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Anatomy of Bank Distress: The Information Content of Accounting Fundamentals Within and Across Countries *

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Abstract. This paper studies the information content of bank accounting fundamental data in the prediction of bank distress using an international sample of banks from 15 Western European countries and the U.S. during the financial crisis of 2007-12. We assemble an exhaustive and unique set of bank distress events, and model bank distress as a function of accounting-based fundamentals, while controlling for country-year fixed effects, and the type of resolution in the distressed entity. The analysis of our bank distress models reveals a substantial cross-country variation in the ability of accounting fundamentals to discriminate between distressed and non-distressed banks within countries. We examine the extent to which the variation in informativeness and accuracy of accounting fundamentals is explained by proxies of country-specific bank disclosure requirements and the enforcement thereof. We show that the association between accounting fundamentals and bank distress is attenuated in jurisdictions with relatively lax bank disclosure laws and their implementation. Accounting ratios, whose information value is the most sensitive to the quality of regulatory disclosure include regulatory capital ratios, loan loss provisions, and unreserved loan losses. The evidence in this paper supports the oft-voiced concern that excessive flexibility in financial reporting undermines the ability of accounting signals to accurately capture the underlying financial health of banks. Obliqueness of the distressed bank's accounting signals makes such information less useful for investors and regulators, and thus has negative regulatory implications.

JEL Classification: G21, G28, G33, G38, K33, M41, M49

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1. Introduction

The recent global financial crisis that began in the dysfunctional U.S. residential mortgage market in late 2007, and quickly spread to the rest of the global financial system, has produced an unprecedented number of bank failures, on par only with the Great Depression era's financial meltdown. During the period of 2007-12, about half of the U.S. and one third of the Western European commercial banking assets belonged to banks that were either closed or experienced some form of government assistance, typically via taxpayer-financed recapitalizations (see Table 1). The sheer extent of the financial distress has kindled a substantial research effort devoted to examining causes, consequences, and government responses to the recent banking crisis. Laeven (2011) and Gorton and Metrick (2012) provide an extensive review of some of the recent work in this area.

A growing number of regulatory reports and academic studies has recently questioned the comparability and risk-sensitivity of bank accounting disclosure during the financial crisis (see Mariathasan and Merrouche, 2014; BCBS, 2013; Le Lesle and Avramova, 2012). The main concern common to these studies is that a substantial accounting discretion of banks may have contributed to systematic reporting biases by weak institutions and thus deteriorated the comparability of reported accounting signals between banks and across countries. We contribute to this literature by (1) providing a comprehensive cross-country analysis of the information content of accounting fundamentals in anticipating bank distress in Western Europe and the U.S. during the period 2007-12, and (2) by studying the nexus between the informativeness of bank accounting and the national bank disclosure requirements (and their enforcement).

To set the stage, we construct a comprehensive database of bank distress events, drawing on a number of publicly available sources. The range of events covered by our database includes bank liquidations, bankruptcies, regulatory receiverships, distressed mergers, distressed dissolutions, and open-bank assistance, typically in the form of government recapitalization of ailing banks. We categorize events into two broad groups of bank resolution: (1) *bank closures*, corresponding to resolutions in which distressed banks cease to exist as independent entities, and (2) *open-bank resolutions*, in which banks are allowed to continue operating with the assistance of a government bail-out.

We analyze the drivers of bank distress by modelling the two competing groups of distressed bank resolutions in a logistic regression framework. In our benchmark specifications we test for a number of bank-specific variables, including size, regulatory capital, asset quality, liquidity, franchise, or charter value[1], and funding costs. We find that both closures and open-bank resolutions tend to occur in severely undercapitalized banks with poor asset quality (measured by the reported risk-weighted assets and loan impairments), low charter values (proxied by the net-interest spread), and high funding costs.

Next, we conduct an in-depth examination of the information content of the accounting fundamentals by studying the ability of accounting numbers (1) to identify distressed banks within individual countries, and (2) to explain the aggregate incidence of bank distress during 2007-10. We show that predictions generated by accounting-based models display a substantial cross-country variation in the bank distress classification perfor-

[1] By bank charter value we refer to the sum of positive NPV projects within the bank. Literature typically attributes positive bank charter values to the presence of financial market frictions, such as search costs, that make banking industry less-than-perfectly competitive and allow banks to generate monopolistic rents.

mance. We also demonstrate that the values of accounting fundamentals, aggregated at the country level during the pre-crisis years of 2006 and 2007, fail to explain the 2007-10 aggregate incidence of bank distress across countries.

The final part of the paper examines the extent to which the observed cross-country variations in the informativeness of bank accounting are explained by differences in the national disclosure standards and their enforcement by the regulators. We measure the national bank disclosure quality by a set of indices from the database of Barth, Caprio, and Levine (2013), who compile a selection of more than 50 different proxies from the Quadrennial World Bank surveys covering 180 countries since 1999. We begin by showing that countries in our sample exhibit a substantial variation in the proxies of disclosure quality. Next, we show that the informativeness of accounting fundamentals in the cross section of banks in a given country-year positively correlates with the quality of accounting standards and the stringency of their enforcement. In particular, accounting signals of bank distress tend to be stronger in countries with strong disclosure laws or with more stringent enforcement of the existing laws. We also demonstrate that the disclosure-quality/informativeness nexus holds when looking at the time series movements in accounting fundamentals at the level of distressed banks prior to the distress event.

Our paper relates to three strands of banking and accounting literature. First, we contribute to the extensive empirical research on the determinants and prediction of bank failures that began with the contributions of Sinkey (1975) and Altman (1977). Most of this research has focused on analyzing bank closures in the U.S., primarily due to the abundance of bank credit events, and the relatively consistent and detailed coverage of bank accounting information[2]. More recently, several studies have also studied bank distress in East Asia (Bongini, Claessens, and Ferri, 2001; Arena, 2008; Wong, Wong, and Leung, 2010), Latin America (Molina, 2002; Arena, 2008) and Europe (Betz, Oprica, Peltonen, and Sarlin, 2014; Cipollini and Fiordelisi, 2012; Cihak and Poghosyan, 2009). We expand this literature by studying bank distress in an international context, which allows us to assess the informativeness of bank accounting across different countries. Our unique database of bank distress events also permits us to discriminate between different types of bank resolution.

Second, our study relates to the accounting literature on firm disclosure. The extensive reviews of theoretical and empirical contributions in this literature can be found in Healy and Palepu (2001) and Beyer, Cohen, Lys, and Walther (2010). Most of the empirical literature in this area measures the information content of accounting signals with the reference to the impact that accounting signals have on firms' security prices. Conversely, papers like Altman, Gande, and Saunders (2010) assess the information content of different types of market prices, by studying their ability to anticipate firm defaults. Our paper combines elements of both approaches and proposes a set of new measures of the information content of accounting fundamentals, all of which correspond to the ability of the accounting fundamentals to anticipate firm distress. As such, our measures are applicable not only to listed but also to private companies.

[2] All chartered U.S. banks are required to disclose their financial information to regulators in the form of Call Reports. Call reports are filed on a quarterly basis, and contain a number of pre-specified balance-sheet and income statement items, in addition to other information required by regulators. The Call Reports are publicly available via the web page of the FDIC.

Finally, we contribute to the literature on the nexus between the accounting disclosure environment and the informativeness of reported financial statements. In addressing this issue, the paper most similar to ours is Beaver, Correia, and McNichols (2012), which examines the impact of managerial financial reporting discretion on the effectiveness of accounting data in predicting *non-financial firm* bankruptcies. They find that the predictive power of accounting-based bankruptcy models deteriorates significantly with increasing levels of managerial reporting discretion, where reporting discretion is proxied by earning restatements, and the impact of discretionary accruals. In contrast to their study, we examine informativeness of bank accounting measure by exploiting substantial cross-country variation in bank regulation on disclosure and monitoring standards.

Given that investors and regulators typically learn about banks' financial condition from the banks' public disclosures, our results have clear implications for bank disclosure regulation. The evidence in this paper supports the oft-voiced belief that excessive flexibility in financial reporting undermines the ability of accounting signals to accurately capture the underlying financial health of banks. Obliqueness of the distressed bank's accounting signals makes such information less useful for investors and regulators. One of the implications of this conclusion is that the information content of accounting fundamentals, at least with respect to the identification of distressed banks, might be improved by increased stringency of bank disclosure laws and their enforcement.

The plan of the paper is as follows. We begin by describing the construction of the database on bank distress during the recent crisis and outlining our sample of banks (Section 2). Sections 3 models the within-country variation in bank distress, and Section 4 studies the variation in effectiveness of accounting fundamentals across countries. Section 5 examines the correspondence between accounting information and the quality of bank disclosure standards and their enforcement by the regulators. Section 6 concludes by providing a discussion of our findings and potential policy implications.

2. Bank Distress During the Great Recession

What is bank distress and in what forms does it manifest? In broad terms, bank distress is a condition in which a bank's realized or expected income from existing assets deteriorates to the extent that it impairs the bank's current or future ability to honor commitments to its creditors. More specifically, following the nomenclature of Demirguc-Kunt (1989), a bank is defined to be economically insolvent when the present value of its assets, net of implicit and explicit external guarantees, falls below the present value of claims from the banks' creditors.

A bank whose asset value deteriorates sufficiently close or below the value of non-equity claims faces a set of possible resolutions, a precise realization of which depends on the size and systemic importance of the bank as well as on the regulatory infrastructure, in particular the bank resolution mechanisms, deposit insurance arrangements, and the allocation of bank supervisory authority. For a more detailed discussion of failed bank resolution options see DeYoung, Kowalik, and Reidhill (2013) and Santomero and Hoffman (1996). At one end of the spectrum, a distressed bank may be closed and its assets liquidated. Alternatively, it may be allowed to continue its operation with explicit government support in the form of asset- or liability-oriented measures.

For the purposes of this paper, we categorize different types of manifestation of bank distress into two broad groups, namely:

- **Bank closure**, which includes all types of resolution in which the charter of the insolvent institution is revoked, or subsumed by a non-distressed acquiring institution. As such, we consider as bank closures the set of the following events: liquidations, court bankruptcies, regulatory receiverships, and distressed mergers. Distressed mergers are defined as mergers, in which the merged entity's regulatory Tier 1 capital ratio falls below the Basel II threshold of 6% for at least two years prior to the merger.
- **Open-bank resolution**, defined as the resolution in which the independent charter of the distressed bank is preserved, and the institution continues to operate as the independent entity. Open-bank resolutions typically consist of a government bailout (e.g. investment in bank capital), coupled with a set of measures to improve the long-term viability of the bank (e.g. reallocation of the toxic assets to a bad bank).

In what follows, we explain the construction of our cross-country database on distressed bank resolutions during the recent financial crisis in the U.S. and Europe. We also report a selection of summary statistics on distressed bank resolution in our sample, which gives a top-down perspective on the type and size of resolutions across different countries.

For a more complete discussion and for the exposition of main developments during the recent banking crisis in the U.S. and Europe, an interested reader may refer to Stolz and Wedow (2010). A more general discussion of failed bank resolution options and of their respective costs and benefits can be found in DeYoung, Kowalik, and Reidhill (2013) and Santomero and Hoffman (1996).

2.1 Construction of the Database on Distressed Bank Resolutions During the 2007-12 Crisis in the U.S. and Europe

This paper features a comprehensive database of distressed bank resolutions during the recent financial crisis in the U.S. and Europe. To construct the database, we collect information from several publicly available sources. First, we use the bank status indicators in the *Bankscope* and the *SNL Financial* databases to construct a list of bank closures during the period 2007-12. The status indicators distinguish between several different types of bank exit, including bankruptcy, liquidation, dissolution of bank charter, and the exit via acquisition by another bank. In most of the cases, *Bankscope* and *SNL* provide a date of the exit. For the subset of cases in which the precise date is not available, we obtain the date by examining the public news sources in *Factiva* and *LexisNexis*.

In order to obtain a comprehensive list of bank closures in the U.S. we supplement the bank status information from Bankscope and SNL by the publicly available Failed Bank list compiled by the FDIC, the U.S. deposit insurance fund. The list includes the set of U.S.-chartered commercial banks that were closed by the FDIC, which acts as a receiver for the failed banks. In this capacity, FDIC is responsible for a disposal of failed bank assets and the distribution of proceeds to the creditors[3]. Most failed banks acquired by the FDIC are sold to other banks via the so-called "purchase-and-assumption" transactions, in which the buyer of the failed bank's assets also acquires its deposits. Since the acquisition of new depositors implies a positive charter value for the acquiring banks (e.g. via the possibility of new lending relationships, or generation of fees), buyers of failed banks are typically

[3] In most cases, proceeds generated by the failed bank asset sale fall below the total value of deposits, making the FDIC the residual claimant in the process.

willing to bid a premium to acquire the failed bank. In Europe, there is unfortunately no other centralized source (not even at the national level) of regulatory closures on-par with the FDIC's failed bank list, so all our bank closure information there comes from *Bankscope* and the *SNL Financial*.

Next, moving to open-bank resolutions, most of our data on open-bank resolutions in the U.S. consist of the bank equity infusions under the Capital Assistance Program (CAP) of TARP. The participating bank names and the corresponding TARP equity issuance dates are obtained from publicly available regulatory sources.

In Europe, the open-bank resolution information is obtained from several sources. For the countries that are part of the European Union (most of our sample), we consult the publicly available database of State Aid cases at the European Commission website. The State Aid request must be submitted by any EU-member government that considers an intervention within the domestic economy that may distort a competitive environment at the EU level. While not specific to the banking sector, the State Aid procedures in practice cover most of the national bail-out programs for banks in the EU countries. European Commission typically conditions the approval of the aid requests on the restructuring of the intervened banks, often laying-out specific requests on the restructuring measures, which made the EU State Aid framework the de-facto failed bank resolution mechanism in the EU during the recent banking crisis. In order to make it consistent with the TARP events in the U.S., the European list of open-bank resolutions is limited to the government recapitalizations. We exclude other types of interventions such as state guarantees on bank liabilities, whose aim was primarily to prevent bank runs (and was typically applied to all major banks in the country), rather than being specifically targeted at the insolvent institutions (see Laeven and Valencia, 2008). For countries, that are not the part of the EU, we obtain the list of bank recapitalizations by manually searching publicly available news sources in *Factiva* and *LexisNexis*.

Table 1 provides a top-down view of the bank distress database. Several interesting observations emerge from the table. First, bank distress has been pervasive during the crisis: in the countries under study, the assets attributed to banks in distress represented on average about 30% of the total commercial banking assets[4], ranging from 5% in Luxembourg to 87% in Greece. Second, banks resolved via closure tend to be smaller on an individual as well as on aggregate basis, compared to banks resolved via open-bank assistance. The average size of a closed bank in Europe (the U.S.) is about 39 billion USD (7 billion USD), whereas the average size of a bank resolved via open-bank assistance is 190 billion USD in Europe and 45 billion USD in the U.S. In aggregate terms, bank closures represent about 15% (30%) of distressed bank assets in Europe (respectively, the U.S.). A further disaggregation of the latter result in Europe reveals a substantial cross-country variation in the occurrence of bank closures relative to open-bank assistance in resolution of banks in distress.

[4] Aggregated commercial banking assets are measured at the outset of the financial crisis in 2008.

Table 1: Bank Distress Events

Country	Bank Distress Events (period 2007-12)								Size of Bank Sector in 2008
	Number of Distressed Banks				Book Assets of Distressed Banks (in Billion USD)				
	Open Bank Assist.	Bank Closure		Total	Open Bank Assist.	Bank Closure		Total	
		Outright	Distr. Merger			Outright	Distr. Merger		
Austria	5	0	1	6	597	0	7	604	2147
Belgium	1	1	1	3	847	4	12	864	3673
Denmark	43	1	1	45	744	2	6	753	1657
France	8	0	1	9	6792	0	663	7455	21728
Germany	7	2	14	23	4112	2	642	4755	12173
Greece	9	0	2	11	496	0	30	526	602
Iceland	5	2	0	7	140	6	0	146	172
Ireland	5	1	1	7	430	12	24	465	1595
Italy	14	11	37	62	320	8	1615	1943	5562
Luxembourg	2	2	0	4	42	13	0	55	1263
Netherlands	8	1	0	9	2355	1	0	2356	7108
Portugal	8	0	3	11	431	0	9	439	704
Spain	8	0	23	31	1071	0	891	1963	5860
Sweden	1	0	1	2	227	0	29	255	1830
United Kingdom	18	7	7	32	8237	28	753	9019	23271
Europe	142	28	92	262	26841	76	4680	31597	89344
USA	275	532	134	941	12341	3602	1132	17075	36235

Notes:

[a] Banks are defined as distressed when they: 1. cease to exist as a going concern ('Closure'), 2. receive an assistance from the domestic authority ('Assistance'), or 3. undergo a distressed merger ('Distr. Merger'). In the U.S., bank closures are identified from the FDIC failed bank list (http://www.fdic.gov/bank/individual/failed/banklist.html). In Europe closed banks are identified as the institutions whose Bankscope 'Status' indicator equals 'Dissolved', 'Liquidation', or 'Bankruptcy'. Distressed mergers are defined as mergers, in which the merged entity's Tier 1 capital ratio (scaled by the risk-weighted assets) falls below the Basel II threshold of 6% for two years prior to the merger. Bank assistance transactions consist of re-capitalizations, bridge loans, and asset purchases by the relevant domestic authority. For European banks we collect the assistance transactions from the European Commission State Aid Cases (http://ec.europa.eu/competition/state_aid/register/). In the U.S., assistance transactions are identified from the FDIC failed bank list.

[b] Some banks experience multiple distress events in a sequence. In such cases, the table reports only the first event in the sequence. Panel A shows the distribution of distressed banks across countries and years. Panel B reports the number of distress events by the type of event, as well as the total amount of assets held by distressed banks (measured as the total book assets at the fiscal year end of 2008). The last column in Panel B is the sum of book assets across all bank within a particular country, at the end of 2008. In computing the total assets of the sector we only take into account the numbers from the consolidated financial statements. If the consolidated statement for a given bank is unavailable we use its unconsolidated report instead. The book value of bank assets is taken from Bankscope.

2.2 Sample

The sample covers banks from the U.S. and the following 15 countries from the Western Europe: Austria, Belgium, Denmark, France, Italy, Iceland, Ireland, Germany, Greece, Luxembourg, Netherlands, Portugal, Spain, Sweden, and United Kingdom. We follow the banks from 2005 until one of the following three types of exits, defined above: (1) bank closure, (2) open-bank assistance, and (3) other censoring events, such as non-distressed mergers or the end of the sample period in December 2012.

Bank balance sheet data are obtained from Bankscope. We limit our analysis to the following types of banks (bank types defined by Bankscope): (1) bank holding companies, (2) commercial banks, (3) cooperative banks, (4) mortgage banks, and (5) savings banks. When a given bank reports accounts at different levels of consolidation, we only keep the reported figures at the highest level of consolidation[5]. Unless otherwise stated, all accounting measures are scaled by the total book value of assets in the same fiscal period. Most of the banks in our sample are private.

Each record in our distress resolution database is manually linked to the bank-level accounting information in *Bankscope*, based on the institution name, and location. We manage to match most of the records in the database of distress events to the corresponding bank records in *Bankscope*. If an institution experiences multiple events in a sequence (for example, several government recapitalizations in succession) the subsequent analyses only considers the first event in the sequence and discards the rest (i.e. this is equivalent to assuming that the bank exited the sample after the first distress event). This is done in order to avoid double counting such institutions as distressed, and thus inflating the significance of any potential differences between the distressed and non-distressed groups of banks.

[5] In practice, keeping only the data at the highest available level of consolidation implies keeping the observations with Bankscope consolidation codes equal to C1, C2, or U1.

Table 2: Sample Summary

	Count	Mean	S.D.	P1	P25	P50	P75	P99
Capital								
Equity / Total Assets	74177	0.103	0.086	0.023	0.074	0.091	0.112	0.532
Regulatory Tier 1 Capital Ratio	57039	0.151	0.169	0.048	0.106	0.127	0.161	0.472
Regulatory Tier 2 Capital Ratio	56622	0.014	0.015	0.000	0.010	0.012	0.013	0.073
Risk-Weighted Assets / Total Book Assets	51067	0.711	1.450	0.274	0.624	0.717	0.798	1.010
Asset Quality								
Unreserved Impaired Loans / Equity	56525	0.115	0.493	-0.164	-0.048	0.005	0.135	1.894
Loan Loss Provisions / Gross Loans	72076	0.010	0.437	-0.012	0.000	0.004	0.009	0.064
Management								
Non-Interest Expense/ Gross Revenues	73323	0.698	0.335	0.195	0.588	0.673	0.763	1.648
Total Non-Interest Expenses / Total Assets	71688	0.007	0.017	0.000	0.002	0.005	0.010	0.032
Earnings								
Return On Avg Assets (ROA)	74107	0.006	0.032	-0.044	0.002	0.006	0.011	0.039
Return On Avg Equity (ROE)	74091	0.053	0.229	-0.616	0.028	0.064	0.113	0.327
Net Interest Margin / Total Assets	73556	0.012	0.026	0.000	0.003	0.008	0.019	0.046
Interest Expense / Interest-Bearing Liab.	71688	0.023	0.059	0.003	0.014	0.021	0.028	0.052
Liquidity								
Net Loans / Tot Dep and Bor	71390	0.723	0.208	0.099	0.623	0.744	0.848	1.071
Liquid Assets / Dep and ST Funding	73515	0.149	0.282	0.011	0.048	0.092	0.166	0.948
Size								
Logarithm of Total Book Assets	74180	6.392	1.502	4.635	5.293	6.052	7.017	11.790
Total Book Assets (in million USD)	74180	7534	73129	103	199	425	1115	131910

Notes:
[a] The table shows summary statistics for a sample of European and U.S. banks with book assets in excess of USD100 million during the period 2005-12. Unless otherwise mentioned, all variables are scaled by the total book value of assets.

Table 2 reports summary statistics for a selection of accounting fundamentals that we study in the subsequent analysis. Our choice of the accounting ratios follows the existing literature and tries to capture the most representative accounting fundamentals from 5 dimensions of the CAMEL assessment framework[6], which is a supervisory rating system developed by the U.S. bank regulators in the early 1980s[7]. The accounting fundamentals studied in the subsequent analysis are the following:

1. *Capital adequacy*: book equity (% of total book assets), regulatory Tier 1 ratio (% of total book assets), regulatory Tier 2 ratio (% of total book assets),
2. *Asset quality*: risk-weighted assets (% of total book assets), unreserved impaired loans (% of book equity), loan loss provisions (% of gross loans),
3. *Management quality*: non-interest expense (% of gross revenues), total non-interest expenses (% of total assets),
4. *Earnings quality*: return on average assets (ROA), return on average equity (ROE), net-interest margin (% of total assets), interest expense (% of interest-earning liabilities),
5. *Liquidity*: net loans (% of non-equity funding), and liquid assets (% of deposits and short-term funding).

Table 3 breaks the total variation in each accounting measure to within-bank, within-country, and between country variation. In most of the subsequent analysis, we control for the country-year interactions (explained in the next section), thus essentially exploiting the within-country variation to identify the coefficients.

3. Explaining Within-Country Variation in Bank Distress by Accounting Fundamentals

We begin by analyzing the extent to which bank closures and open-bank resolutions are explainable by bank accounting fundamentals. In this section, we only focus at modelling the within-country variation in bank distress and control for the unobservable country-year trends by including a set of country-year dummies[8]. Section 3.1 analyzes the univariate dynamics of a set of accounting covariates prior to the onset of bank distress, with the aim of identifying the covariates that best discriminate between distressed and non-distressed banks prior to the actual distress events. Section 3.2 presents the estimation results of the multivariate bank failure models.

[6] In selecting the subset of CAMEL variables, we test about 500 accounting ratios contained in *Bankscope* database. Our final choice of variables considers the level of missing values, and the fraction of variation captured by a variable within each CAMEL group.

[7] The name of the system is an acronym that relates to the dimensions of bank conditions assessed by the system, namely: Capital adequacy, Asset quality, Management quality, Earnings, Liquidity, and Sensitivity to market risk.

[8] Country-year trends are likely to influence the probability of bank distress directly as well as via the bank accounting fundamentals. The consistent estimation of coefficients on accounting fundamentals thus necessitates inclusion of county-year fixed effects.

Table 3: Decomposition of Variation in Accounting Fundamentals

Variable	Fraction of the Total Sum of Squared Errors		
	Within Firm	Within Country	Between Country
Capitalization			
Equity / Total Assets	0.231	0.753	0.016
Regulatory Tier 1 Capital Ratio	0.247	0.714	0.039
Regulatory Tier 2 Capital Ratio	0.573	0.398	0.029
Risk-Weighted Assets / Total Book Assets	0.197	0.771	0.032
Asset Quality			
Loan Loss Res / Gross Loans	0.389	0.546	0.065
Unreserved Impaired Loans/ Equity	0.525	0.441	0.034
Management			
Non-Interest Expense/ Gross Revenues	0.342	0.641	0.017
Total Non-Interest Expenses / Total Assets	0.227	0.739	0.035
Earnings			
Return On Avg Assets (ROA)	0.257	0.552	0.191
Return On Avg Equity (ROE)	0.450	0.543	0.007
Net Interest Margin / Total Assets	0.483	0.467	0.050
Interest Expense/ Interest Bearing Liab.	0.605	0.351	0.044
Liquidity			
Net Loans / Tot Dep and Bor	0.246	0.564	0.190
Liquid Assets / Dep & ST Funding	0.240	0.530	0.230

Notes:

[a] The sample consists of the Western European and the U.S. banks covered by Bankscope. For each bank we use the accounting information from its consolidated statements (Bankscope codes C1 or C2), or from the unconsolidated statements, if the consolidated statements are unavailable (Bankscope code U1). The time period of the analysis is January 2005 - December 2012.

[b] Let C, I, and T denote total number of countries, firms and time units (years) in the sample. We measure the total variation in variable x as $\sum_{c,i,t}(x_{c,i,t} - \bar{\bar{\bar{x}}})^2$, where c, i, and t are indexes for countries, firms, and time, respectively, and $\bar{\bar{\bar{x}}} = \frac{1}{I*T}\sum_{i,t} x_{c,i,t}$. It can be shown that the total variation is a sum of within-firm variation ($\sum_t(x_{c,i,t} - \bar{x}_{c,i})^2$), within-country variation ($\sum_i(\bar{x}_{c,i} - \bar{\bar{x}}_c)^2$) and between-country variation ($\sum_c(\bar{\bar{x}}_c - \bar{\bar{\bar{x}}})^2$). The tables reports each of the three components as a fraction of the total variation.

3.1 Time Path of Bank Performance Indicators Prior to Distress Event

It is instructive to begin by analyzing bank solvency from developments in a selection of bank indicators in the periods leading up to a distress event. The main aim of this analysis is to identify the performance dimensions in which distressed banks diverge from their non-distressed peers and shed light on the possible drivers (or at least symptoms) of bank distress. The subsequent analysis in this section distinguishes between closed- and open-bank distress resolutions, thus trying to capture any potential heterogeneity in the drivers of the two manifestations of bank distress. In order to avoid results being driven by a relatively large number of distress events in the U.S. (see Table 1), we split the estimation sample to subsamples of the U.S. and Western European banks.

We approach the identification of the relative performance of distressed to non-distressed banks in the periods leading up to distress by estimating a series of specifications of the following form:

$$y_{ict} = \alpha_{ct} + \sum_{j=0}^{n} \phi_j f_{ict}^j + \epsilon_{ict}, \tag{1}$$

(a) Europe

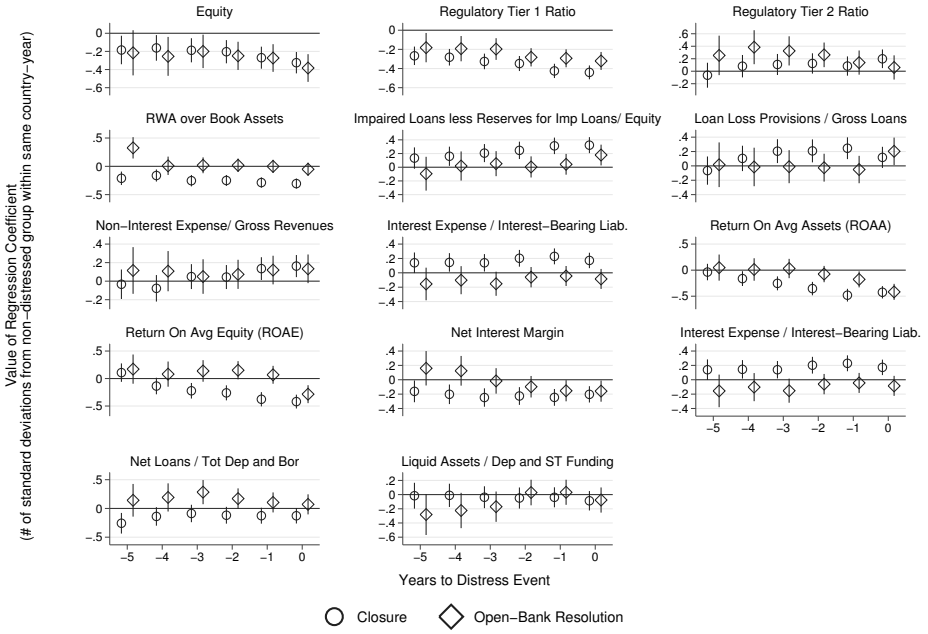
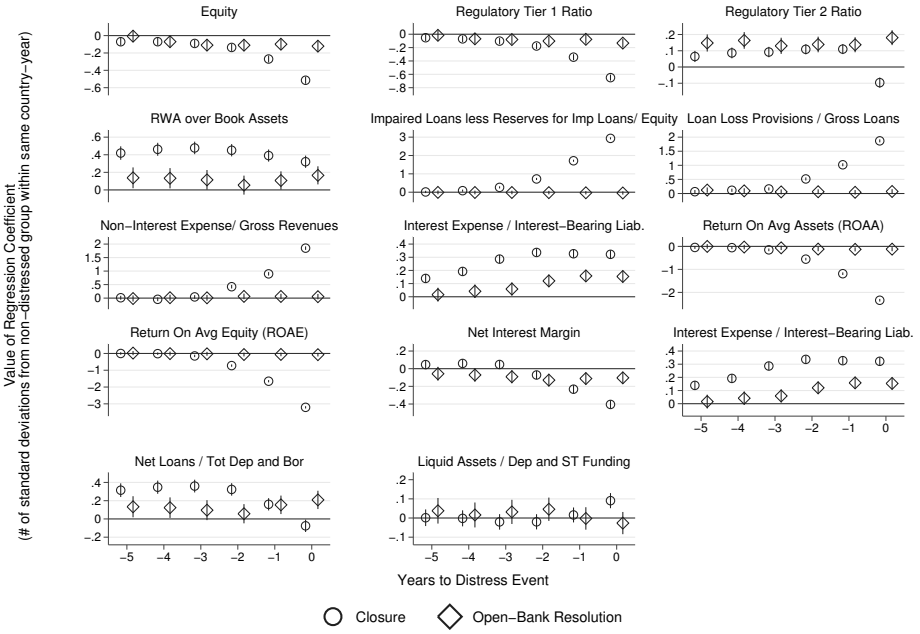


Fig. 1: Relative performance of distressed banks along select accounting ratios in years prior to the distress event. The figure plots the estimated coefficients together with corresponding confidence intervals from the following specification:

$$y_{ict} = \alpha_{ic} + \sum_{j=0}^{5} \phi_j f_{ict}^j + \epsilon_{ict},$$

where $f_{ict}^j = 1_{\text{Bank i becomes distressed within [j,j+1) year from time t}}$, and i, c, t denote firm, country, and time indices, respectively. α_{ic} denotes country-year fixed effects. The model is estimated separately for bank closures (closure by the regulator, bankruptcy, liquidation, distressed dissolution, distressed merger) and for open-bank resolutions (government recapitalizations). Panel A (resp. B) shows the estimated coefficients together with the 95% confidence intervals for the models estimated in the EU (resp. U.S.). Standard errors are clustered at the firm level. Each of the y variables is standardized to have a zero mean and variance of one, implying the following interpretation of a coefficient ϕ_j: banks experiencing distressed event between j and $j+1$ years in the future display on average ϕ_j standard deviations higher/lower value of y than their non-distressed peers, controlling for country-year specific trends.

(b) United States



where y is a bank-specific performance measure of interest, f_{ict}^{j} is an indicator of bank i becoming distressed within $[j, j+1)$ year from time t, and i, c, t denote firm, country, and time indices, respectively. We control for country-year specific trends and invariant characteristics by including country-year fixed effects, α_{ct}. The model is estimated separately for bank closures (closure by the regulator, bankruptcy, liquidation, distressed dissolution, distressed merger) and for open-bank resolutions (consisting primarily of government recapitalizations), as well as for the U.S.[9] and Western Europe.

Within this context, we trace the evolution of CAMEL bank performance measures, y_{ict}, described in Section 2.2 (see Table 2). Each of the accounting variables is standardized to have a zero mean and variance of one, implying the following interpretation of a coefficient ϕ_j: banks experiencing distress event between j and $j+1$ years in the future display on average ϕ_j standard deviations higher or lower value of y than their non-distressed peers, controlling for country-year specific trends.

Panels A and B of Figure 1 present the results from the estimation of equation 1, for European and the U.S. samples[10], respectively. The figure plots the estimates of coefficients ϕ_j for each bank performance measure listed above.

The most important result pertains to bank capitalization: distressed banks in both Europe and the U.S. tend to be significantly under-capitalized with respect to their non-

[9] Model 1 in the U.S. is estimated only with year-fixed effects.

[10] In the case of the U.S., the country-year fixed effects are substituted with year-fixed effects.

distressed peers. The economic magnitude of the result is particularly sizable for bank closures, with the distressed/non-distressed Tier 1 capital lag reaching 0.4 standard deviations in a year before the distress event. In Europe, the relative Tier 1 under-capitalization of distressed banks spans the period of at least 5 years before the distress event, while in the U.S. the under-performance is particularly notable during the three years before the event. Finally, U.S. distressed banks undergoing an open-bank resolutions are on average significantly better capitalized than their European counterparts in the same distress group.

While undercapitalized along the Tier 1 capital metric, distressed banks, perhaps surprisingly, exhibit higher levels of Tier 2 capital than their non-distressed counterparts. This pattern is particularly distinguishable in the U.S., whereas in Europe it applies only to bank closures. The positive relation between Tier 2 capital and bank risk suggests that Tier 2 capital should not be considered as a gauge of bank health and resilience, at least not in the same manner as Tier 1 capital. If anything, high levels of Tier 2 capital (i.e. relative to other banks) are indicative of high bank risk. Unfortunately, sparsity of Bankscope coverage of regulatory capital components prevents us from exploring the source of the disparity in more detail. One plausible explanation for the observed pattern is that banks that eventually become distressed engage in relatively risky lending and account for this risk by increasing the amount of general loan loss provisions and loan loss reserves, both of which under some conditions count as Tier 2 capital.

Decline in Tier 1 capitalization of distressed banks coincides with deterioration in their profitability, particularly for the group of banks that are eventually closed. Deterioration in profitability, in turn, is related to increasing loan-loss provisions and impairment charges, as well as to declining interest margins and operating efficiency (measured by the fraction of non-interest expenses in bank gross revenues). A notable exception to the above pattern are the U.S. banks involved in open-bank resolution; for this group, profitability, asset impairments, and operating efficiency are on par with the non-distressed banks, suggesting that apart from being undercapitalized these banks were relatively healthy in terms of their quality of earnings and assets.

In terms of their funding, distressed banks of both types tend to rely on less stable sources of funding and pay on average a higher price for funding then their non-distressed peers. This pattern is especially pronounced for banks that are subsequently closed.

Finally, a comparison of pre-event trends in accounting fundamentals between banks in Europe and the U.S. reveals a strong deterioration in fundamentals for bank closures in the U.S., whereas no such clear time-pattern is present in Europe. A temporal deterioration in fundamentals of the closed banks in the U.S. is particularly pronounced in the case of Tier 1 capital, unreserved impaired loans, loan loss provisions, non-interest expenses, and profitability.

3.2 Multivariate Prediction of Bank Distress

After analyzing the univariate divergences between distressed and non-distressed banks for select performance metrics, we now turn to modelling bank distress within a multivariate setting. Specifically, we model the probability of a bank becoming distressed within one year from the publishing of its accounting information as a function of the accounting

performance measures analyzed in the previous section[11]. To this end, we estimate the following specification:

$$Pr(\text{Distressed}_{ict} = 1) = \text{Logit}(\alpha_{ct} + x'_{ict}\theta + \epsilon_{ict}), \tag{2}$$

where D_{ict} is the indicator of a bank becoming distressed within 1 year from time t, and i, c, and t denote firm, country, and time indices, respectively. As before, we present results separately for the two types of distress, as well as for Europe and the U.S. Estimation of specification in Equation 2 is equivalent to the estimation of an exponential hazard model, in which a firms' probability of distress does not depend on its age.

The estimation results are reported in Table 4. As in the previous section, all explanatory variables are standardized to have a mean zero and a unit variance, so that the magnitude of the reported coefficient corresponds to the impact of one standard deviation increase in the explanatory variable on the log-odds ratio. Consequently, the absolute magnitude of the coefficient can be used to judge the relative economic importance of different variables in the specification.

The overall outcome of the regression analysis reveals that the likelihood of bank closure increases with (1) the degree of Tier 1 undercapitalization, (2) asset risk (measured by the ratio of RWA to book assets), (3) the amount of unreserved loan loss impairments, (4) cost of funding, and (5) the degree of operational inefficiency, (6) a decrease in bank profitability, measured by the interest margin, and (7) a decrease in asset liquidity, though the effect of the latter is statistically insignificant.

[11] Accounting measures within some CAMEL dimensions, e.g. earnings quality, are highly correlated. In order to avoid multicollinearity, the multivariate analysis below only includes one of the highly correlated pair in the same CAMEL category.

Table 4: Modelling of European and the U.S. Bank Distress

	Dependent variable is distress within 1 year					
	Bank Closure			Open-Bank Resolution		
	(1) EU	(2) US	(3) Combined	(4) EU	(5) US	(6) Combined
Regulatory Tier 1 Ratio	−2.202***	−3.169***	−3.210***	−0.715**	0.156	0.073
	[0.351]	[0.219]	[0.180]	[0.280]	[0.101]	[0.103]
Regulatory Tier 2 Ratio	0.324***	−0.303***	−0.007	−0.132	0.130	−0.020
	[0.094]	[0.116]	[0.081]	[0.117]	[0.142]	[0.087]
RWA over Book Assets	0.031	0.506***	0.365***	0.369***	−0.180*	0.028
	[0.122]	[0.100]	[0.073]	[0.122]	[0.104]	[0.074]
Unreserved Impaired Loans/ Equity	0.185**	0.223***	0.199***	0.087	−0.140*	−0.052
	[0.092]	[0.028]	[0.026]	[0.090]	[0.080]	[0.056]
Loan Loss Provisions / Gross Loans	0.007	0.323***	0.284***	0.271***	0.121*	0.152***
	[0.103]	[0.038]	[0.032]	[0.062]	[0.066]	[0.045]
Interest Expense / Interest-Bearing Liab.	0.253*	1.098***	0.724***	0.013	−0.243	−0.102
	[0.140]	[0.089]	[0.064]	[0.122]	[0.181]	[0.104]
Net Interest Margin	−0.390	−0.170	−0.330***	0.072	−0.164	−0.042
	[0.284]	[0.114]	[0.112]	[0.151]	[0.122]	[0.093]
Non-Interest Expense/ Gross Revenues	0.096	0.113***	0.145***	0.098	0.149***	0.117***
	[0.114]	[0.034]	[0.032]	[0.093]	[0.051]	[0.044]
Liquid Assets / Dep and ST Funding	0.073	0.019	0.136*	−0.048	−0.393***	−0.188**
	[0.118]	[0.122]	[0.077]	[0.113]	[0.148]	[0.085]
Net Loans / Tot Dep and Bor	−0.001	−0.004	0.058	0.177	0.473***	0.285***
	[0.129]	[0.109]	[0.079]	[0.128]	[0.109]	[0.079]
Log(Assets)	0.062	0.076*	0.066**	0.463***	0.492***	0.488***
	[0.058]	[0.043]	[0.033]	[0.058]	[0.037]	[0.028]
No. Events	112	533	645	137	273	410
No. Obs.	14786	46930	61716	8664	33110	41774
Pseudo R2	0.128	0.406	0.348	0.149	0.095	0.097
Effects	Country * Year	Year	Country * Year	Country * Year	Year	Country * Year

Notes:

[a] The table reports the estimation coefficients from the following specification:

$$P(D_{ict} = 1) = \text{Logit}(\alpha_{ic} + x'_{ict}\theta_t + \epsilon_{ict}) \quad (3)$$

where D_{ict} is the indicator of a bank becoming distressed within 1 year from time t, and i, c, and t denote firm, country, and time indices, respectively.

[b] Each column corresponds to the vintage of the accounting information that is used to model the bank distress events. In Europe, distress events are defined as the first time a given bank in a sample experiences one of the following: (a) bankruptcy/liquidation, (b) equity injection by the st ate (including nationalization), or (c) bridge loan by the state. For the U.S. banks, the distress indicator is constructed from the FDIC Failed Bank List (http://www.fdic.gov/bank/individual/failed/banklist.html). The accounting information is from Bankscope. The analysis considers the bank distress events that took place in the period 2005-13. The models are estimated for the sample of banks with assets larger than 100 million USD, for the period between January 2005 and December 2012. All explanatory variables are standardized to have a mean of zero and standard deviation of one. Standard errors are clustered by country.

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

The relation between bank closure and Tier 2 capitalization is positive in Europe and negative in the U.S. (both highly statistically significant). The opposite sign may be explained by the fact that the composition of regulatory capital strongly depends on the regulatory requirements and enforcement within the specific country. The World Bank survey of bank regulators conducted in 2011 reveals substantial cross-country variation in the instruments that count as capital. To the extent that these instruments differ in their capacity to absorb losses, their implication for predicting bank closure is obviously country-dependent. Therefore, it is important to explore the regulatory consequences for predicting bank distress across countries, which we do in the next section.

In terms of its explanatory power, the bank closure model explains bank closures with substantially higher degree of accuracy in the U.S. (with pseudo R-squared of 40%) than in Europe (13%). In the light of the univariate dynamics reported in Figure 1 this is not surprising, because most accounting ratios reported by the distressed banks in the U.S. exhibit clear negative trends already several years prior to the distress event. If we change the forecasting horizon in the U.S. to two years in the future, the R-squared of the model drops to around 20%.

Moving next to the results for open-bank resolutions, we note that the correlations between the likelihood of the event and covariates display similar directional patterns as in the case of bank closures, even though with varying degrees of statistical and economic significance.

In contrast to bank closures, bank size is statistically and economically more significant in the case of open-bank resolutions (the size coefficient being more strongly positive), which is consistent with the too-big-to-fail proposition, asserting that a failure of large institutions engenders disproportionately larger costs for the economy, prompting regulators and governments to resolve these institutions on a going concern basis.

In terms of the economic magnitude, particularly important determinants of open-bank distress resolution are the riskiness and liquidity of bank assets. Banks experiencing state or regulatory intervention tend to have more risky and less liquid assets than their surviving counterparts.

Comparison of the direction and magnitude of coefficients across all models suggests a high degree of overlap between the bank closure models in the U.S. and Europe and the open-bank assistance model in Europe. On the other hand, accounting fundamentals perform relatively poorly in explaining open-bank assistance events (i.e. TARP) in the U.S., suggesting that these events were driven by other non-fundamental drivers. This is in line with Bayazitova and Shivdasani (2012), who show that capital infusions under TARP were driven by strategic considerations, such as certification effects, and the constraints that TARP funds imposed on banks' compensation schemes.

4. Further Analysis on the Information Content of Accounting Fundamentals

The previous section demonstrated that the accounting fundamentals explain a significant proportion of within-country variation in the incidence of bank distress. This section examines the information content of the accounting fundamentals by studying the ability of bank accounting numbers (1) to identify distressed banks within individual countries (Section 4.1), and (2) to explain the country-level incidence of bank distress during 2007-10 (Section 4.2).

4.1 How informative is bank accounting disclosure in identifying distressed banks within countries?

In this section we evaluate the informativeness of the bank failure models developed in Section 3.2 in discriminating between distressed and non-distressed banks within each country in our sample. The informativeness of a model is measured by the area under the ROC curve[12] (henceforth AUC) from a classification exercise in which the model-implied predictions are used to predict bank distress within a specific country. A particularly useful interpretation of the AUC is that it is the probability that the randomly chosen distressed bank observations exhibit higher values of the predicted model score than the randomly chosen surviving observation. At one end of the spectrum, a completely uninformative classifier has the AUC of 0.5, whereas a perfectly predictive classifier has an ROC of 1[13].

We assess the within-country predictive performance of different model predictions, by computing AUCs for each individual country. AUCs are obtained from the non-parametric ROC estimation, using bootstrap.

Panels A, B, and C of Table 5 report the ROC results for predicting bank closure, open-bank assistance, and generally defined bank distress events (either closure or assistance), respectively. Each column corresponds to the AUCs pertaining to the particular model. For each country/predictor we report the estimated AUC and its standard error. The table includes the results only for countries with more than six events of a particular type[14]

Table 5: Informativeness of Accounting-Based Bank Distress Prediction Models: Areas Under ROC Curve[d] Across Countries

Model type:		Logistic Regression Model[b] (all countries)								
Dependent variable:		Open-Bank Assist.			Bank Closure			Bank Distress		
Estimation sample:	# Events[c]	All	EU	U.S.	All	EU	U.S.	All	EU	U.S.
Panel A: Use model score to predict **bank closure events** in...										
ALL	786	0.617	0.826	0.361	0.937	0.926	0.935	0.928	0.912	0.927
		[0.027]	[0.029]	[0.040]	[0.014]	[0.015]	[0.014]	[0.016]	[0.018]	[0.016]
DEU	16	0.426	0.500	0.376	0.932	0.918	0.908	0.890	0.865	0.779
		[0.067]	[0.068]	[0.064]	[0.014]	[0.027]	[0.025]	[0.023]	[0.051]	[0.073]
ESP	23	0.783	0.799	0.737	0.922	0.942	0.898	0.901	0.906	0.889
		[0.030]	[0.034]	[0.027]	[0.010]	[0.012]	[0.011]	[0.014]	[0.018]	[0.011]
GBR	14	0.647	0.623	0.665	0.698	0.697	0.679	0.680	0.627	0.690
		[0.078]	[0.074]	[0.080]	[0.076]	[0.086]	[0.069]	[0.076]	[0.091]	[0.073]
ITA	48	0.667	0.724	0.612	0.849	0.841	0.839	0.839	0.825	0.836
		[0.057]	[0.040]	[0.067]	[0.026]	[0.028]	[0.026]	[0.026]	[0.029]	[0.028]
USA	665	0.637	0.855	0.321	0.954	0.949	0.953	0.945	0.934	0.945
		[0.019]	[0.025]	[0.048]	[0.012]	[0.014]	[0.013]	[0.014]	[0.015]	[0.015]

[12] Receiver Operating Characteristic (ROC) curve summarizes the performance of a continuous predictor in predicting a binary outcome by plotting the false-positive rates against the true-positive rates for varying models score threshold levels.

[13] This assumes that a classifier is positively associated with bank distress, i.e. higher values of the classifier signal a higher likelihood of a distress event.

[14] The variability of AUC estimates for countries with lower number of events makes the resulting estimates less meaningful.

Model type:		Logistic Regression Model[b] (all countries)								
Dependent variable:		Open-Bank Assist.			Bank Closure			Bank Distress		
Estimation sample:	# Events[c]	All	EU	U.S.	All	EU	U.S.	All	EU	U.S.
Panel B: Use model score to predict **open-bank assistance events** in...										
ALL	417	0.838	0.819	0.833	0.709	0.675	0.705	0.763	0.762	0.762
		[0.031]	[0.018]	[0.062]	[0.052]	[0.050]	[0.056]	[0.042]	[0.034]	[0.056]
DEU	7	0.785	0.791	0.773	0.782	0.680	0.793	0.789	0.750	0.798
		[0.254]	[0.255]	[0.250]	[0.253]	[0.242]	[0.255]	[0.254]	[0.248]	[0.256]
DNK	43	0.655	0.708	0.600	0.537	0.526	0.517	0.598	0.621	0.557
		[0.028]	[0.018]	[0.038]	[0.109]	[0.102]	[0.118]	[0.078]	[0.047]	[0.098]
ESP	8	0.739	0.873	0.524	0.799	0.818	0.809	0.876	0.886	0.871
		[0.069]	[0.075]	[0.120]	[0.187]	[0.165]	[0.178]	[0.119]	[0.100]	[0.118]
FRA	8	0.833	0.837	0.729	0.776	0.787	0.783	0.812	0.836	0.799
		[0.015]	[0.008]	[0.076]	[0.015]	[0.039]	[0.019]	[0.012]	[0.014]	[0.011]
GBR	18	0.818	0.802	0.834	0.776	0.798	0.734	0.790	0.796	0.790
		[0.011]	[0.016]	[0.041]	[0.083]	[0.059]	[0.106]	[0.064]	[0.046]	[0.066]
GRC	9	0.813	0.778	0.770	0.800	0.788	0.794	0.774	0.785	0.797
		[0.057]	[0.076]	[0.069]	[0.033]	[0.030]	[0.040]	[0.042]	[0.041]	[0.042]
ITA	14	0.743	0.771	0.688	0.720	0.726	0.707	0.740	0.755	0.737
		[0.107]	[0.089]	[0.139]	[0.106]	[0.097]	[0.109]	[0.100]	[0.094]	[0.097]
NLD	8	0.791	0.741	0.807	0.675	0.652	0.635	0.716	0.699	0.727
		[0.021]	[0.065]	[0.024]	[0.062]	[0.076]	[0.054]	[0.024]	[0.017]	[0.026]
PRT	8	0.665	0.638	0.683	0.564	0.624	0.543	0.589	0.626	0.567
		[0.123]	[0.139]	[0.097]	[0.096]	[0.080]	[0.095]	[0.122]	[0.118]	[0.125]
USA	275	0.867	0.823	0.884	0.710	0.692	0.704	0.771	0.780	0.773
		[0.053]	[0.072]	[0.038]	[0.092]	[0.097]	[0.089]	[0.087]	[0.102]	[0.090]
Panel C: Use model score to predict **bank distress events** in...										
ALL	1203	0.693	0.826	0.520	0.862	0.844	0.860	0.875	0.864	0.873
		[0.037]	[0.015]	[0.085]	[0.031]	[0.032]	[0.032]	[0.023]	[0.021]	[0.022]
AUT	6	0.940	0.875	0.962	0.901	0.915	0.887	0.924	0.936	0.925
		[0.065]	[0.142]	[0.037]	[0.037]	[0.046]	[0.049]	[0.044]	[0.046]	[0.043]
DEU	23	0.535	0.589	0.497	0.887	0.846	0.873	0.859	0.830	0.785
		[0.091]	[0.084]	[0.093]	[0.058]	[0.060]	[0.064]	[0.061]	[0.057]	[0.093]
DNK	45	0.661	0.709	0.612	0.535	0.525	0.516	0.594	0.617	0.554
		[0.034]	[0.051]	[0.056]	[0.165]	[0.158]	[0.167]	[0.152]	[0.130]	[0.159]
ESP	31	0.777	0.815	0.700	0.902	0.923	0.885	0.899	0.905	0.889
		[0.040]	[0.044]	[0.037]	[0.053]	[0.052]	[0.046]	[0.037]	[0.037]	[0.030]
FRA	9	0.850	0.855	0.750	0.801	0.810	0.807	0.833	0.854	0.822
		[0.029]	[0.029]	[0.066]	[0.040]	[0.043]	[0.044]	[0.036]	[0.034]	[0.038]
GBR	32	0.743	0.724	0.761	0.744	0.755	0.712	0.743	0.722	0.748
		[0.047]	[0.045]	[0.049]	[0.046]	[0.046]	[0.048]	[0.050]	[0.052]	[0.049]
GRC	11	0.787	0.799	0.684	0.842	0.836	0.828	0.822	0.829	0.835
		[0.054]	[0.067]	[0.110]	[0.052]	[0.061]	[0.057]	[0.069]	[0.056]	[0.056]
IRL	7	0.582	0.575	0.594	0.562	0.581	0.543	0.587	0.557	0.579
		[0.054]	[0.040]	[0.076]	[0.118]	[0.133]	[0.093]	[0.091]	[0.086]	[0.091]
ISL	7	0.715	0.727	0.653	0.747	0.737	0.731	0.839	0.793	0.857
		[0.169]	[0.175]	[0.175]	[0.112]	[0.115]	[0.106]	[0.120]	[0.136]	[0.099]
ITA	62	0.685	0.736	0.630	0.821	0.817	0.811	0.818	0.810	0.815
		[0.069]	[0.043]	[0.085]	[0.025]	[0.028]	[0.022]	[0.028]	[0.030]	[0.027]
NLD	9	0.666	0.652	0.657	0.552	0.519	0.540	0.588	0.576	0.604
		[0.109]	[0.045]	[0.180]	[0.140]	[0.174]	[0.099]	[0.125]	[0.107]	[0.113]
PRT	11	0.632	0.604	0.646	0.644	0.683	0.624	0.620	0.641	0.607
		[0.082]	[0.099]	[0.070]	[0.101]	[0.064]	[0.110]	[0.093]	[0.068]	[0.101]
USA	941	0.704	0.848	0.482	0.886	0.878	0.884	0.897	0.892	0.898
		[0.043]	[0.017]	[0.120]	[0.046]	[0.047]	[0.047]	[0.033]	[0.029]	[0.033]

[a] This table presents the Areas Under ROC Curve (AUC) for predictors generated by a set of bank failure models, applied to predicting different types of bank distress events (1 year prediction horizon) within a set of 15 Western European Countries and the U.S. in the period 2006-2012.
[b] Each column in the table corresponds to the model that is used to generate bank distress predictions. Each model is a logistic regression using the same vector of covariates as models in Table 4. The models differ in the sample used to estimate the model (i.e Europe, U.S., or both) and in the event that serves as the dependent variable in the model estimation (i.e. bank closure, open-bank resolution, or a generally defined distressed event).
[c] In order to be included in the table, the number of events in a country must be larger than six.
[d] AUCs are obtained from the non-parametric ROC estimation, using bootstrap. For each country/predictor we report the estimated AUC and its standard error. The AUC may be interpreted as the probability that the randomly chosen distressed bank observation exhibits higher value of the predicted model score than the randomly chosen surviving observation.

We begin by noting several general patterns observed in Table 5:

- The best prediction of a given type of distress event is produced by the models that are built using the same type of distress event as the dependent variable. This result is unsurprising for the in-sample predictions where the estimation and the hold-out sample overlap. However, in most cases, the conclusion remains valid in the out-of-sample predictions. For example, the bank closure models estimated in Europe classify the U.S. bank closures with a similar level of accuracy than the bank closure models estimated in the U.S. (AUC of around 90%).
- Open-bank assistance models estimated on the European sample of banks have high accuracy in predicting bank closures in the U.S., with AUC of about 85%. This result is consistent with the conjecture that the bailed-out banks in Europe resemble the U.S. closed banks in the nature of their distress.
- Conversely, the U.S. open-bank assistance model, built primarily on TARP events, predicts the U.S. and European bank closures with only modest levels of accuracy.
- Open-bank assistance events are in general less predictable than the outright bank closures. Specifically, for bank closure and open-bank assistance events, the same-event AUCs are on average 90% and 80%, respectively.
- Bank closure models, both in the U.S. and Europe, predict open-bank assistance events with AUCs of about 70%, suggesting that the bank closure models are relatively ill-suited for identifying government recapitalizations of distressed banks.

We now turn to addressing the main question of this section, namely, assessing the extent to which bank distress is predictable by accounting fundamentals within specific countries. The main conclusions that emerge from Table 5 are as follows:

- Predictions generated by any given model display substantial cross-country variation in the accuracy of the within-country forecasts of any of the three types of bank distress events.
- Some of the countries with consistently low accuracy of distress predictions include Netherlands, Portugal, Ireland, and Denmark. In these countries, the accuracy of predictions in general does not exceed the AUC of 70%, and is, in many cases, close to the uninformative benchmark of 50%.
- Countries with consistently high levels of accuracy include the U.S., Austria, France, and Germany. The accuracy of predictions in these countries is typically above AUC of 80%.

4.1.1 Information content of the individual accounting ratios.

In order to examine the sources of poor predictive performance of the accounting-based models in some countries but not others, it is instructive to examine the informativeness of the individual accounting fundamentals that comprise the bank distress models, whose accuracy was estimated in the previous section.

For each of the 10 accounting fundamentals used in the models in Table 4 we proceed by computing the country-specific AUC from using the ratio in the prediction of generally-defined distress events (either closure or the open-bank resolution) within 1 year in the future. In Figure 2 we plot the resulting AUCs, together with the 95% confidence intervals, for each country and for each accounting fundamental.

The main conclusions from Figure 2 are summarized in the following points:

- The accounting variable that predicts bank distress with the highest level of accuracy and consistency across countries is Tier 1 regulatory capital ratio. The AUCs close to zero indicate that in most countries the randomly chosen distressed bank observations exhibit lower Tier 1 capital ratios than randomly chosen surviving observations. This is in line with the results in Table 4, in which the variation in Tier 1 capital is found to have the strongest economic impact on the probability of bank closure.
- Poor performance of the accounting-based models in countries like Luxembourg, Netherlands, Portugal, Ireland, and Denmark (see Table 8) appears to stem directly from the poor univariate predictive performance of the Tier 1 capital ratio (see Figure 2).
- Tier 2 capital ratio, asset risk weights, and unreserved impaired loans exhibit high cross-country variation in the accuracy of predicting bank distress.

4.2 How informative are the pre-crisis bank accounting figures in explaining the aggregate incidence of bank distress across countries during 2007-10?

In this section we examine an alternative way to measure the information content of accounting fundamentals. Specifically, we study whether the pre-crisis levels of the accounting fundamentals, when aggregated at the country level, explain the variation in the observed country level of bank distressed assets during the financial crisis episode.

Our main dependent variable of interest is the fraction of book assets attributable to banks that became distressed during the period 2008-10 relative to the total amount of banking sector book assets in the fiscal year-end of 2008[15], formally defined as:

$$FRAC\_DISTR_{c,[2008,2010]} = \frac{\sum_{i \in c \wedge i \in \text{Distressed}} \bar{A}_{i,t \in [2008,2010]}}{\sum_{i \in c} A_{i,t=2008}} \quad (4)$$

where A_i denotes the book value of bank i's assets, and c denotes a country. $FRAC\_DISTR$ is designed to proxy for the severity of a banking crisis at a country level, and it implicitly assumes an equal fractional impairment of distressed bank assets across countries. Countries with the largest fraction of bank assets in distress include Ice-

[15] The results of the analysis are robust to different choices of the base years for computing the aggregated banking sector assets.

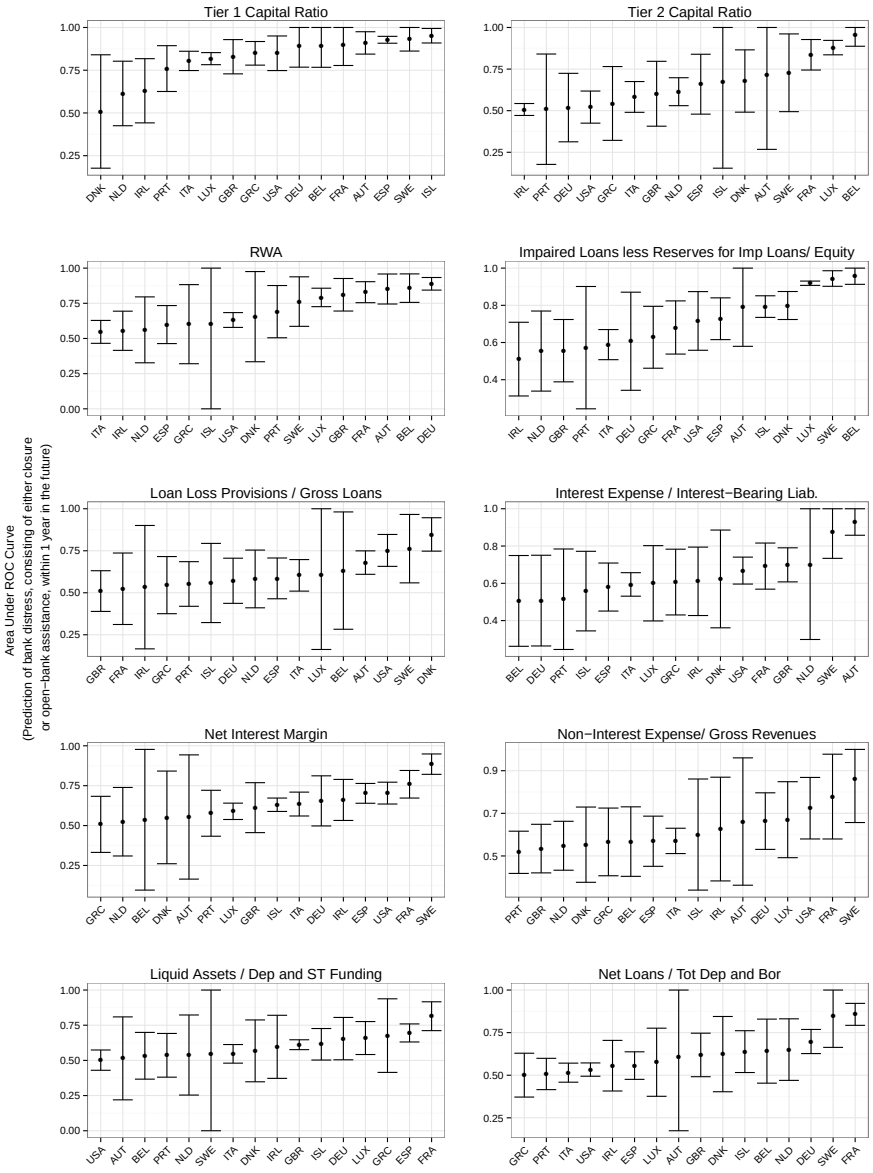


Fig. 2: Country-by-Country Areas under ROC Curve (AUC) for the Select Accounting Ratios. The figure shows the classification accuracy, measured by the AUC, in predicting bank distress (either closure or open-bank assistance) within 1 year in the future. AUCs are obtained from the non-parametric ROC estimation, using bootstrap. For each country/measure we report the estimated AUC and its 95% confidence interval. The AUC may be interpreted as the probability that the randomly chosen distressed bank observation exhibits higher value of the accounting ratio than the randomly chosen surviving observation.

land, Greece, and Portugal, whereas the ones with the lowest observed bank distress rate include Luxembourg and Sweden.

Having defined the benchmark measure of country-wide bank distress, we now analyze the extent to which the variables that explain the within-country variation also explain the cross-country variation in bank distress.

First, we aggregate bank-level accounting variables, X_{ict}, into the country-level indicators, $\bar{X}_{ct}$, by weighting each bank-year observation of a variable by the bank's level of book assets (as a share of total banking assets in that country-year)[16]:

$$\bar{X}_{ct} = \sum_{i \in c} \frac{A_{ict}}{\sum_{i \in c} A_{ict}} X_{ict}. \tag{5}$$

Next, we investigate the extent to which pre-crisis accounting-based bank fundamentals anticipated the scale of country-specific bank distress in period 2008-2010 by plotting each aggregated accounting measure, measured at the end of year 2006[17] (i.e. $\bar{X}_{c,2006}$) against $FRAC\_DISTR_{c,[2008-2010]}$. Figure 3 plots the result of the exercise. Before interpreting the results, one should be mindful of the somewhat low number of countries in the study (i.e. 15 Western European countries and the U.S.), and all the caveats that pertain to drawing conclusions from small samples of observations. That said, we believe that studying cross-country patterns of bank accounting ratios in the context of the recent banking crisis is instructive in elucidating their ability to capture risks at the country level.

Several observations emerge from Figure 3. First, reported Tier 1 and Tier 2 regulatory capital ratios (reported as a fraction of risk-weighted assets) serve as poor predictors of banking problems at the country level. If anything, banks in countries with high rates of distress in 2008-10 report on average higher levels of both forms of regulatory capital in years preceding the crisis. In principle, this pattern could emerge simply as a result of banks in ex-post riskier countries recognizing their higher risk of distress already in 2006, and anticipating this risk by holding additional regulatory capital. Indeed, the plot of reported risk-weighted assets in Figure 3 reveals that banks in countries with high observed level of distress on average reported significantly higher asset risk-weights in 2006. In unreported country-level regressions, which control for the bank asset risks, the sign of Tier 1 capital ratio becomes negative, but is statistically insignificant, with p-value of 65%.

A second conclusion that can be drawn from Figure 3 is that, apart from the reported asset risk weights, the only bank accounting-based aggregate in 2006 that exhibits a clear relation with the ex-post bank distress in 2008-10 is the net-interest margin. Specifically, countries with banks that reported on average higher net-interest margins in 2006 experienced higher incidence of bank distress during 2008-10.

[16] We also repeat entire analysis with equally weighted accounting fundamentals, and the main results remain qualitatively similar to the ones we report below.

[17] We repeat the analysis by using the 2007 fiscal-year results and the results remain qualitatively unchanged.

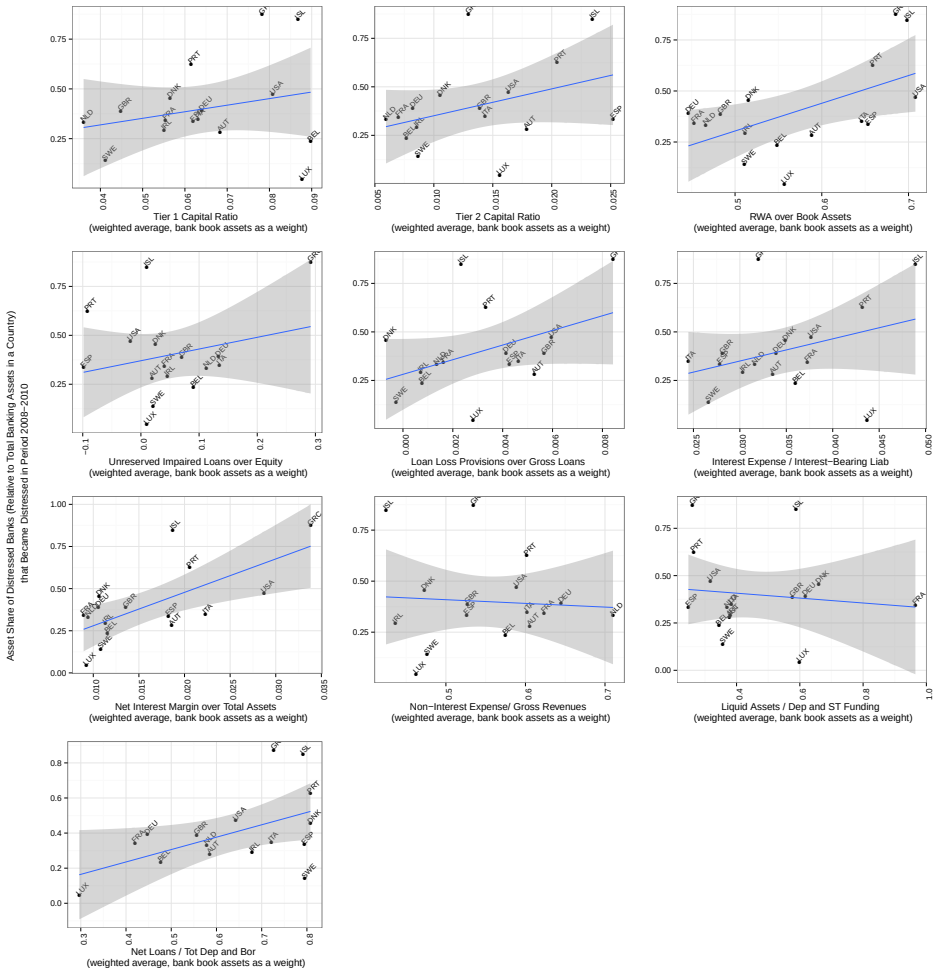


Fig. 3: Cross-Country Variation in Bank Distress and its Correspondence with the Aggregated Bank Accounting Measures. The figure plots $FRAC\_DISTR$, a country-wide measure of severeity of bank distress during the period 2008-10, against a set of aggregated bank accounting measures, used in the analysis of within-country variation in bank distress. $FRAC\_DISTR$ is defined as: $FRAC\_DISTR_{c,[2008,2010]} = \frac{\sum_{i \in c \wedge i \in \text{Distressed}} \bar{A}_{i,t \in [2008,2010]}}{\sum_{i \in c} A_{i,t=2008}}$, where A_i denotes the book value of bank i's assets, and c denotes a country. We aggregate bank-level accounting variables, X_{ict}, into the country-level indicators, $\bar{X}_{ct}$, by weighting each bank-year observation of a variable by the bank's level of book assets (as a share of total banking assets in that country-year): $\bar{X}_{ct} = \sum_{i \in c} \frac{A_{ict}}{\sum_{i \in c} A_{ict}} X_{ict}$.

5. Bank Disclosure Quality

The main conclusion that emerges from the analyses in Sections 4.1 and 4.2 is that predictability of bank distress by accounting fundamentals varies substantially across countries. This section takes a closer look at variations in the informativeness of bank accounting and examines the extent to which such variations are explained by national bank disclosure standards and their enforcement by the regulators.

To motivate the analysis, it should first be noted that the state of bank financial condition, especially for non-listed banks, is predominately inferred from bank accounting disclosure. Bank management possesses substantial discretion over multiple reporting attributes, and consequently has the capacity to report inaccurate information. Apart from having the *capacity* to hide bad performance, a compelling case can be made that banks, especially the ones in the lower tail of performance distribution, also have *incentives* to use accounting discretion to improve their reported performance. Specifically, a bank close to distress may use accounting discretion to improve its reported regulatory capital ratio in order to avoid negative attention of its regulator, or to avoid a run on its funding.

To the extent that banks in financial distress are more likely to use accounting discretion to improve their reported performance relative to their healthier peers, the ability of the accounting numbers to discriminate between distressed and non-distressed banks is necessarily reduced. In the extreme case, in which the reported accounts of the distressed and non-distressed banks are indistinguishable, the information value of the accounting fundamentals in prediction of distress is essentially non-existent.

A combination of reporting discretion and the incentives to use it is particularly acute in the following areas of bank disclosure: (1) computation of regulatory capital, (2) computation of asset risk weights, (3) accounting for losses, and (4) loan loss provisioning. For example, management can improve the reported regulatory capital ratio by delaying recognition of loan impairments[18], by counting as capital the hybrid instruments with poor loss-absorption qualities, or by underweighting risks of certain assets in the computation of risk-weighted assets (RWA), the denominator in the regulatory capital ratio formula. The latter is of a particular concern, because after the enactment of Basel II most banks compute their risk weights according to their internal rating-based approaches[19], which allows for a substantial degree of flexibility.

In principle, bank disclosure standards and their enforcement by regulators provide a constraint on banks' accounting discretion and on their information revelation incentives. Banks in jurisdictions with more restrictive disclosure laws, or with more diligent supervisory enforcement of the stated standards, are presumably less willing and able to engage in accounting manipulation to hide poor performance. Obviously, low levels of discretion and strong supervisory enforcement come at a cost. First, by potentially decreasing the informativenenss of accounting reports by banks that are not in distress, and second, by draining limited supervisory resources.

As we show below, countries in our sample exhibit substantial variations in proxies of bank accounting discretion and regulatory enforcement stringency. Following the previous line of reasoning, such variations could conceivably influence the informativeness

[18] Recognition of loan impairments may be delayed by a bank rolling-over their non-performing loans.

[19] The main benefit of the IRB approach is that in principle it allows for a more accurate measurement of bank risks. However, degrees of freedom inherent in this approach, give banks a leeway to misrepresent their financial health.

of accounting ratios in bank distress prediction. Our objective in the remainder of this section is to examine whether and how different bank disclosure regimes influence the informativeness of accounting fundamentals.

5.1 Measurement of Bank Disclosure Standards and Their Enforcement by the Regulators

We obtain a set of proxy measures of country-specific bank disclosure quality from the database of Barth, Caprio, and Levine (2013), who compile a set of more than 50 different indices from the quadrennial World Bank surveys covering 180 countries since 1999. The indices in their database measure several different aspects of domestic bank regulation, including capital regulation, disclosure and monitoring environment, failed bank resolution, bank competition, and supervisory structure. In the following analysis we only use the subset of indices measuring the quality of countries' disclosure and monitoring environment. Descriptions of the indices can be found in Table 6. Each index is standardized according to the following formula:

$$R_c^* = \frac{R_c - min(R)}{max(R) - min(R)} \in [0, 1],$$

where R_c is the raw value of the index for country c, and $min(R)/\ max(R)$ represent minimum/maximum value of the index in the entire database of 180 countries across all times. The index value for each country is averaged over the period 2007-2012. For each index, higher values of the index correspond to either better disclosure standards, or a more stringent implementation of the standards by the regulator. Values of the standardized indices for each country are presented in Figure 4.

5.2 Test 1: Bank Disclosure Quality and Accounting Information Content in a Cross-Section of Banks

We next examine the association between country-specific quality of disclosure, R, and a cross-sectional measure of accounting informativeness.

We measure the information of content of an accounting fundamental, x, as the absolute magnitude of the marginal impact of x on the probability that a bank becomes distressed 1 year in the future, within a cross section of banks in country c at time t:

$$INFO_{ct}(x) = \left|\left| \left. \frac{\partial Pr(\text{Distressed}_{ict} = 1)}{\partial x_{ict}} \right|_{\text{c,t fixed}} \right|\right|$$

The intuition of the measure is simple: the information value of an accounting fundamental increases with its ability to identify distress in a cross section of banks in a given country-year. In line with the discussion above we expect the informativeness of an accounting measure to be greater in countries with more stringent standards or with more vigilant implementation of the standards by the regulators. Following the previous

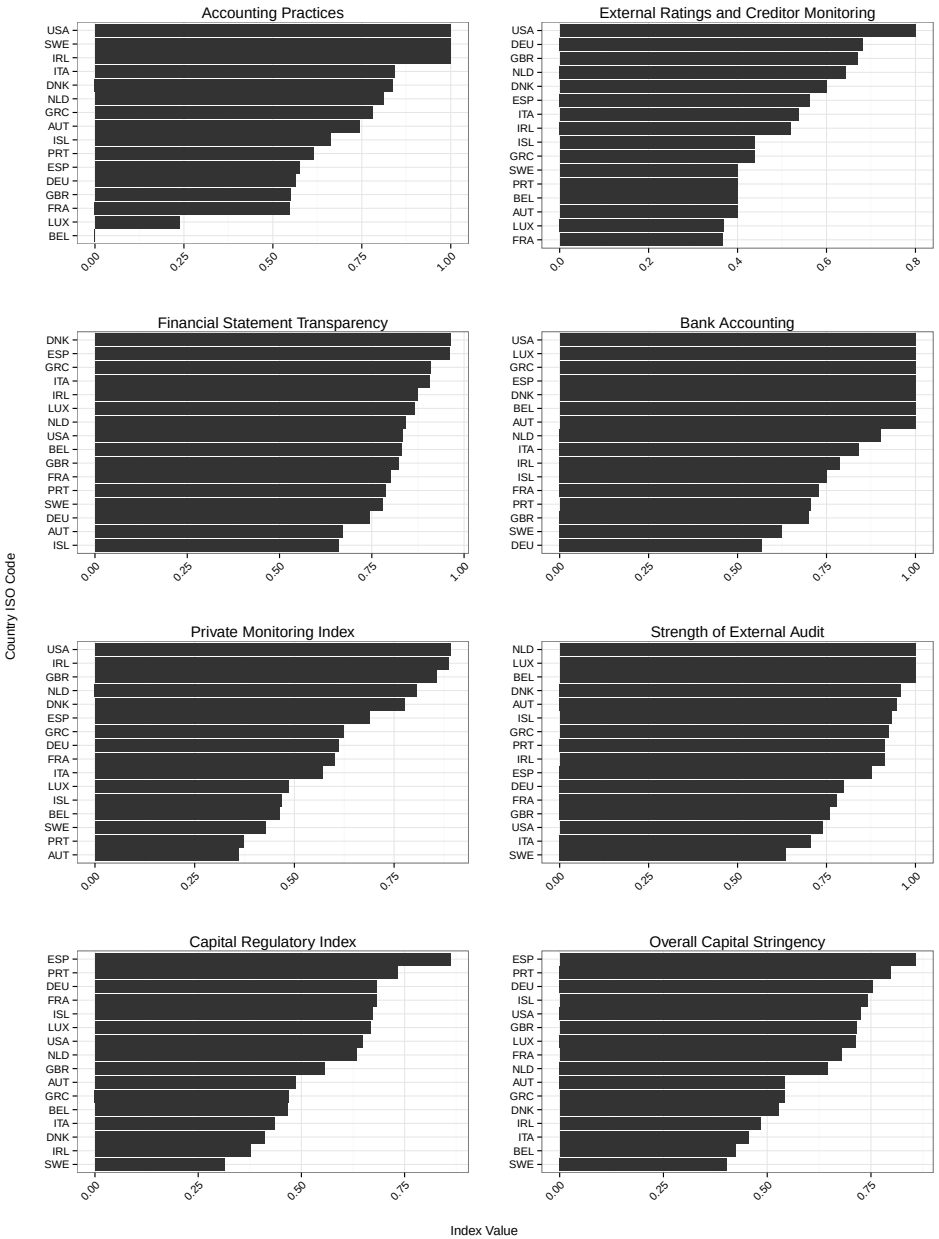


Fig. 4: Bank Regulation across Countries: Bank Disclosure. The figure plots the regulatory indices from the database of Barth, Caprio, and Levine (2013). Each index is standardized according to the following formula: $X_c^* = \frac{X_c - min(X)}{max(X) - min(X)} \in [0, 1]$, where X_c is the raw value of the index for country c, and $min(X)/\ max(X)$ represent minimum/maximum value of the index in the entire database of 180 countries across all times. The index value for each country is averaged over the period 2007-2012.

Table 6: Definition of Regulatory Indices from Barth, Caprio, and Levine (2013)

Index Name	Description
Accounting Practices	The type of accounting practices used (higher values indicate better practices).
Bank Accounting	Measures whether the income statement includes accrued or unpaid interest or principal on nonperforming loans and whether banks are required to produce consolidated financial statements (higher values indicate more informative accounts).
Certified Audit Required	Measures the presence of a requirement of a compulsory external audit by a licensed or certified auditor,
External Ratings and Creditor Monitoring	Captures the extent of evaluations by external rating agencies and incentives for creditors of the bank to monitor bank performance (higher values indicate better creditor monitoring).
Private Monitoring Index	Measures whether there are incentives for private monitoring of firms, with higher values indicating more private monitoring.
Overall Capital Stringency	Measures whether the capital requirement reflects certain risk elements and deducts certain market value losses from capital before minimum capital adequacy is determined (higher values correspond to greater stringency).
Capital Regulatory Index	Similar to the "overall capital stringency", except that it also measures whether certain funds may be used to initially capitalize a bank (higher values correspond to greater stringency).

Notes:
[a] This table defines the bank regulatory disclosure proxies used in the paper. The regulatory indices come from the database of Barth, Caprio, and Levine (2013).

notation, this can be stated as:

$$INFO_{ct}(x)\Big|_{\substack{\text{c,t fixed}\\ c\in\text{Good Disclosure Country}}} > INFO_{ct}(x)\Big|_{\substack{\text{c,t fixed}\\ c\in\text{Bad Disclosure Country}}} \geq 0 \qquad (6)$$

Eq. 6 implies that the marginal contribution of accounting ratio x in bank distress prediction is a function of the regulatory index, R. In the context of the framework introduced in Section 3.2, we can test this implication by interacting the accounting ratio x with the value of R:

$$\begin{aligned} Pr(\text{Distressed}_{ict}=1) &= \text{Logit}(\alpha_{ct}+x'_{ict}\theta+\epsilon_{ict}) \\ &= \text{Logit}(\alpha_{ct}+x_{ict}*(\phi_1+\phi_2 R_{ct})+\epsilon_{ict}) \\ &= \text{Logit}(\alpha_{ct}+\phi_1*x_{ict}+\phi_2*R_{ct}*x_{ict}+\epsilon_{ict}) \end{aligned} \qquad (7)$$

where α_{ct} controls for country-year specific trends, x_{ict} is one of the bank-specific accounting measures of interest, and R denotes a country-specific proxy for regulatory disclosure and monitoring requirements. The hypothesis in Eq. 6 implies that $|\phi_1+\phi_2|>|\phi_1|$. To see this, notice that a sum of ϕ_1 and ϕ_2 represents the marginal contribution of an ac-

counting ratio to the log-odds of distress in countries with most stringent disclosure laws and their implementation (i.e. $R_{ct} = 1$). Conversely, ϕ_1 represents a marginal contribution in countries with weak bank disclosure environment (i.e. $R_{ct} = 0$). The hypothesis in Eg. 6 postulates that the absolute marginal contribution of an accounting ratio is stronger in countries with stringent bank disclosure environment, hence $|\phi_1 + \phi_2| > |\phi_1|$.

Notice that the hypothesis in Eg. 6 does not postulate the *direction* of the correlation between the accounting signal and bank distress, but concerns only the *magnitude* of the correspondence. The implications of the hypothesis can be nuanced further, by taking into account the direction of the associations between bank distress and fundamentals, predicted by the banking theory. Theoretically, one expects to observe a negative association between bank distress and bank capital (both Tier 1 and Tier 2), and a positive association between bank distress and RWA, unreserved impaired loans, and loan loss provisions. We expect the theoretically predicted *direction* of the correspondence to be stronger in countries with better disclosure laws, which implies a negative interaction term, θ_2, for bank capital, and a positive interaction term for RWA, unreserved impaired loans, and loan loss provisions.

Table 7 reports the estimates of the specification of Eq. 7. We separately estimate the specification for five accounting ratios that are often considered as the most prone to manipulation, namely: (1) Tier 1 capital ratio, (2) Tier 2 capital ratio, (3) risk-weighted assets[20], (4) unreserved loan losses, and (5) loan loss provisions. Columns 1-7 report the estimates for the regressions with regulatory interactions for each of the disclosure and monitoring indices described in Section 5.1[21]. Estimates reported in different panels of Table 7 come from separate estimations of specification in Eq. 7. Since our regulatory variables are standardized to lie in the range between 0 (worst disclosure quality) and 1 (best disclosures quality), the interpretation of the interaction term coefficient is straightforward: it represents a change in the marginal contribution of the accounting fundamental on the probability of bank distress as one moves from the worst-disclosure jurisdiction to the best-disclosure jurisdiction.

Results are consistent with the disclosure-quality hypothesis for Tier 1 regulatory capital ratio, unreserved loan losses and loan loss provisions. In each of the cases, an accounting signal of bank distress tends to be stronger in countries with strong disclosure laws and/or with more stringent enforcement of the existing laws. Additionally, the direction of the accounting signal in each of the three cases is consistent with the theoretical prior. Specifically, Tier 1 regulatory capital ratio exhibits a negative relation with bank distress, whereas the unreserved loan losses and the loan loss provisions exhibit a positive association.

In the cases of the Tier 2 regulatory capital ratio and the RWA ratio, the association between accounting signals and bank distress shifts in the direction of the theoretical prior as one moves to the jurisdictions with more stringent disclosure environments. In particular, both Tier 2 capital ratio and the RWA have a theoretically counter-intuitive correspondence with bank distress in countries with poor disclosure quality, and a theoretically predicted correspondence in countries with better disclosure quality.

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[20] As before, we scale the reported risk-weighted assets by the total book values of assets. The resulting measure may be interpreted as the aggregate (at the bank level) asset risk weight.

[21] The seven regulatory indices exhibit high levels of positive pairwise correlations (with Pearson correlation coefficients above 0.6). As a result, estimation of a specification that includes the interactions with all regulatory indices is infeasible due to multicollinearity.

Table 7: Within-Country Cross-Sectional Evidence on the Association between Accounting Informativeness and Bank Disclosure Quality

	Type of Regulatory Index:						
	(1) Accounting Practices	(2) Bank Accounting	(3) Certified Audit Required	(4) External Ratings and Creditor Monitoring	(5) Private Monitoring Index	(6) Capital Regulatory Index	(7) Overall Capital Stringency
θ_1: Regulatory Tier 1 Ratio	−3.199***	−0.442	−3.578***	0.100	−1.305**	1.639***	0.693
	[0.452]	[0.883]	[0.500]	[0.539]	[0.657]	[0.468]	[0.463]
θ_2: Regulatory Tier 1 Ratio * [Regulatory Index]	−0.714	−3.619***	−0.294	−5.581***	−3.171***	−8.912***	−6.676***
	[0.471]	[0.929]	[0.518]	[0.746]	[0.809]	[0.769]	[0.681]
Test: $\lvert\theta_1+\theta_2\rvert-\lvert\theta_1\rvert>0$	1	1	1	1	1	1	1
P-value	0.065	0.000	0.285	0.000	0.000	0.000	0.000
θ_1: Regulatory Tier 2 Ratio	0.269**	−0.619**	0.503***	0.661***	0.616**	0.290	0.565***
	[0.117]	[0.288]	[0.149]	[0.200]	[0.247]	[0.193]	[0.197]
θ_2: Regulatory Tier 2 Ratio * [Regulatory Index]	−0.277**	0.949***	−0.509***	−0.993***	−0.807**	−0.426	−0.867***
	[0.137]	[0.314]	[0.164]	[0.329]	[0.350]	[0.331]	[0.324]
Test: $\lvert\theta_1+\theta_2\rvert-\lvert\theta_1\rvert>0$	0	0	0	0	0	0	0
P-value	0.972	0.855	0.999	0.993	0.991	0.874	0.968
θ_1: RWA over Book Assets	−0.506***	−2.232***	−0.251*	−0.975***	−1.614***	−0.169	−0.194
	[0.173]	[0.329]	[0.144]	[0.214]	[0.260]	[0.189]	[0.177]
θ_2: RWA over Book Assets * [Regulatory Index]	0.689***	2.562***	0.447***	1.666***	2.249***	0.531*	0.603**
	[0.183]	[0.349]	[0.158]	[0.303]	[0.324]	[0.322]	[0.263]
Test: $\lvert\theta_1+\theta_2\rvert-\lvert\theta_1\rvert>0$	0	0	0	0	0	1	1
P-value	0.961	1.000	0.636	0.969	1.000	0.058	0.046
θ_1: Impaired Loans less Reserves for Imp Loans/ Equity	0.428***	−1.014**	0.477***	−0.632***	−0.376*	0.040	0.291**
	[0.166]	[0.400]	[0.121]	[0.237]	[0.217]	[0.166]	[0.127]
θ_2: Impaired Loans less Reserves for Imp Loans/ Equity * [Regulatory Index]	0.389**	1.847***	0.343***	1.867***	1.393***	1.145***	0.698***
	[0.168]	[0.403]	[0.124]	[0.304]	[0.253]	[0.246]	[0.170]
Test: $\lvert\theta_1+\theta_2\rvert-\lvert\theta_1\rvert>0$	1	0	1	1	1	1	1
P-value	0.010	0.676	0.003	0.000	0.000	0.000	0.000
θ_1: Loan Loss Provisions / Gross Loans	0.180*	−0.805***	0.306***	−0.552***	−0.479**	0.220*	0.381***
	[0.099]	[0.282]	[0.109]	[0.214]	[0.206]	[0.131]	[0.117]
θ_2: Loan Loss Provisions / Gross Loans * [Regulatory Index]	0.357***	1.404***	0.199*	1.420***	1.218***	0.430**	0.164
	[0.102]	[0.288]	[0.112]	[0.279]	[0.246]	[0.200]	[0.162]
Test: $\lvert\theta_1+\theta_2\rvert-\lvert\theta_1\rvert>0$	1	0	1	1	1	1	1
P-value	0.000	0.771	0.500	0.019	0.063	0.016	0.156

Notes:

[a] The table reports the estimation coefficients of the interaction terms in the following specification:

$$Pr(D_{ict}=1)=\text{Logit}(\alpha_{ct}+\theta_1*x_{ict}+\theta_2*R_{ct}*x_{ict}+\epsilon_{ict}) \quad (8)$$

where $D_{i,c,t}$ is the indicator of a bank becoming distressed within 1 year from the publishing of the accounting information, and i, c, and t denote firm, country, and time indices, respectively.

[b] R_{ct} is one of seven regulatory indices, obtained from the database of Barth, Caprio, and Levine (2013), who construct the indices from quadrennial World Bank surveys covering 180 countries since 1999. Definitions of the indices used in our paper are given in Table 6.

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

Table 8: Within-Firm/Time-Series Evidence on the Association between Accounting Informativeness and Bank Disclosure Quality

	Type of Regulatory Index:						
	(1) Accounting Practices	(2) Bank Accounting	(3) Certified Audit Required	(4) External Ratings and Creditor Monitoring	(5) Private Monitoring Index	(6) Capital Regulatory Index	(7) Overall Capital Stringency
θ_1: Regulatory Tier 1 Ratio	−8.951***	−2.802**	−6.995***	0.917	−4.997**	−1.780*	−1.975**
	[1.129]	[1.381]	[1.986]	[1.295]	[2.069]	[0.946]	[0.862]
θ_2: Regulatory Tier 1 Ratio * [Regulatory Index]	3.144***	−3.012**	1.310	−9.092***	−0.765	−5.434***	−4.538***
	[1.051]	[1.411]	[1.991]	[1.780]	[2.450]	[1.431]	[1.183]
Test: $\lvert\theta_1+\theta_2\rvert-\lvert\theta_1\rvert>0$	0	1	0	1	1	1	1
P-value	0.999	0.016	0.745	0.000	0.377	0.000	0.000
θ_1: Regulatory Tier 2 Ratio	0.423**	1.329**	0.163	1.710***	3.966***	1.927***	2.029***
	[0.208]	[0.588]	[0.411]	[0.621]	[0.623]	[0.334]	[0.347]
θ_2: Regulatory Tier 2 Ratio * [Regulatory Index]	−0.861***	−1.670***	−0.373	−2.835***	−5.477***	−3.503***	−3.213***
	[0.221]	[0.636]	[0.425]	[0.895]	[0.809]	[0.547]	[0.497]
Test: $\lvert\theta_1+\theta_2\rvert-\lvert\theta_1\rvert>0$	1	0	1	0	0	0	0
P-value	0.479	0.959	0.455	0.927	1.000	0.914	0.998
θ_1: RWA over Book Assets	−1.235***	−1.783***	−0.506*	0.462	−0.187	−1.071***	−0.583**
	[0.264]	[0.570]	[0.271]	[0.517]	[0.702]	[0.314]	[0.288]
θ_2: RWA over Book Assets * [Regulatory Index]	0.368	1.008*	−0.330	−1.853**	−0.849	0.082	−0.728*
	[0.239]	[0.571]	[0.292]	[0.726]	[0.874]	[0.494]	[0.426]
Test: $\lvert\theta_1+\theta_2\rvert-\lvert\theta_1\rvert>0$	0	0	1	1	1	0	1
P-value	0.938	0.961	0.129	0.005	0.166	0.566	0.044
θ_1: Impaired Loans less Reserves for Imp Loans/ Equity	1.572***	0.670	1.725***	−0.022	0.387	1.691***	1.336***
	[0.354]	[0.614]	[0.445]	[0.578]	[0.443]	[0.322]	[0.235]
θ_2: Impaired Loans less Reserves for Imp Loans/ Equity * [Regulatory Index]	−0.134	0.842	−0.268	1.983**	1.297**	−0.616	−0.149
	[0.354]	[0.634]	[0.449]	[0.794]	[0.558]	[0.461]	[0.299]
Test: $\lvert\theta_1+\theta_2\rvert-\lvert\theta_1\rvert>0$	0	1	0	1	1	0	0
P-value	0.648	0.092	0.725	0.000	0.010	0.909	0.691
θ_1: Loan Loss Provisions / Gross Loans	0.460**	−0.843	0.974**	0.240	−0.226	3.281***	3.040***
	[0.189]	[0.552]	[0.396]	[0.378]	[0.557]	[0.378]	[0.333]
θ_2: Loan Loss Provisions / Gross Loans * [Regulatory Index]	0.732***	2.076***	0.178	1.212**	1.665**	−3.463***	−2.806***
	[0.200]	[0.569]	[0.402]	[0.508]	[0.674]	[0.565]	[0.455]
Test: $\lvert\theta_1+\theta_2\rvert-\lvert\theta_1\rvert>0$	1	1	1	1	1	0	0
P-value	0.000	0.238	0.329	0.008	0.004	1.000	1.000

Notes:

[a] The table reports the estimation coefficients of the interaction terms in the following specification:

$$Pr(D_{ict}=1)=\text{Logit}(\alpha_i+\theta_1*x_{ict}+\theta_2*R_{ct}*x_{ict}+\epsilon_{ict}) \quad (9)$$

where $D_{i,c,t}$ is the indicator of a bank becoming distressed within 1 year from the publishing of the accounting information, and i, c, and t denote firm, country, and time indices, respectively.

[b] R_{ct} is one of seven regulatory indices, obtained from the database of Barth, Caprio, and Levine (2013), who construct the indices from quadrennial World Bank surveys covering 180 countries since 1999. Definitions of the indices used in our paper are given in Table 6.

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

5.3 Test 2: Disclosure Quality and Accounting Informativeness: Within-Firm (Time-Series) Evidence

An alternative way to assess the informativeness of accounting reports is to examine whether a time series of accounting signals produced by a distressed bank anticipates the bank's eventual failure. Following the nomenclature of the previous section, the informativeness of an accounting fundamental, x, is now defined as the marginal impact of x, reported by bank i, on the probability that bank i becomes distressed 1 year in the future:

$$INFO_{ic}(x) = \left|\left| \frac{\partial Pr(\text{Distressed}_{ict} = 1)}{\partial x_{ict}} \right|_{\text{i fixed}} \right|$$

The intuition of the measure is as follows: the information value of an accounting fundamental increases with the ability of its time-series movements to anticipate eventual distress of the reporting institution. To illustrate, if a bank, which eventually becomes distressed, reports the same value of an accounting fundamental in all periods leading up to a distress event, the accounting signal is judged as uninformative according to the above definition. On the other hand, the signal is judged as informative if its reported value immediately before the distress period is distinct from its value in the periods further from the distress event.

As before, we expect the informativeness of an accounting measure to be greater in countries with more stringent standards or with more vigilant implementation of the standards by the regulators:

$$INFO_{ic}(x)\Big|_{\substack{\text{i fixed} \\ c\in\text{Good Disclosure Country}}} > INFO_{ic}(x)\Big|_{\substack{\text{i fixed} \\ c\in\text{Bad Disclosure Country}}} \geq 0 \qquad (10)$$

We test the above prediction by estimating the following specification (notice the inclusion of firm-fixed effects):

$$Pr(\text{Distressed}_{ict} = 1) = \text{Logit}(\alpha_i + \phi_1 * x_{ict} + \phi_2 * R_{ct} * x_{ict} + \epsilon_{ict}). \qquad (11)$$

The above specification is estimated only on the subsample of banks that become distressed at some point in the sample. The main difference between Eq. 7 and Eq. 11 is that the latter exploits the within-firm variation to estimate the coefficients, whereas the former relies on the within-country/year variation.

Table 8 shows the results of the within-firm estimation. The main conclusions are similar to the previous section. The informativeness of the Tier 1 capital ratio, unreserved loan losses, and loan loss provisions tends to be greater in countries with better disclosure quality. On the other hand, the disclosure-contingent reversion in the association between bank distress and Tier 2 capital is even more pronounced within a firm than in a cross section. Specifically, prior to their distress event, banks in countries with low disclosure quality tend to increase their Tier 2 capital whereas their counterparts in countries with better disclosure quality tend to decrease the reported levels of Tier 2 capital.

6. Concluding Remarks

This article provides a comprehensive account and analysis of bank failures in the U.S. and Western Europe during the recent financial crisis. The major contribution of our paper is to provide an in-depth examination of the information content of the accounting fundamentals and to study the relation between the observed variations in accounting informativeness and the stringency of bank disclosure standards and their enforcement by regulators.

We show that predictions generated by accounting-based models display a substantial cross-country variation in bank distress classification performance. We also demonstrate that the pre-crisis values of accounting fundamentals, aggregated at the country level, fail to explain the 2007-10 aggregate incidence of bank distress across countries. We show that the informativeness of accounting fundamentals in the cross section of banks in a given country-year positively correlates with the quality of accounting standards and the stringency of their enforcement. In particular, accounting signals of bank distress tend to be stronger in countries with strong disclosure laws or with more stringent enforcement of the existing laws. We also show that the disclosure-quality/information content nexus continues to hold when looking at the informativeness of the time series movements in accounting fundamentals for distressed banks prior to the distress event.

A combination of reporting discretion and the incentives of distressed banks to use accounting discretion to improve the reported performance in order to avoid negative regulatory action or deposit runs, will decrease the informativeness of accounting fundamentals. In the case of an extreme 'signal-jamming', a distressed bank may report performance that mimics the performance of its non-distressed peers, thus essentially nullifying the information value of the accounting signal.

Given that investors and regulators typically learn about banks' financial condition from the banks' public disclosures, our results have clear implications for bank disclosure regulation. The evidence in this paper supports the oft-voiced concern that excessive flexibility in financial reporting undermines the ability of accounting signals to accurately capture the underlying financial health of banks. Obliqueness of the distressed s accounting signals makes such information less useful for investors and regulators, and thus has negative regulatory implication. Perhaps the main implication of this conclusion is that the information content of accounting fundamentals, at least with respect to the identification of distressed banks, will be improved by increased stringency of bank disclosure laws and their enforcement.

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