or all OBS items by total assets. The coefficients are close to 0 and fail to be statistically significant at conventional levels.

[11] These results are robust to using VAR_90% instead of VAR_95%, which indicates the lowest 10% quantile of daily stock returns in the past 12 months.

[12] We estimate ROA_VOLATILITY using yearly accounting data. Therefore, the measurement of ROA_VOLATILITY is clearly noisier than the measurement of asset volatility. This observation suggests that the coefficient of the bank dummy will be upwardly biased in the regression where we control for ROA volatility (errors-in-variables problem). Our estimate of a 50%–60% reduction thus likely constitutes a lower bound for the leverage difference that can be explained by ROA_VOLATILITY.

[13] Approximately 0.6% of banks in our sample are defined as high-OBS banks according to this definition.

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TABLE 9
Off-Balance-Sheet Activities

Table 9 provides the results of a linear regression of BOOK_LEVERAGE on a measure of off-balance-sheet (OBS) activities, ASSET_RISK, TOTAL_ASSETS, and control variables. The sample includes only banks for which regulatory data by the Federal Deposit Insurance Corporation (FDIC) are available. In column 1, we measure OBS with a dummy variable equal to 1 if the notional value of OBS derivatives is more than 10 times greater than total assets (HIGH_OBS_BANK_DERIVATIVES). Column 2 defines the same dummy based on the notional value of all OBS items (HIGH_OBS_BANK_ALL). Columns 3 and 4 use continuous measures that are based on the natural logarithm of 1 plus the notional of OBS derivatives, or all OBS items, respectively, scaled by total assets. The table reports point estimates and *t*-statistics in parentheses. *** indicates statistical significance at the 1% level. Variable definitions are provided in Table 1.

	Dependent Variable = BOOK_LEVERAGE			
Variable	1	2	3	4
BANK (d)	0.043***	0.043***	0.043***	0.042***
	(4.02)	(4.01)	(4.02)	(3.98)
HIGH_OBS_BANK_DERIVATIVES (d)	−0.004			
	(−0.26)			
HIGH_OBS_BANK_ALL (d)		−0.003		
		(−0.19)		
LOG_OBS_DERIVATIVES			0.004	
			(0.72)	
LOG_ALL_OBS				0.005
				(0.89)
LOG_ASSET_RISK	−0.198***	−0.198***	−0.198***	−0.198***
	(−98.10)	(−98.10)	(−98.24)	(−98.20)
Constant	0.199***	0.199***	0.199***	0.199***
	(12.39)	(12.40)	(12.40)	(12.40)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
No. of obs.	132,128	132,128	132,128	132,128
R^2	0.634	0.634	0.634	0.634

Taking a step back, there are 2 channels through which OBS activities might affect our estimates for the difference in leverage between banks and nonbanks. First, the raw leverage difference (i.e., before controlling for asset risk and other factors) is even larger than it appears. Second, asset risk might be overestimated in the presence of OBS activities because the riskiness stemming from OBS activities is likely reflected in our measures of asset risk. As a purely illustrative example, assume that a bank has US$100 in cash and an OBS credit derivative with a notional of US$100 on an underlying corporate bond with a volatility of 10%. Depending on the data a researcher uses, this bank can either look like a bank with US$100 in assets and 0% risk (if OBS activities are fully ignored), a bank with US$200 in assets and 5% asset volatility (if OBS activities are fully recognized), or a bank with US$100 in assets and 10% asset volatility (if OBS activities are excluded from the total assets number but are included in the measurement of asset risk). Please note that only the first case (US$100 in assets, 0% risk) would clearly bias our results. In the latter case, assets are lower than in the "OBS fully recognized" case, whereas asset risk is higher. We therefore refer to the latter case as leverage being underestimated due to OBS items and asset volatility being overestimated due to OBS items.

It is thus important to analyze to what extent our measures of asset risk include gains/losses from OBS activities. For example, ROA_VOLATILITY is defined as the standard deviation of net income divided by total assets (see Table 1).

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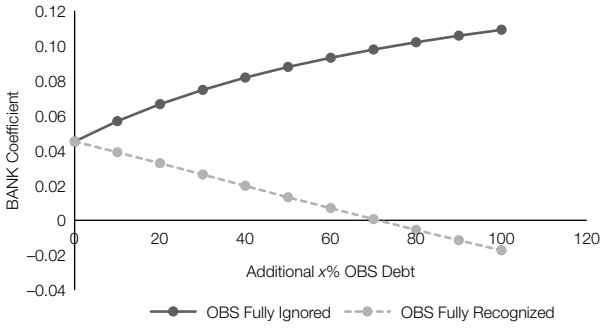
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If net income includes gains/losses from OBS activities, ROA_VOLATILITY already includes risk stemming from OBS activities. As an example, a credit derivative does not appear on the balance sheet at inception, but changes in the value of a credit derivative are usually part of the trading income, and thus of net income. A similar reasoning applies to our measure of asset volatility. It seems reasonable to assume that the risk from some OBS activities are reflected in the volatility of a bank's stock price and thus lead to an overestimation of asset risk.[14]

We provide 2 scenarios in Figure 2. The figure plots the coefficient of the bank dummy from column 5 of Table 4 under the additional assumption that all banks uniformly conduct OBS activities equal to $x\%$ of their total assets, with x being plotted on the x-axis. In the first scenario, represented by the dotted line, we assume that none of the OBS activities are reflected in our measure of asset risk.[15] In this case, OBS activities lead to an underestimation of leverage without affecting our estimate for asset risk. As a consequence, our coefficient of interest, that is, the dummy variable BANK, increases with an increase in OBS activities. For example, for OBS activities equal to 50% of assets, the coefficient of BANK increases from 4.5% to 8.8%.

FIGURE 2
Leverage Difference with Varying Levels of Off-Balance-Sheet Activities

Figure 2 illustrates varying assumed levels of debt-financed off-balance-sheet (OBS) items k on the x-axis and the coefficient of the bank dummy variable estimated in a regression of book leverage on log asset risk, control variables, and time fixed effects on the y-axis. In the "OBS fully ignored" case (dark color, solid line), assets are increased by $x\%$. However, asset risk is constructed based on actual book leverage, which has not been adjusted to account for the additional OBS debt. In the "OBS fully recognized" case (light color, solid line), assets are increased by $x\%$, leading to an increase in book leverage of $(x\% - 1)/x\%$, and asset risk is constructed based on this updated leverage ratio that accounts for OBS debt. Variable definitions are provided in Table 1.



[14] A similar argument is made by Demsetz and Strahan (1997) who observe that banks' OBS positions affect their stock return variance.

[15] Formally, for all banks in our sample, we replace TOTAL_ASSETS by $(1 + \text{OBS}) \times$ TOTAL_ASSETS, where OBS reflects the amount of OBS activities as a percentage of total assets. We leave our estimate for asset risk unchanged. Please note that the amount of OBS activities should not necessarily be interpreted as a notional. For many derivatives, such as interest rate derivatives, the notional is a pure unit of measurement, with little connection to anything one would reasonably call an "asset." Rather, OBS activities of, for example, 100% of total assets should rather be interpreted as half of banks' risk stemming from OBS activities.

In the second scenario, we assume that all of the OBS activities are reflected in our measure of asset risk.[16] In this case, OBS activities lead to an underestimation of leverage and an overestimation of asset risk. As a result, the coefficient of BANK decreases with an increase in assumed OBS activity. For example, for OBS activities equal to 50% of assets, the bank dummy decreases from 4.5% to 1.3%.

E. The Role of Size

The objective of this section is to investigate whether our results differ by bank size. Large banks are more likely to be too big to fail and thus make different capital structure decisions than small banks make.[17] Therefore, our results from the previous section, which average across all banks, might not be representative of the largest banks. To evaluate the role of size, we start by regressing BOOK_LEVERAGE on 3 dummies for size terciles for banks and nonbanks, using the dummy for large nonbanks as the baseline category.[18] Small and medium-sized nonbanks have significantly less leverage than large nonbanks; that is, we find a positive relation between leverage and firm size for nonbanks. Relative to nonbanks, all bank categories have significantly more leverage than their respective nonbank peers in the same size tercile (see column 1 of Table 10). After controlling for ASSET_RISK (column 2) and other control variables as well as year fixed effects (column 3), the coefficients of BANK vary from 3.6% (largest banks) to 6.2% (small and medium banks).

These results suggest that it is not the largest banks, but rather the small and medium-sized banks, that have the highest leverage relative to their nonbank benchmarks. The explanation of this finding is twofold: First, although larger banks have more leverage than smaller banks, this size effect exists for nonbanks as well. Second, ASSET_RISK decreases with size, a finding that is documented for banks by Demsetz and Strahan (1997). More important, ASSET_RISK decreases faster with size for banks than it does for nonbanks (see Figure 3). Although ASSET_RISK of banks declines by a factor of approximately 17 from the smallest size decile of banks (35.7%) to the largest size decile of banks (2.1%), the corresponding decline for nonbanks is much smaller with a factor of 4 (40.4% in the smallest size decile vs. 10.9% in the largest size decile).

As an additional test, we divide our sample into 10 size groups and include a dummy variable for each of these 10 size groups and an interaction term with

[16] Formally, for all banks in our sample, we replace TOTAL_ASSETS by $(1+\text{OBS})\times$ TOTAL_ASSETS, where OBS reflects the amount of OBS activities as a percentage of total assets. Furthermore, we replace ASSET_RISK by ASSET_RISK/$(1+\text{OBS})$. As an example, for a bank with 100 assets, 10 equities, 5% asset risk, and 100% OBS activities (as a percentage of total assets), we substitute leverage from 90% to 95% and asset risk from 5% to 2.5%.

[17] For example, Acharya, Anginer, and Warburton (2016) find that in general, bond credit spreads react to changes in risk. The authors find that this does not apply to the largest financial institutions, which suggests that according to investor expectations, large banks enjoy implicit state guarantees. For our purposes, this claim implies that large institutions benefit from state-funded subsidies for debt financing, which should be reflected in greater debt-to-asset ratios.

[18] We define size terciles by year based on the TOTAL_ASSETS. This approach ensures that the same number of observations falls into each tercile every year.

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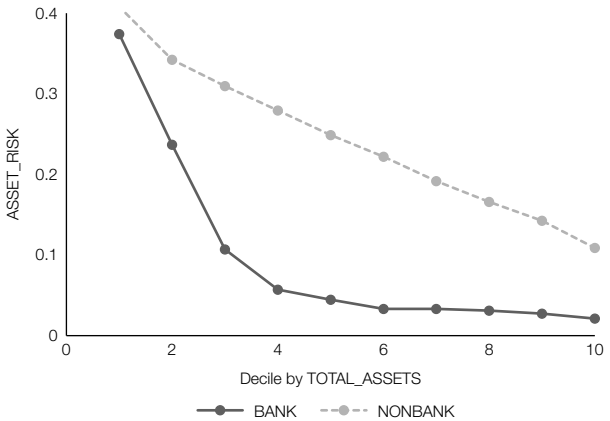
TABLE 10
The Role of Size

Columns 1 to 3 of Table 10 provide the results of a linear regression of BOOK_LEVERAGE on an interaction term of the dummy variable BANK and size terciles and dummies for size terciles. Column 2 adds ASSET_RISK and column 3 adds control variables. Standard errors are clustered at the firm and year levels. The table reports point estimates and *t*-statistics in parentheses. The bottom part of the table provides differences in the coefficients between the interaction of bank and size terciles and corresponding *t*-statistics.*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are provided in Table 1.

	Dependent Variable: BOOK_LEVERAGE		
Variable	1	2	3
BANK × SMALL	0.286***	0.056***	0.062***
	(9.23)	(3.89)	(4.73)
BANK × MEDIUM	0.400***	0.056***	0.062***
	(58.84)	(4.65)	(6.34)
BANK × LARGE	0.345***	0.041***	0.036***
	(51.28)	(5.00)	(4.13)
SMALL (d)	−0.147***	−0.001	−0.037***
	(−16.01)	(−0.17)	(−7.27)
MEDIUM (d)	−0.087***	−0.005	−0.025***
	(−11.11)	(−1.04)	(−5.73)
LOG_ASSET_RISK		−0.175***	−0.192***
		(−55.04)	(−91.78)
Constant	0.569***	0.195***	0.146***
	(114.63)	(17.82)	(6.21)
Controls	No	No	Yes
Year fixed effects	No	No	Yes
No. of obs.	138,461	138,461	138,461
R^2	0.352	0.612	0.671
Differences between Bank and Size Tercile Interactions			
BANK × LARGE − BANK × MEDIUM	−0.055***	−0.015**	−0.026***
	(−24.02)	(−4.30)	(−19.51)
BANK × LARGE − BANK × SMALL	0.059*	−0.015	−0.026***
	(2.95)	(−1.42)	(−4.40)
BANK × MEDIUM − BANK × SMALL	0.114***	0.000	0.000
	(14.83)	(0.00)	(0.00)

FIGURE 3
Risk by Size Deciles

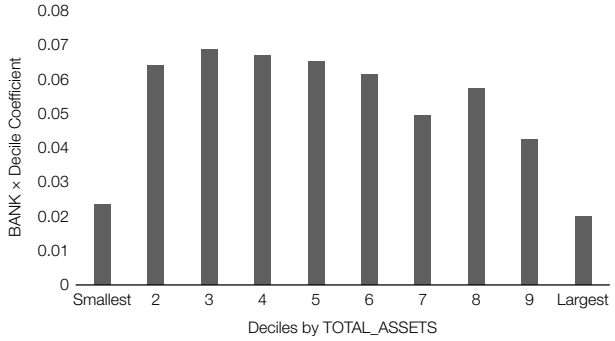
Figure 3 illustrates the size decile on the *x*-axis and mean asset risk on the *y*-axis for banks and nonbanks. The firm-year observations are sorted into 10 quantiles based on the deflated book value of assets. Variable definitions are provided in Table 1.



the bank dummy in our leverage regression. Figure 4 plots the coefficients of the interaction term between BANK and the size group dummies. We find that medium-sized banks have more leverage than would be predicted based on their ASSET_RISK, TOTAL_ASSETS, and other time-varying control variables. However, this relation does not hold for the largest banks. This observation is inconsistent with the notion that banks considered to be too big too fail have the highest leverage ratios.[19] Overall, the empirical evidence above does not support the notion that very large banks take on more leverage relative to their asset risk than small banks.

FIGURE 4
Size Coefficients

Figure 4 illustrates the coefficients of the interaction of BANK and size decile dummy variables on the *y*-axis over the respective deciles on the *x*-axis. These coefficients are estimated in a regression of BOOK_LEVERAGE on ASSET_RISK, control variables, time fixed effects, size deciles, and interactions between size deciles and BANK. The firm-year observations are sorted into 10 quantiles based on the deflated book value of assets. Variable definitions are provided in Table 1.



F. Financial Crisis versus Normal Times

Berger and Bouwman (2013) show that capital is particularly important for large bank performance during financial crises. It is thus interesting to examine to what extent our findings hold during crisis times. We follow Berger and Bouwman in defining periods for both banking crises (1990:Q1–1992:Q4, 2007:Q3–2009:Q4) and market crises (1987:Q4, 1998:Q3–1998:Q4, 2000:Q2–2002:Q3). Years not falling within a banking or market crises are defined as normal times and serve as the baseline category in the following analysis. We restrict the sample period to 1984–2010, that is, the period also covered in Berger and Bouwman.

Results are reported in Table 11. All columns report results with control variables as in the prior tables, and year fixed effects are omitted as they would be collinear with the crisis dummies. Column 1 reports results for the total sample. The coefficient of BANK is 4.1% during normal times and 9.5% (4.1% + 5.4%)

[19]Our classification into 10 deciles may raise the concern that it is not sufficiently granular to capture the leverage gap for very large financial institutions. We thus construct a dummy variable TOP10, which equals 1 if the bank (nonbank) is among the top 10 banks (nonbanks) according to the book value of total assets in a given year, and 0 otherwise. In robustness checks, we include these dummies in the regression to test whether the largest institutions have more leverage. The coefficient of the TOP10 bank dummy is very small and negative (−0.3%), and fails to be statistically significant at conventional levels.

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TABLE 11

Banking Crises, Market Crises, and Normal Times

Table 11 provides the results of a linear regression of book leverage on BANK and the interaction terms of the dummy variable BANK and BANKING_CRISIS and MARKET_CRISIS, ASSET_RISK, and control variables. The dummy variable BANKING_CRISIS (MARKET_CRISIS) is equal to 1 for the periods 1990:Q1–1992:Q4 and 2007:Q3–2009:Q4 (1987:Q4, 1998:Q3–1998:Q4, and 2000:Q2–2002:Q3), and 0 otherwise (see Berger and Bouwman (2013)). Column 2 presents the results for the bottom size tercile of banks and nonbanks, respectively; column 3 for the medium size tercile; and column 4 for the top size tercile. Standard errors are clustered at the firm and year levels. The table reports point estimates and *t*-statistics in parentheses. *** indicates statistical significance at the 1% level. Variable definitions are provided in Table 1.

	Dependent Variable: BOOK_LEVERAGE			
	All	Small	Medium	Large
Variable	1	2	3	4
BANK (d)	0.041***	0.079***	0.042***	0.039***
	(3.81)	(4.43)	(2.91)	(3.75)
BANK × BANKING_CRISIS	0.054***	0.008	0.039	0.051***
	(2.63)	(0.31)	(1.58)	(3.38)
BANK × MARKET_CRISIS	−0.001	0.036	−0.008	−0.012
	(−0.10)	(1.32)	(−0.58)	(−0.87)
LOG_ASSET_RISK	−0.191***	−0.200***	−0.192***	−0.160***
	(−65.95)	(−69.47)	(−51.90)	(−42.10)
Constant	0.240***	0.280***	0.191***	0.441***
	(5.05)	(6.13)	(3.64)	(10.03)
Controls	Yes	Yes	Yes	Yes
No. of obs.	93,934	31,324	31,308	31,302
R^2	0.683	0.487	0.685	0.756

during banking crisis, with the difference between normal times and the banking crisis being significant at the 1% level. The coefficient of BANK × MARKET_CRISIS is nearly 0, suggesting that the difference in leverage between banks and nonbanks is not different between normal times and market crises.

Columns 2–4 in Table 11 split the results by size tercile. The effect of a banking crisis is most pronounced for large banks, with a coefficient of BANK × BANKING_CRISIS of 5.1% (significant at the 1% level). Berger and Bouwman (2013) document that capital helps small banks increase their probability of survival and their market share at all times, whereas it enhances performance of large banks primarily during banking crises. Our results show that leverage of small banks does not differ much relative to their nonbank peers during normal times versus during banking crisis. Conversely, large banks look much more undercapitalized during banking crisis than during normal times as compared to their nonbank peers. This finding is consistent with the result of Berger and Bouwman: The average large bank looks in particular undercapitalized during a banking crisis, which might help explain why cross-sectional variation in leverage across large banks is so important during banking crises. Put differently, cross-sectional variation between banks should matter most when the average bank is "close to the cliff"; for large banks, this is in particular the case during banking crises.

G. Government Safety Net

Government safety nets are important and they may significantly affect bank risk relative to nonbank risk. Furthermore, government safety nets extend beyond too big to fail, for example, in the form of deposit insurance or access to the discount window. Thus, the missing evidence for a size effect should not be misinterpreted as evidence against the argument that the government safety net reduces bank risk.

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Ideally, we want to have an estimate of banks' asset risk in the absence of any government safety net. Both our measures of asset risk discussed above may be affected by the government safety net. If government safety nets protect shareholders, either directly via bail outs or indirectly, for example, via access to the discount window, then estimates for equity volatility are biased downward by the safety net. As a consequence, our estimate for asset volatility will also be biased downward by the safety net. ROA_VOLATILITY might also be affected by the government safety net, for example, a small volatility of deposit interest rates due to deposit insurance can lead to a lower volatility of ROA.

In the following, we provide an estimate for bank asset risk that is not affected by the government safety net. It is intentionally kept simple to foster presentation and discussion. The key idea is to synthetically replicate banks' asset side from traded bond and loan indices, and then derive asset risk from the volatility of these bond and loan indices.

Panel A of Table 12 provides the balance sheet composition of U.S. bank holding companies using call report data for our sample. Liquid assets make up

TABLE 12
Bank Balance Sheets

Table 12 provides estimates for the asset risk of a synthetic bank balance sheet and the corresponding bank leverage implied by the baseline leverage regression. Panel A provides a composition of bank assets based on year-end regulatory filings by bank holding companies (the Consolidated Financial Statement for Bank Holding Companies FR Y-9C) from 1997 to 2013. Panel B provides volatility estimates for various government bond, corporate bond, and equity indices from 1997 to 2013 (i.e., the period during which all indices are consistently available). Panel C provides the volatility of a combination of these indices and the corresponding bank leverage implied by the baseline leverage regression. The first column of Panel C reports the weightings of the government bond, corporate bond, and equity indices; the second column reports the resulting average volatility over 1997–2013; and the third column reports the leverage implied for these levels of volatility from the baseline leverage regressions.

Panel A. Composition of Bank Assets

Balance Sheet Item	All	Low Liquidity	High Liquidity
Liquid assets	26.6%	17.3%	35.8%
Cash and reserves	5.4%	4.5%	6.3%
Securities (incl. maturity < 1 yr.)	21.2%	12.8%	29.5%
Loans	65.5%	74.7%	56.3%
Residential real estate	18.7%	20.2%	17.1%
Commercial real estate	17.6%	22.1%	13.2%
Commercial and industrial	10.2%	11.4%	9.0%
Other	19.0%	21.0%	17.0%
Other	7.9%	8.0%	7.9%
Total	100%	100%	100%

Panel B. Volatility of Various Bond and Equity Indices

Asset Class	History	Volatility	Index
Cash	1997–2013	0.00%	By assumption
Securities	1997–2013	3.35%	Barclays U.S. Government Bond Index (maturity ≥ 1Yr)
Investment grade (IG) debt	1997–2013	3.92%	Barclays U.S. Corporate Bond Index
Junk debt	1997–2013	4.74%	50% LSTA/S&P U.S. Leveraged Loan Index, 50% Barclays U.S. Corporate High Yield Bond Index
Equities	1997–2013	14.79%	S&P 500 Total Return Index

Panel C. Asset Volatility and Implied Leverage Ratios

Asset Composition	Asset Volatility	Implied Leverage
10% cash, 20% securities, 35% IG, 35% junk	2.78%	85.48%
+5pp cash (remaining items reduced pro rata)	2.64%	86.36%
+5pp securities (remaining items reduced pro rata)	2.75%	85.53%
+5pp IG loans (remaining items reduced pro rata)	2.77%	85.46%
+5pp junk loans (remaining items reduced pro rata)	2.85%	85.18%
+5pp equities (remaining items reduced pro rata)	2.97%	84.22%

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27% of bank assets, loans make up 66% of bank assets, and other assets constitute 8% of total assets. Disregarding other assets and scaling liquid assets and loans correspondingly gives us an asset composition of 30% liquidity and 70% loans. Panel B provides a list of indices that can be used to match these positions.

We assume that cash has zero risk, and we match the non cash part of liquid assets to the Barclays U.S. Government Bond Index.[20] The index does not include bonds with a remaining maturity of less than 1 year, so we slightly increase the cash position and assume that liquid assets consist of one-third cash and two-thirds Barclays U.S. Government Bond Index. For the loan item, we assume it consists of 50% investment grade loans and 50% of junk loans. We match the junk loans to the average of the LSTA/S&P U.S. Leveraged Loan 100 Index, which is the capitalization-weighted total return index of leveraged (junk) loans, and the Barclays U.S. Corporate Bond Index. The investment-grade loans are matched to the Barclays U.S. Corporate Bond Index, which is composed of roughly 40% BBB-rated bonds, 40% A-rated bonds, and 20% AAA/AA-rated bonds. The indices are consistently available from 1997 on (the LSTA/S&P U.S. Leveraged Loan Index starts in 1997) and we thus restrict the period to 1997–2013.

The volatility of the resulting synthetic bank assets is 2.78% on average over 1997–2013 (Panel C of Table 12). Using our estimate of the relation between asset risk and leverage (from column 2 of Table 4) gives us an implied leverage of 85%. This number is similar to mean bank leverage (87%; see Table 2) and lower than median bank leverage (91%; see Table 2), but significantly higher than mean and median nonbank leverage (50% and 49%, respectively; see Table 2). Panel C of Table 12 also provides sensitivities for increasing cash, securities, investment-grade loans, junk loans, and equities in our synthetic bank balance sheet. For example, an increase of 5 percentage points (pp) in junk loans increases asset risk from 2.78% to 2.85% and decreases implied leverage from 85.48% to 85.18%. Assuming that some of the bank assets (e.g., trading assets or other assets) are more equity-like by adding a 5 pp exposure to the S&P 500 total return index increases bank risk from 2.78% to 2.97% and decreases implied leverage from 85.48% to 84.22%. All in all, this exercise results in low bank asset risk and high bank leverage, which is comparable to the results from our baseline regression.

We intentionally keep the procedure simple and researchers should be aware of its shortcomings. First, bank loans differ from traded bonds and traded loans because banks cater to a specific borrower group, predominantly those with larger information asymmetries (Diamond (1984), Petersen and Rajan (1994)). Importantly though, we are interested in the riskiness of a diversified loan portfolio and there is no compelling argument why bank borrowers should have more systematic risk than nonbank borrowers. To the contrary, there is some evidence that small and opaque borrowers actually have lower systematic risk than large and transparent borrowers (Lopez (2004), Dietsch and Petey (2004)). Second, the loan and bond indices we use consist of corporate borrowers, whereas banks have a significant amount of residential and commercial real estate exposure on their balance sheets. Real estate loans can pose a systematic risk to banks as observed

[20] This index includes U.S. dollar-denominated, fixed rate, nominal U.S. Treasury, and U.S. Agency debentures with at least 1 year until final maturity.

during the past financial crisis. Conversely, real estate loans are usually collateralized and they help to further diversify bank assets, and thus might lower asset risk. Third, we fully ignore risk stemming from banks' liability side. Deposits or trading liabilities, for example, might pose specific risks to banks. However, this ignorance is intentional: Our aim is to estimate the leverage that markets would allow banks to operate with if they need to fund themselves the same way as nonbanks. In this sense, "the same way as nonbanks" not only applies to the mix of equity and debt but also to the type of debt funding.

Most important, the exercise conducted here conveys the gist of our argument: Bank assets primarily consist of nonbank debt, and nonbank debt is much less risky than nonbank assets. For example, even the volatility of the LSTA/S&P U.S. Leveraged Loan Index, which consists of BB/B-rated syndicated loans, is a factor of 5 smaller than the average volatility of nonbanks assets. As lower asset risk is associated with higher leverage, a large difference between bank and nonbank leverage can thus be explained by differences in asset risk.

IV. Conclusion

There is a large difference in leverage between banks and nonbanks. In this article, we empirically analyze the determinants of this difference using a joint sample of banks and nonbanks from 1965 to 2013. We find that although banks have much more leverage than nonbanks, banks also have much less asset risk than nonbanks. The difference in asset risk between banks and nonbanks is not surprising given that banks' assets typically consist of a diversified portfolio of nonbank debt. Furthermore, asset risk is known to be a major determinant of capital structure choice. Therefore, although the raw difference in debt-to-asset ratios between banks and nonbanks is almost 40%, this leverage gap shrinks substantially to below 5% after controlling for asset risk.

Our results have several implications: First, differences in average leverage ratios between banks and nonbanks can largely be explained using standard capital structure regressions with commonly used explanatory variables. Even though standard cross-sectional determinants of nonbanks' leverage carry over to banks (Gropp and Heider (2010)), the average magnitude of these determinants is different for banks and nonbanks. This applies in particular to asset risk, where banks' asset risk is a magnitude of 7 smaller than nonbanks' asset risk. Second, our results contribute to the discussion on the level and structure of capital requirement. As an example, the importance of asset risk in explaining capital structure choice suggests that regulators should be cautious in fully decoupling the riskiness of banks' assets from regulatory capital requirements.

Appendix. Robustness Checks

The analysis in Table A1 provides further robustness checks. First, we investigate whether the findings are robust to estimating asset risk based on daily instead of monthly returns. Second, we use MARKET_LEVERAGE, which is total debt scaled by the market value of assets, instead of BOOK_LEVERAGE as the dependent variable.

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TABLE A1
Robustness Checks

Table A1 provides the results of a linear regression of BOOK_LEVERAGE and MARKET_LEVERAGE on ASSET_RISK, TOTAL_ASSETS, and control variables. Standard errors are clustered at the firm and year levels. The table reports point estimates and *t*-statistics in parentheses. *** indicate statistical significance at the 1% level. Variable definitions are provided in Table 1.

	Dependent Variable: LEVERAGE		
	BOOK	MARKET	MARKET
Variable	1	2	3
BANK (d)	0.043***	0.094***	0.089***
	(3.97)	(6.59)	(6.32)
LOG_ASSET_RISK (daily)	−0.214***		
	(−74.69)		
LOG_ASSET_RISK		−0.197***	
		(−59.60)	
LOG_ASSET_RISK (daily, market)			−0.220***
			(−68.97)
Constant	0.336***	0.302***	0.191***
	(10.86)	(11.12)	(12.62)
Other covariates	Yes	Yes	Yes
Year	Yes	Yes	Yes
No. of obs.	138,459	138,458	138,456
R^2	0.691	0.736	0.737

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