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Abstract

Using a large sample of business groups from more than one hundred countries around the world, we show that group information matters for parent and subsidiary default prediction. Group firms may support each other when in financial distress. Potential group support represents an off-balance sheet asset for the receiving firm and an off-balance sheet liability for the firm offering support. We find that subsidiary information improves parent default prediction over and above group-level consolidated information possibly because intra-group exposures are netted out upon consolidation. Moreover, we document that the improvements in parent default prediction are decreasing in the extent of parent-country financial reporting transparency which suggests that within-group information matters most when consolidated financial statements are expected to be of lower quality. We also show that parent and other group-firms' default risk exhibits predictive power for subsidiary default. Lastly, we find that within-group information explains cross-sectional variation in CDS spreads. Taken together, our findings contribute to prior literature on default prediction and have direct relevance to investors, credit-rating agencies and accounting regulators.

Keywords: Default prediction, Business groups, Consolidation, Financial reporting transparency, Credit spreads

JEL Classification: G12, G14, G15, G33, M41

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Using a large sample of business groups from more than one hundred countries around the world, we show that group information matters for parent and subsidiary default prediction. Group firms may support each other when in financial distress. Potential group support represents an off-balance sheet asset for the receiving firm and an off-balance sheet liability for the firm offering support. We find that subsidiary information improves parent default prediction over and above group-level consolidated information possibly because intra-group exposures are netted out upon consolidation. Moreover, we document that the improvements in parent default prediction are decreasing in the extent of parent-country financial reporting transparency which suggests that within-group information matters most when consolidated financial statements are expected to be of lower quality. We also show that parent and other group-firms' default risk exhibits predictive power for subsidiary default. Lastly, we find that within-group information explains cross-sectional variation in CDS spreads. Taken together, our findings contribute to prior literature on default prediction and have direct relevance to investors, credit-rating agencies and accounting regulators.

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1. Introduction

In this paper we investigate whether business group information matters for default prediction. Business groups are a widespread organizational form in many countries and account for a large fraction of the world's economic activity (La Porta et al., 1999; Claessens et al., 2000). A business group consists of a parent company and legally independent subsidiaries that function as a single economic entity through a common source of control.

Group-affiliated firms may take advantage of their internal capital markets to overcome difficulties in accessing external finance (e.g., Desai et al., 2004; Claessens et al., 2006). The idea of group firms supporting each other (i.e., *propping*) is effectively described in the seminal study of Friedman et al. (2003). This sharing of intra-group resources often extends beyond financial resources and is an important determinant of firm performance (Chang and Hong, 2000).[1] Business groups may be thought of as a nexus of implicit coinsurance contracts whereby group-affiliated firms financially support each other in case of need (Khanna and Yafeh, 2005; Riyanto and Toolsema, 2008). Through these mutual coinsurance agreements, business groups effectively engage in risk sharing thus preventing the failure of solvent entities subject to temporary liquidity shortfalls (Khanna and Yafeh, 2005; Gopalan et al., 2007; Beaver et al., 2016).

Following the argument above, one would expect intra-group dynamics to play an important role in the assessment of group-affiliated firms' credit risk. However, whether business group affiliation matters for default prediction, and if so to what extent, is *a priori* unclear. On the one hand, an important *raison d'être* of business groups is that ultimate owners can exercise control over a large number of companies while containing their risk exposure through *limited liability*. Under the general principle of limited liability, because parents cannot be held responsible for the obligations of their subsidiaries, they may decide not to support a distressed subsidiary when this is too costly for the group (e.g., the *selective default* option). Notwithstanding the existence of active internal capital markets, limited liability plays an important role for business groups (e.g., Posner, 1976), a role which, according to Cestone and Fumagalli (2005), has often been neglected in the corporate finance

[1] A detailed discussion of the *propping* literature is presented in Section 2 along with a discussion of the studies that examine the *tunneling* phenomenon (Bertrand et al., 2002; Siegel and Choudhury, 2012), whereby intra-group resource transfers may lead to capital misallocation.

literature. Support for the role of limited liability can, nonetheless, be found in Johnson et al. (2000) and Bianco and Nicodano (2006) who respectively highlight how, precisely because of limited liability, parent companies often shift risky projects to subsidiaries and raise group debt at the subsidiary level. Parents engaging in this type of strategic behavior seek to intentionally exploit limited liability to insulate themselves from the obligations of their subsidiaries (Blumberg, 1985). These parents are therefore very unlikely to bail out their financially distressed subsidiaries. Following this argument, group affiliation should, in principle, not matter for default prediction.

On the other hand though, bankruptcy courts may rule to lift a parent's limited liability protection (i.e., *veil piercing*) and hold the parent responsible for its subsidiaries' obligations (Thompson, 1991; Vandekerchove, 2005; Erens et al., 2008; Matheson, 2008; Mevorach, 2009). Moreover, the default of a subsidiary can impose non-trivial costs on the parent (e.g., operational disruption, limited access to external capital, reputational loss), and generate a cascade of defaults within a group (e.g., due to cross-default clauses) (Gopalan et al., 2007; Elliott et al., 2014). As a result of these costs and the possibility of veil piercing, parents may choose to support their distressed subsidiaries. Thus, according to this alternative reasoning, group affiliation should, instead, matter for default prediction.[2]

From a financial reporting perspective, the resources that are expected to flow from a parent to its financially distressed subsidiaries would represent an off-balance sheet asset for those subsidiaries. Conversely, a subsidiary's implicit obligation to provide resources to a distressed parent (or other distressed subsidiaries) could be regarded as an off-balance sheet liability. The potential support received (offered) may represent an off-balance sheet asset (liability) in the *separate* financial statements of a parent as well.

Group parents also typically prepare a set of *consolidated* financial statements whose goal is to reflect the financial position of the group as a whole.[3] While in general a parent's consolidated

[2] Moreover, prior studies further suggest that, in part because of limited liability, resource transfers that *decrease* credit risk (e.g., Hoshi et al., 1990; Gopalan et al., 2007) and resource transfers that *increase* credit risk (e.g., Bertrand et al., 2002) may as well co-exist within the same business group, which renders the overall net effect of intra-group transactions on parent and subsidiary default risk *ex ante* unclear.
[3] Both under U.S. GAAP and IFRS, a reporting entity that guarantees the debt of another entity may have to consolidate that entity, even if it has no voting control. *Recourse debt* issued by affiliates will therefore likely be reflected in the parent's consolidated financial statements. However, this is not necessarily the case for *non-recourse debt*, where the parent and the other subsidiaries in the corporate structure have no legal performance

financial statements are considered to be more comprehensive than its separate financial statements, not much is known about the loss of information that occurs as a result of this aggregation process. If consolidation does not leave behind credit-relevant within-group information, subsidiary financials should not add to consolidated statements for parent default prediction. However, the process of aggregation underlying consolidation may entail a loss of information (Demski, 1973). Upon consolidation in fact, intra-group exposures, which may contain credit-relevant information, are typically netted out and, as a result, consolidated financial statements may not be fully informative about a group's overall credit standing. Therefore, whether parent consolidated financial statements fully subsume within-group credit-relevant information is an open empirical question. Furthermore, in the presence of information costs, it is crucial to understand the usefulness of more disaggregated subsidiary-level information for users of financial statements other than equity investors (Pendlebury, 1980), and specifically the degree to which the inclusion of more disaggregated information improves default prediction (i.e., the materiality of this information for credit-risk assessment).[4]

Moreover, whether group-level financial information improves on default prediction is an open question also because financial markets could already incorporate into prices all credit-relevant information that group firms' separate and consolidated financial statements leave behind. It is in fact possible that traditionally-used market-based default predictors (e.g., distance to default) could (in part or in full) subsume this information.

Consistent with the idea that group affiliation may matter for default prediction, credit rating agencies pay attention to the role played by internal capital markets as the group approaches financial distress. While Moody's and Standard and Poor's (S&P) rate most group firms on a standalone basis (Moody's, 1999; S&P, 2014), they factor parent influence over subsidiaries' credit worthiness into their assessments: "*Potential for support or negative intervention from the parent company or group is a major rating consideration*." (S&P, 2014). For example, over the recent years S&P has made adjustments to the credit ratings of Caterpillar Inc., Chrysler Group LLC, The Coca-Cola Co., and

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obligation in case of default. In that case, the amount the parent would likely spend to support or bail out the subsidiary is an off-balance sheet liability for the parent (and an off-balance sheet asset for that subsidiary).

[4] Broadening the set of default predictors (in this case by considering more disaggregated information) does not necessarily increase the out-of-sample predictive power of our models, which may in fact decrease as a result of over-fitting.

Hewlett-Packard Co.[5] However, these adjustments are usually rather *ad hoc* and mainly rely on "soft" information that may be private to credit rating agencies. Hence, whether default prediction can be improved upon by using publicly available financial statements remains an open question.

From the discussion above, whether group information matters for default prediction likely depends on the interplay and relative importance of: (i) limited liability protection, (ii) possibility of veil piercing, (iii) informativeness of market data, and (iv) quality of the consolidation process. Individually considered, these factors may lead to opposing empirical predictions. Thus, this inherent tension renders our investigation an important endeavor.

There has been considerable empirical research on the ability of financial ratios, in isolation or in combination with market data, to predict financial distress (Beaver, 1966; Altman, 1968; Ohlson, 1980; Shumway, 2001; Hillegeist et al., 2004; Beaver et al., 2005). The unit of analysis of this line of the literature (for a review see Beaver et al., 2010 and Ak et al., 2013) has typically been the *firm* with its consolidated financial statements, regardless of whether operating as a standalone entity or as part of a business group.[6]

The role of group affiliation in default prediction has likely been neglected by prior studies for two main reasons. First, high-quality group structure and ownership information, as well as granular financial statement data for (often private) group-affiliated firms, has only recently become available (e.g., Shroff et al., 2014; Beaver et al., 2016; Beuselinck et al., 2018). Second, most default-prediction studies typically focus on the U.S. market where in general business groups are less common than in Continental Europe and East Asia (Faccio and Lang, 2002; OECD, 2012).[7] Collectively, these factors highlight the relevance of our research question and the importance of relying on a cross-country sample to study the role of group affiliation in default prediction.

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[5] S&P *North American Corporate Rating Scores by Industry Sector* as of February 6th, 2014.

[6] Typically, prior literature focuses on the "firm" as the unit of analysis without a clear distinction on whether the firm is a *standalone* entity or a *group* of separate legal entities operating as a single economic entity. Throughout the paper, we use the term "firm" to refer to a separate legal entity, which may be standalone or a parent/subsidiary belonging to a group. While the term subsidiary is typically used to refer to an affiliate company in which the parent entity holds the majority of voting rights, we use the term subsidiary loosely to refer to an affiliate firm in which the parent has an ownership stake.

[7] While business groups may be less prevalent in the U.S. than in other countries, the U.S. foreign direct investment (FDI) outflows in 2014 represented approximately \$300 billion (UNCTAD World Investment Report, 2016). Therefore, knowledge of how to price (credit) securities of foreign issuers, which are often part of business groups, is of paramount importance to U.S. investors alike.

In order to understand whether, and to what extent, group information aids in predicting and explaining credit risk of group-affiliated firms, we seek to answer the following questions: (1) Can group information help predict parent bankruptcy? (2) Do parent consolidated financial statements subsume within-group credit-relevant information? (3) If not, does parent-country financial reporting transparency explain differences in the incremental predictive ability of group information? (4) Can group information help predict subsidiary bankruptcy? (5) Finally, does group information help explain cross-sectional variation in credit default swap (CDS) spreads?

Collectively, our findings provide evidence that group information matters for default prediction at both the parent and subsidiary level. Our study relies on the Orbis database which provides financial and ownership information for a large number of group-affiliated firms from around the world. We exploit granular data provided by financial statements of individual entities within the group to assess whether parent-subsidiary links and the financial health of group firms improve default prediction over and above group-level consolidated information.

Using two different estimation approaches (i.e., a discrete hazard estimation and a Classification and Regression Trees (CART) estimation), we show that subsidiary-level default risk improves parent out-of-sample default prediction over and above consolidated financial statement information. This result is consistent with a loss of credit-relevant information resulting from the information aggregation process underlying accounting consolidation. Moreover, we show that the improvement in parent default prediction holds even when we control for market information. Similarly, parent and other group-firms' default risk exhibits predictive power for subsidiary default prediction. *Ceteris paribus*, subsidiaries and their parent are more likely to file for bankruptcy if other group firms are close to financial distress. Furthermore, and in line with our expectations, we document a larger predictive power increase in the case of subsidiary default prediction. This is because consolidated financial statements provide (at least in part) information regarding subsidiaries' overall credit worthiness.[8]

[8] We conduct an extensive set of additional tests to ensure that accounting for sharing of group resources (Chang and Hong, 2000), such as reputation and other intangibles, as well as for common business exposure, does not affect the tenor of our main findings.

The inherent complexity of business group ownership and financial structures often makes it difficult for enforcement authorities, auditors and regulators to assess the soundness and comprehensiveness of the consolidation process. When parent-country financial infrastructures are underdeveloped (i.e., poor investor protection, lax reporting enforcement, etc.), managers may have more leeway to opportunistically obscure subsidiary credit-relevant information through the consolidation process.[9] The extent to which parent consolidated financial statements reflect group credit-relevant information is therefore likely to vary with parent-country financial reporting transparency.[10] Accordingly, we next take advantage of the cross-country nature of our data to investigate whether the improvement in parent default prediction generated by the inclusion of subsidiary-level information varies with the extent of parent-country financial reporting transparency. Our findings suggest that: (i) the predictive power of a parent default prediction model based on consolidated financial information is lower when parents are domiciled in low financial reporting transparency countries, and more importantly (ii) subsidiary-level information improves the predictive ability of the parent default model more when parents are domiciled in low financial reporting transparency countries.

Default, arguably, represents an extreme realization of credit risk. To examine the extent to which group information explains variation in credit risk more broadly, we test whether group information also determines cross-sectional variation in the pricing of credit-risk-sensitive securities. We show that subsidiary-level (parent-level) accounting information incrementally explains cross-sectional variation in parent (subsidiary) CDS spreads, controlling for a set of market variables that include a distance to default measure based on Merton (1974). By showing that group information plays a role beyond predicting realizations in the right tail of the credit-risk distribution, this analysis specifically highlights the economic significance of our findings.

Our study contributes to the extensive literature on bankruptcy prediction and default risk (e.g., Altman, 1968; Ohlson, 1985; Begley et al., 1996; Hillegeist et al., 2004; Beaver et al., 2005; Mayew

[9] Joos and Lang (1994) document substantial cross-country variation in the measurement of financial ratios as well as in the market valuation of accounting data.
[10] Prior studies find that the quality of country-level financial reporting infrastructures (e.g., auditing, enforcement, etc.) improves liquidity and valuations (Lang et al., 2012; Lang and Maffett, 2011).

et al., 2015) in several ways.[11] First, we show how granular within-group ownership and financial information improves bankruptcy prediction and explains cross-sectional variation in CDS spreads even when controlling for market information.

Second, our evidence highlights an important potential limitation of consolidated financial statements. Demski (1973) shows that any process of information aggregation entails a loss of information which varies across different financial statement users. Our results show that the information aggregation process involves some loss of credit-relevant information, and therefore can inform accounting standard setters and financial statement users (e.g., credit suppliers in general and lending officers in particular) who seek to understand the relative merits of consolidated financial information for credit-risk assessment.

Third, we examine whether bankruptcy models, which have been extensively tested using consolidated financial information for firms listed in the U.S., can be extended to a cross-country setting with both public and private firms.[12] We find that these bankruptcy models extend to privately-held firms from a large sample of countries with considerable predictive power. This is an issue which has been largely unexplored in the U.S. because of lack of data availability, yet plays an important institutional role in private (e.g., bank) lending.

Fourth, to the best of our knowledge, our study is the first that attempts to quantify the economic magnitude of intra-group support by estimating its net effect on group firms' off-balance sheet assets and liabilities.

Lastly, by showing that the parent model predictive power improvement due to subsidiary-level information varies with parent-country financial reporting transparency, our study contributes to the international accounting literature that examines the economic consequences of financial reporting transparency (e.g., Leuz, 2010; Lang et al., 2012; Lang and Maffett, 2011; Maffett et al., 2017). In particular, our evidence is consistent with the idea that different sources of information may complement each other in that when the degree of parent-country financial reporting transparency is

[11] Note that default-risk measures are often used either as primary variables of interest or as control variables in different settings. For example, Dechow et al. (2010) highlight the importance of properly controlling for default risk in earnings quality studies.
[12] Xu and Zhang (2009) stress the importance of assessing whether models developed for U.S. companies also work outside the U.S.

low, creditors can benefit more from relying on granular within-group information. We view our results as nicely complementing the evidence in Maffett et al. (2017) who examine whether the quality of accounting information affects the extent to which it can compensate for impaired market information. We examine, instead, the extent to which disaggregated subsidiary-level information can add to consolidated financial statements when the consolidation process is expected to be of lower quality (i.e., because of weak country-level institutions).

The remainder of the paper proceeds as follows. Section 2 reviews the literature on the role of group affiliation; Section 3 describes the data; Section 4 presents our base default prediction model; Section 5 examines whether group information can help predict parent default; Section 6 investigates the role of parent-country financial reporting transparency; Section 7 examines whether group information can help predict subsidiary default; Section 8 discusses the economic magnitude of our main findings; Section 9 investigates whether group information explains cross-sectional variation in CDS spreads; Section 10 presents the results of the analysis using the CART default estimation approach; and Section 11 concludes.

2. The Role of Group Affiliation

Prior studies on business groups (cf. Khanna and Yafeh (2007) for a review of the literature) have examined the value of group affiliation focusing on its potential benefits and costs.

On the *potential benefits* side, a stream of the literature posits and finds that business groups take advantage of their internal capital markets to overcome difficulties in accessing external finance especially in emerging markets (e.g., Hoshi et al., 1991; Desai et al., 2004; Chittoor et al., 2005; Claessens et al., 2006). Business groups may in fact offer financial support to their financially distressed subsidiaries (i.e., *propping*). Friedman et al. (2003) provide empirical evidence consistent with propping taking place in pyramidal groups surrounding the 1997-1998 Asian crisis.[13] Follow-up studies provide further evidence of propping in various settings (e.g., Bae et al. (2008) and Byun et al. (2013) for South Korea and Gopalan et al. (2007) for India). Propping may occur via a large set of related-party transactions including sales (e.g., Jian and Wong, 2010), trade credit (Kim and Nilsen,

[13] Specifically, Friedman et al. (2003) show that, compared to standalone firms and other group-affiliated firms, firms within pyramidal structures exhibit on average higher debt ratios and an attenuated negative association between debt ratios and stock returns during the crisis period.

2014), equity issuances (Almeida et al., 2015), and intra-group loans and loan guarantees (e.g., Gopalan et al., 2007; Jia et al., 2013; Buchuk et al., 2014; Beaver et al., 2016). Consistent with the idea of within-group financial support, a number of studies in the management literature emphasize the role of intangible-resource sharing, such as technological innovation and reputation. A notable example is Chang and Hong (2000; 2002) who document that intangible-resource sharing is an important determinant of performance for South Korean group-affiliated firms.

On the *potential costs* side, another strand of the literature (e.g., Claessens et al., 1999; Johnson et al., 2000 and Bertrand et al., 2002) draws attention to a possible misallocation of capital across group firms at the expense of minority shareholders (i.e., *tunneling*). However, evidence on the costs associated with group affiliation is still subject to debate. Siegel and Choudhury (2012), for example, argue that the empirical findings in Bertrand et al. (2002) may be confounded by differences in business strategy and corporate governance between group-affiliated and standalone firms.

Riyanto and Toolsema (2008) point out that the costs and benefits of group affiliation should not be considered in isolation. They argue that group affiliated firms trade off the costs of tunneling with the benefits of future expected propping, that is, they are willing to provide resources to other group firms in return for implicit insurance against their own future bankruptcy. Support for this *coinsurance* mechanism is offered by the theoretical model of Luciano and Nicodano (2014) that identifies conditions under which coinsurance may be optimal (i.e., it may increase the joint value of parents and their subsidiaries). Khanna and Yafeh (2005) examine the coinsurance mechanism empirically and find that it is prevalent in Japanese, South Korean and Thai business groups.

In summary, while prior studies suggest that interdependencies among group firms may influence credit risk for the group as a whole, the empirical evidence on the role of group affiliation for default prediction is scant. Prior literature does not examine the incremental out-of-sample predictive power of group information for subsidiary and parent default, nor does it examine how this incremental predictive power changes across countries or firms. Also, prior studies do not speak to the loss of information in the consolidation process and mostly provide evidence based on single-country samples (e.g., Gopalan et al., 2007) with the resulting inferences potentially hinging on poor institutional quality settings where internal capital markets are a frequent alternative to external finance (Khanna and Palepu, 2000). Therefore, whether intra-group firm dynamics have implications for bankruptcy prediction remains an open empirical question.

3. Data

The main data we use for our empirical analysis come from Orbis, a database published by Bureau van Dijk Electronic Publishing (BvDEP). Orbis relies on global data providers, such as the World Vest Base, as well as many well-established local data providers. To date, Orbis provides ownership, governance, and financial data for over 200 million public and private firms around the world. The extensive coverage of Orbis *vis-à-vis* other commercial databases which typically cover only large listed firms, is particularly important in this setting because large listed firms represent a small fraction of the economic activity for several of our sample countries (Kalemli-Ozcan et al., 2015). Further, for our tests relying on market data, we source equity returns and market capitalization data from Datastream, distance to default information from the National University of Singapore Risk Management Institute, and CDS data from Markit.[14] We provide additional details on the construction of our dataset in the Online Appendix.

4. Default Prediction Model

We use a two-pronged approach to test whether group information matters for default prediction at the parent and subsidiary levels. *First*, we estimate a discrete hazard model within the sample of non-bankrupt firms and bankrupt firms that includes data for all the years prior to the final year before bankruptcy (following Shumway (2001)). *Second*, because this estimation relies on assumptions regarding the functional form of the association between bankruptcy probability and the different predictors and does not capture non-linearities and interactions among these variables, we also rely on a non-parametric estimation approach. In particular, we use the CART methodology developed by Breiman et al. (1984). We discuss the relative advantages and disadvantages of these two estimation techniques in the Online Appendix.

While each methodology (hazard and CART estimation) has its advantages and disadvantages, we choose to use a hazard model approach in our main analysis because this is the approach most

[14] Several other studies rely on Markit as a source of CDS spread data (e.g., Kim et al., 2013).

commonly used in the default prediction literature (e.g., see Beaver et al., 2010). Moreover, this ensures that our findings are comparable to those of prior default prediction studies. Nonetheless, we also report for robustness the results from the CART analysis as the complementarity of the two approaches ensures that the results that we document do not hinge on the specificities of a particular model.

Our hazard model analysis is based on the Beaver et al. (2005) accounting model. We use an accounting-based model since 60% of parents and 66% of subsidiaries in our sample are private.[15]

We extend the model by including a loss indicator (Beaver et al., 2012) and the logarithm of the parent/subsidiary total assets.[16] Furthermore, we estimate the model with a country/industry/time varying baseline, by including the country-industry-level bankruptcy rate of the previous year as an additional explanatory variable. We use a varying baseline to take into account the fact that bankruptcies are likely correlated with (country- and industry-specific) macroeconomic fluctuations and country-level institutional characteristics. This approach is in line with Chava and Jarrow (2004) and Hillegeist et al. (2004). We compare this model with alternative model specifications using a constant sample in the Online Appendix and show that this model has higher out-of-sample predictive power compared to the other models presented.[17] These include country-specific estimations that account for heterogeneity in legal regimes and accounting systems around the world, as well as specifications that directly control for macroeconomic factors (e.g., GDP growth ($FGDPg_{i,t}$) and inflation ($FINF_{i,t}$)).

Our analysis is thus based on the following model (hereafter, the *base model*):

$$Pr\left(Y_{i,t+1} = 1\right) = f(NROAI_{i,t}, ROA_{i,t}, LTA_{i,t}, ETL_{i,t}, LN(TA_{i,t}), BANKRATE_{i,t}), \tag{1}$$

[15] One caveat of our analysis, which we share with many default prediction studies, is that, by construction, we are unable to consider every single variable that could potentially be relevant for bankruptcy prediction. Therefore, we choose to base our analysis on Beaver et al. (2005) who find that their parsimonious accounting model produces similar results in terms of predictive ability to other accounting models, such as the ones developed by Altman (1968), Ohlson (1980) and Zmijewski (1984).

[16] The original Beaver et al. (2005) combined model includes a size proxy based on market capitalization.

[17] Our analysis also suggests that, although the predictive power of the default prediction model for private firms is not as high as for public firms, it is still highly significant, implying economically important likelihood ratios. Some of the documented public-private difference could be due to heterogeneity in the quality of accounting information (Ball and Shivakumar, 2005).

where the subscripts i and t denote the firm and the year, respectively. $Y_{i,t+1}$ is an indicator variable equal to one if the firm files for bankruptcy in year $t+1$, and zero otherwise; $NROAI_{i,t}$ is an indicator variable equal to one if the return on assets ($ROA_{i,t}$) is negative, and zero otherwise; $ROA_{i,t}$ is the ratio of net income to lagged total assets; $LTA_{i,t}$ is book leverage, the ratio of total liabilities to total assets; $ETL_{i,t}$ is the ratio of earnings before interest and tax to total liabilities; $LN(TA_{i,t})$ is the natural logarithm of the book value of the firm's total assets and $BANKRATE_{i,t}$ is the country-industry-level bankruptcy rate. Following the approach in Beaver et al. (2005), we fill in missing values of the explanatory variables with their lagged values (using up to two lags). We also winsorize all continuous variables at the 2nd and 98th percentile of their distributions to mitigate the influence of outliers and potential data errors.[18] We estimate our base model separately for parents, subsidiaries, and standalone firms.[19] All variables are defined in the Appendix.

We expect loss-making firms (with $NROAI_{i,t}$ equal to one), firms with higher leverage ($LTA_{i,t}$), smaller size ($LN(TA_{i,t})$) and firms in countries and industries with higher bankruptcy rates ($BANKRATE_{i,t}$) to exhibit a higher probability of default. Conversely, more profitable firms (higher $ROA_{i,t}$ and $ETL_{i,t}$) should exhibit lower bankruptcy rates. Based on this model, we estimate the probability that each firm in the sample files for bankruptcy within the following 12 months as follows: $Pr\left(\widehat{Y_{\iota,t+1}}=1\right)=\frac{exp(X_{i,t}\widehat{\beta})}{1+exp(X_{i,t}\widehat{\beta})}$. We describe our sample selection procedure and present descriptive statistics for our main variables of interest in the Online Appendix.

5. Can Group Information Help Predict Parent Default?

5.1. Augmenting the Parent Default Prediction Model

Table 1, Panel A, Column (1) presents the coefficients from the estimation of the base default prediction model for the sample of parent firms. We limit the analysis to business groups where we have available ownership information to compute control rights, i.e., the *Base Model Sample* (see

[18] We choose to winsorize variables at the 2nd and 98th percentiles of their distributions because large outliers remain when we, consistent with other studies in the bankruptcy literature, winsorize the data at the 1st and 99th percentiles. In untabulated robustness tests, we repeat our analysis by winsorizing variables at the 1st and 99th percentiles of their distributions. Our findings are unaffected by this alternative design choice.

[19] We estimate our bankruptcy models separately to account for potential confounding effects due to the inherent heterogeneity across these different types of firms.

Table OA-2 in the Online Appendix). We find that small, loss-making parents, with high leverage and low profitability, are more likely to file for bankruptcy.

To test the extent to which group-level information contributes to parent default prediction, we begin by examining whether the parent default prediction model in Column (1) can be improved by incorporating subsidiary-level financial information. In particular, we augment the base model (equation (1)) by incorporating the average bankruptcy probability of the parent's subsidiaries ($\overline{Pr(Y_{s,t+1})}$) estimated using "expanding windows" to avoid a potential look-ahead bias and the risk of ex post over-fitting the data.[20, 21]

Note that the simple inclusion of an additional explanatory variable (in this case $\overline{Pr(Y_{s,t+1})}$) *does not* automatically increase the out-of-sample predictive power of our model. On the contrary, a more complex model could pick up on spurious patterns of the learning sample and, as a result, may exhibit lower out-of-sample predictive power.

We estimate the following hazard model, where the subscripts p and s are used to identify parent- and subsidiary- level variables, respectively.

$$Pr(Y_{p,t+1} = 1) = f\left(NROA_{p,t}, ROA_{p,t}, LTA_{p,t}, ETL_{p,t}, LN(TA_{p,t}), BANKRATE_{p,t}, \overline{Pr(Y_{s,t+1})}\right). \tag{2}$$

Because the significance of the coefficients may be affected by cross-sectional and time-series correlation, we cluster, unless otherwise stated, standard errors by parent country and year.[22] This clustering strategy takes into account the correlation of bankruptcy probabilities over time for a given parent country and across parent countries within a given year.[23] Column (2) reports the results from this analysis. Compared to Column (1), the number of observations decreases as we include

[20] Table OA-1, Panel B, Column (5) in the Online Appendix reports the coefficients from the model that we use to estimate subsidiary default probability ($Pr(Y_{s,t+1})$).

[21] The *expanding window approach* consists of estimating a different set of coefficients for each year using all available information up to that year. For example, the probability that a firm goes bankrupt in 2007 (calculated at the end of 2006) is the product of the financial ratios at the end of 2006 and a set of coefficients estimated by running a regression that includes all bankruptcy years up to 2006). The probability that the firm goes bankrupt in 2008 (calculated at the end of 2007) is based on a set of coefficients estimated by running a regression that includes all sample years up to 2007, and so forth.

[22] Throughout the paper, whenever not feasible to estimate standard errors clustered by parent (subsidiary) country and year, we cluster by parent (subsidiary) and year instead.

[23] In untabulated robustness tests, we re-run all our models that include generated regressors (such as the estimated bankruptcy probability of another firm) with bootstrapped standard errors to mitigate a potential "errors in variables" problem (Carroll et al., 2006).

$\overline{Pr(Y_{s,t+1})}$ due to data availability requirements on subsidiary bankruptcy information. Controlling for their own financial ratios, parents whose subsidiaries exhibit a high average bankruptcy probability are more likely to file for bankruptcy themselves. Specifically, a one standard deviation increase in average subsidiary bankruptcy probability is associated with a 20% relative increase in parent bankruptcy probability.

The findings above document an increase in the predictive power of the parent default model once subsidiary-level financial information is taken into account. However, since the *Base Model Sample* includes all available subsidiaries (i.e., also unconsolidated subsidiaries) we cannot entirely attribute the increase in the predictive power to a potential loss of credit-relevant information generated by the accounting consolidation process. On the contrary, the predictive power improvement may well be due to the exclusion of credit-risk relevant subsidiaries from the consolidation perimeter.

To better identify the extent to which the predictive power improvement is due to a loss of credit-relevant information that occurs as a result of the aggregation process underlying accounting consolidation, we repeat our tests on a sub-sample of parents for which (i) consolidated financial statements are available, and (ii) only consolidated subsidiaries are retained, i.e., where these parents have control rights higher or equal to 50%.[24] We accordingly compute $\overline{Pr(Y_{s,t+1})}$ only for the subset of consolidated subsidiaries and find that it is still significant (Column (5)). This result suggests that consolidated financial statements entail a potential loss of credit-relevant information. Because accounting consolidation may leave behind credit-relevant information, granular within-group information has incremental predictive power. Nonetheless, the lower economic magnitude of the coefficient on $\overline{Pr(Y_{s,t+1})}$ in Column (5) compared to Column (2) is consistent with consolidated financial statements reflecting (at least in part) group-level information.

[24] This approach for identifying consolidated subsidiaries is subject to type 1 and type 2 errors. On the one hand, voting rights are measured with noise, namely if there are dual-class shares. On the other hand, both under U.S. GAAP (FASB Accounting Standards Codification 810) and IFRS (IFRS 10), a reporting entity with no voting control in another entity may have to consolidate that entity if it has the power to direct its most significant economic activities. In that case, the owner of a majority (or all) of the voting rights may be required to deconsolidate the subsidiary.

Because several group parents take the organizational form of financial holding companies (i.e., financial parents), a potential concern with our previous results is that the predictive power improvement that we document may be driven by the specific limitations of financial holding companies' accounting information (i.e., "shell" companies whose balance sheet merely reflects interests in other corporate entities). To mitigate this potential concern, we repeat the analysis by restricting our sample to business groups whose parents are not financial holding companies. We find our results to be qualitatively similar (Columns (7) to (9)). This provides reassurance that our inferences are not driven by the inclusion of financial parents in our sample.

Moreover, to mitigate the possibility that our findings may be driven by within-group bankruptcies, we expand equation (2) to include an indicator ($\bar{Y}_{s,t}$) for whether any of the group's subsidiaries files for bankruptcy in year t (Columns (3), (6) and (9)). This variable is positive and incrementally significant as expected.[25]

Panel B compares the predictive ability of the different models. We use the coefficients from Panel A to obtain forecasts of the probability of bankruptcy. We rank those forecasts within the sample of parents with available information on subsidiary bankruptcy probability. This ensures that a constant sample is used in the comparison of the different models. The predictive ability of the base model is comparable to that reported in Table OA-1, Panel C in the Online Appendix for all parents.[26] We document an increase in the percentage of bankruptcies in the top three deciles of predicted bankruptcy probability and in the AUC as the average subsidiary bankruptcy probability ($\overline{Pr(Y_{s,t+1})}$) and the subsidiary bankruptcy indicator ($\bar{Y}_{s,t}$) are added to the base model. The predictive power

[25] In untabulated analyses available upon request, we test alternative ways to combine subsidiary bankruptcy probabilities. In particular, we compute: (1) a weighted average, where each subsidiary bankruptcy probability is weighted by the magnitude of its assets relative to the group's consolidated assets; (2) the maximum probability of bankruptcy across all subsidiaries within the business group; (3) an indicator variable equal to one if there is a high-risk subsidiary in the group (i.e., if there is a subsidiary whose predicted bankruptcy probability is in the top three deciles of the distribution); and (4) the percentage of consolidated assets that belong to high-risk subsidiaries. We find that each of these alternative measures is incrementally associated with the parent bankruptcy probability, controlling for the parent's financial ratios. Furthermore, we test whether the association we document is incremental to the previously documented diversification effect (e.g., Hann et al., 2013). We compute industry and geographic diversity indices based on the Shannon entropy index and find that, while both indices are negative and significant, consistent with the diversification effect, the average probability of bankruptcy of the group's subsidiaries remains significant when we control for these two indices.

[26] In the Online Appendix, we present the estimation of default prediction models for the full sample of parents and subsidiaries irrespective of whether ownership information required to compute control rights is available.

increases not only in the *Base Model Sample* but also in (i) the sub-sample of business groups with consolidated subsidiaries whose parents have consolidated financial statements available, and (ii) the sub-sample of business groups whose parents are non-financial holding companies.[27]

The AUC reflects the trade-off between the *sensitivity* and *specificity* of a model. Sensitivity measures the extent to which the model correctly identifies bankrupt firms. It reflects the percentage of bankrupt firms that the model accurately classifies as bankrupt (i.e., the "true positive rate," TPR). In contrast, specificity measures the extent to which the model correctly identifies non-bankrupt firms. It reflects the percentage of healthy (i.e., non-bankrupt) firms that the model correctly classifies as healthy (i.e., the "true negative rate," TNR). Sensitivity and specificity are both desirable features of a default prediction model, and considering the two is essential to evaluate a model's predictive power. While in a high sensitivity model, a low estimated bankruptcy probability provides substantial reassurance that a firm will not file for bankruptcy, a high estimated bankruptcy probability has low information content. In contrast, while bankruptcy will likely occur if a low specificity model predicts a high bankruptcy probability, a low estimated bankruptcy probability is not useful for ruling out bankruptcy in this case. We examine how the inclusion of the average subsidiary bankruptcy probability ($\overline{Pr(Y_{s,t+1})}$) improves the sensitivity and specificity of the base model in Figure OA-2 in the Online Appendix. The augmented model exhibits higher sensitivity and specificity than the base model. This indicates that the inclusion of group information helps to correctly classify *both* bankrupt and non-bankrupt firms.

5.2. Placebo Test

To mitigate the concern that our results may be driven by country- and/or industry-level default correlations not attributable to business group dynamics, we construct a counterfactual for our main analysis by conducting a placebo test on a sample of *pseudo-groups*. We match each individual subsidiary to the respective median-sized standalone firm in the same country-industry. In each

[27] The model's predictive power is higher for non-financial than for financial firms. This is as expected because financial firms' accounting ratios have different properties and a highly-regulated industry, such as the financial sector, has special forces at play (e.g., "too big to fail" phenomenon) that could influence the ability of financial statement information to assess probability of failure. In fact, most bankruptcy studies exclude financial firms. However, because financial institutions within a group can play an important role in financial distress (Hoshi et al., 1990; Claessens et al., 2003), we choose to keep them in the sample. Moreover, although lower, the predictive ability of the models for financial firms is still significant.

business group we then replace each real subsidiary with the respective matched standalone (i.e., the *pseudo-subsidiary*) firm to form a pseudo-group. If results of our main tests are driven by unobservable common factors, the placebo test results should closely mirror the results of our main analysis. Placebo test results are reported in Table OA-3 in the Online Appendix. We find that the average estimated pseudo-subsidiary bankruptcy probability ($\overline{Pr(Y_{stdln,t+1})}$) is not significant in any of the specifications, and neither is their observed default rate ($\bar{Y}_{stdln,t}$).

Most importantly, neither the AUC nor the percentage of bankruptcies in the top three deciles of predicted probability increase as standalone information is added to the model. Collectively, results from these placebo tests increase our confidence that the incremental explanatory power of subsidiary-level information for parent bankruptcy is not an artifact of country and industry correlations.

5.3. Incremental Predictive Power of Group Information with Respect to Market Data

Prior research has documented that default prediction models that combine accounting and market information exhibit a higher predictive power compared to pure accounting models (for a survey of this literature, please refer to Beaver et al. (2010) and Ak et al. (2013)). While only a small percentage of our sample firms are publicly listed entities, it may still be the case that, for listed firms, market variables subsume all group information. To investigate whether this is the case, we estimate a parent combined model where we add distance to default to the financial ratios in our base model. Distance to default ($D2D_{p,t}$) is based on a modification of the Merton (1974) model, as outlined in Duan et al. (2012). The main determinants of distance to default are market leverage and asset volatility. Table OA-4, Panel A in the Online Appendix presents the results of this analysis.[28] As expected, $D2D_{p,t}$ exhibits a negative and significant association with the parent bankruptcy probability. Most importantly, the average subsidiary bankruptcy probability ($\overline{Pr(Y_{s,t+1})}$) remains positive and significant. This is also the case when distance to default is replaced by a linear combination of the variables in the Beaver et al. (2005) market model: equity volatility ($VOL_{p,t}$), size ($RSIZE_{p,t}$) and equity returns ($RET_{p,t}$). Most importantly, the inclusion of group information

[28] All unlisted parent companies are excluded from this analysis.

increases the out-of-sample predictive ability of the combined models, as measured both by the AUC and the percentage of bankrupt firm-years in the top three deciles of predicted probability (Panel B).

Our findings suggest that the market variables traditionally used in default prediction do not subsume subsidiary-level information and, therefore, a parent default prediction model that combines accounting and market information can still be improved by taking into account subsidiary default-risk information.

6. The Role of Financial Reporting Transparency

Our evidence thus far suggests that the predictive ability of a default prediction model based on parent consolidated accounting information can be improved by including subsidiary-level information. We have also shown that the improvement in predictive power is likely due to a loss of credit-relevant information resulting from the information aggregation process underlying accounting consolidation. Hence, our results are suggestive that the process of accounting consolidation may leave behind valuable credit-relevant information.

The conclusion above hinges on whether the consolidation process takes properly into account all subsidiary-level information relevant for credit-risk assessment. However, when parent-country financial reporting transparency is weak (e.g., because country-level financial infrastructures are underdeveloped) parent managers may have more leeway to obfuscate credit-relevant intra-group transactions in the process of accounting consolidation. We therefore expect that when parent-country financial reporting transparency is low, the improvement in the model's predictive ability is higher.

In order to test this conjecture, we examine whether the incremental predictive power of the parent default model induced by the inclusion of subsidiary-level information is higher when parent-country reporting transparency is low. We classify a parent as having high (low) financial reporting transparency if a parent country falls in the Leuz (2010) institutional clusters 1 or 2 (3, 4, or 5) (Lang and Maffett, 2011; Maffett et al., 2017). These clusters are based on several securities regulation, investor protection and enforcement characteristics that support financial reporting transparency.

Table 2 presents the results of this analysis. We focus on the sub-sample of the *Base Model Sample* which is limited to parents with consolidated financial statements available and subsidiaries that are included in the consolidation perimeter. We estimate the base and augmented models separately for the sub-samples of parents with *high* and *low* financial reporting transparency (Table 2, Panel A). In line with our expectations, we find that the predictive power of the base and augmented models is higher when parent-country financial reporting transparency is high (Table 2, Panel B). This is consistent with country-level reporting transparency increasing the informativeness of accounting information for default prediction. Most interestingly, we find that the incremental predictive power of the augmented model (with respect to the base model) is higher for parents domiciled in countries with low levels of financial reporting transparency. In fact, while for parents domiciled in low reporting transparency countries both the percentage of defaults in the top three deciles of predicted bankruptcy probability and the AUC increase as subsidiary-level information is added to the base model, this is not the case for parents domiciled in countries with high levels of reporting transparency. The increase in the AUC for parents from low reporting transparency countries as group information is included appears to be mainly driven by an increase in specificity. A model that incorporates subsidiary-level information is less likely to misclassify solvent firms as bankrupt.

It is also interesting to note that the higher increase in predictive power for business groups whose parents are located in low reporting transparency countries is unlikely driven by their subsidiaries' reporting quality. This is because most business groups tend to invest in subsidiaries from the same (or similar) countries, which is consistent with the home bias phenomenon (Shroff et al., 2014; Beuselinck et al., 2018).

To address a potential concern that the results we document in this analysis are driven by a likely negative association between financial reporting quality and importance of internal capital markets in parent countries, we perform additional tests in which we further partition our sample based on the strength of parent-country capital market development and rule of law. We report these results in Table OA-5 in the Online Appendix. We find a significant increase in predictive power for sample partitions where financial reporting transparency is low, irrespective of the strength of parent-country capital market development or rule of law. These findings, therefore, rule out the potential alternative explanation described above and further support our inferences.

7. Can Group Information Help Predict Subsidiary Default?

7.1. Augmenting the Subsidiary Default Prediction Model

Having established that parent default prediction can be improved by incorporating subsidiary default-risk information, we next examine whether a subsidiary default prediction model can be improved by incorporating financial information regarding the parent as well as the other subsidiaries in the same business group. Naturally, we expect the magnitude of the predictive power increase to be greater for the subsidiary model than for the parent model, because parent consolidated financial statements capture, at least in part, subsidiary-level information.

To conduct this analysis, for each subsidiary in the *Base Model Sample*, we retain the parent with highest control rights. We then augment the subsidiary default prediction model by incorporating the parent bankruptcy probability estimated as per equation (1) as follows:[29]

$$Pr\left(Y_{s,t+1} = 1\right) = f(NROA_{s,t}, ROA_{s,t}, LTA_{s,t}, ETL_{s,t}, LN(TA_{s,t}), BANKRATE_{s,t}, Pr(Y_{p,t+1})\ ). \tag{3}$$

We hypothesize that the coefficient on $Pr(Y_{p,t+1})$ in equation (3) is positive and significant. We also estimate augmented versions of equation (3) by including an indicator variable for whether the parent files for bankruptcy in year t ($Y_{p,t}$), the average probability of bankruptcy of other group subsidiaries ($\overline{Pr(Y_{others,t+1})}$), as well as an indicator variable equal to one if any of the group's subsidiaries files for bankruptcy in year t ($\overline{Y_{others,t}}$).

Table 3, Panel A presents the results from the estimation of these augmented models. We cluster, unless otherwise stated, standard errors by subsidiary country and year. We find that the parent bankruptcy probability is positively and significantly associated with the subsidiary bankruptcy probability, controlling for the subsidiary's own characteristics (Column (2)).[30] When the parent bankruptcy probability increases by one standard deviation, the subsidiary bankruptcy probability experiences a relative increase of 26.8%. Controlling for their own financial health and for the parent bankruptcy probability, subsidiaries in groups where the average default risk of the other subsidiaries

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[29] In untabulated analysis, we also examine an unconstrained specification in which we include the parent's financial ratios linearly in the regression. We find that the financial ratios of the parent are significant and exhibit the predicted sign, with the exception of $ETL_{p,t}$.

[30] The number of observations in Columns (2) to (6) is lower than in Column (1) due to the availability of subsidiary bankruptcy information.

is higher, are also more likely to file for bankruptcy in the following year (Column (3)). Observed bankruptcy rates in the group in year t are also significantly associated with future subsidiary bankruptcy (Columns (4) to (6)).

Panel B examines the predictive power of the models using a constant sample. Compared to the base model in Column (1) the augmented model in Column (2), which includes an estimate of the parent bankruptcy probability, exhibits a higher percentage of bankrupt firms and years before bankruptcy in the top three deciles of predicted bankruptcy probability (53.55 vs. 52.68 and 46.69 vs. 45.68). The AUC is also significantly higher, increasing from 68.04 to 72.45. The predictive power of the model increases when we include the average default probability of the other subsidiaries ($\overline{Pr(Y_{others,t+1})}$) (model (3)), and when we include information on actual bankruptcies within the same group in year t ($\overline{Y_{others,t}}$), in addition to the predicted bankruptcy probabilities (models (4) and (5)). A model that also includes an indicator for whether the parent files for bankruptcy in year t ($Y_{p,t}$) (model (6)) performs better than the base model, but underperforms the models that include estimated probabilities of parent and subsidiary bankruptcy.

The increase in AUC is mostly driven by an increase in sensitivity (Figure OA-2 in the Online Appendix). The specificity of the augmented model is similar to that of the base model indicating that, compared to the base model, the augmented model is better able to identify bankrupt firms and does so without at the same time misclassifying healthy firms as bankrupt.

The previous analysis shows that, consistent with our initial hypothesis and the evidence of the parent default prediction analysis presented in Section 5, group affiliation plays a role in bankruptcy and should be taken into account for parent, as well as subsidiary, default prediction. Furthermore, and as expected, group information plays a more significant role in subsidiary (as opposed to parent) default prediction, consistent with parent consolidated financial statements capturing, *albeit* not to a full extent, subsidiary-level credit risk.

7.2. Placebo Test

Similar to the case of parent default prediction, a potential concern with our analysis is that the association between parent and subsidiary bankruptcy reported in Table 3, Panels A and B, might be due to industry and country unobservable common factors. In order to mitigate this concern, we repeat our tests using *pseudo-groups* where, for each business group, we replace the parent with the median-sized country-industry standalone firm (i.e., the *pseudo-parent*). We report the results of this analysis in Table OA-6 in the Online Appendix. We find that the estimated pseudo-parent bankruptcy probability ($Pr(Y_{stdln,t+1})$) is not significant in any of the specifications. Moreover, the AUC and the percentage of bankruptcies in the top three deciles of predicted probability decrease as the pseudo-parent information is added to the model. Results of this placebo test increase our confidence that the incremental explanatory power of parent-level information for subsidiary bankruptcy is not an artifact of country and industry correlations.

7.3. Resource Sharing and Common Business Exposure

Our placebo tests indicate that the incremental predictive power of group information is unlikely to be driven by country and industry unobservable common factors. However, our placebo tests do not directly address the fact that group-affiliated firms may share different types of resources and capabilities (e.g., Chang and Hong, 2000), as well as business exposure, as a result of intra-group transactions. We therefore conduct an additional set of tests to ensure that accounting for the sharing of group resources, such as reputation and other intangibles, as well as for common business exposure, does not affect the tenor of our main findings. We build upon the discussion and analysis in Chang and Hong (2000) to identify factors associated with the likelihood of resource sharing and common business exposure. We then use these factors to identify sub-samples of parent-subsidiary pairs for which resource sharing and common business exposure are less likely to play an important role. Finding that predictive power increases also in the sub-samples where shared resources and common business exposure are less likely would provide reassurance that these factors are not the sole driver of our findings.

To gauge the extent of resource sharing, we partition our sample relying on four different proxies based on: (1) whether a subsidiary is named after its parent. This proxy reflects the likelihood that external stakeholders perceive the group as a unique entity (Beuselinck et al., 2018), and hence that reputation and brand loyalty are shared among group firms (Chang and Hong, 2000); (2) whether a parent has specialized knowledge. Knowledge is a fundamental intangible resource that is often shared across firms within the same business group. To capture knowledge sharing, we follow a similar approach to Christie et al. (2003) to identify parent firms with high and low degrees of knowledge specialization; (3) whether a subsidiary is domestic. Resource sharing is more likely to occur when a subsidiary and its parent are in close geographic proximity (Giroud, 2013; Bahar, 2016); (4) whether a subsidiary operates in the same industry of its parent. Resource sharing is likely more pronounced when a subsidiary and its parent operate in the same industry (Alfaro and Charlton, 2009).

Results documented in Table 4, Panel A show that parent default risk information has incremental predictive power also in sub-samples of parent-subsidiary pairs where resource sharing is less likely to occur (i.e., the subsidiary is not named after its parent; the parent has no specialized knowledge; the subsidiary is not domestic; and the subsidiary is in a different industry than the parent). This provides reassurance that our findings are above and beyond the effect of resource sharing.

With the caveat that sharing of resources and common business exposure are inherently intertwined and therefore our proxies likely capture both constructs, we rely on three additional proxies to capture common business exposure more directly: (1) whether a parent is a major supplier of its subsidiary; (2) whether a parent is a major customer of its subsidiary; and (3) whether a parent is either a major supplier or a major customer of its subsidiary. Following Bena and Ortiz-Molina (2013), we utilize the industry input-output matrix to determine the likelihood that a parent is a major customer or supplier of its subsidiary, based on the observed input-output flows of their respective industries.[31]

Table 4, Panel B presents the results of these tests. We find that parent default probability remains significant and has incremental predictive power also within sub-samples of parent-subsidiary pairs with low common business exposure (i.e., where the parent is not a major supplier and/or customer of

[31] We classify a parent as a *major supplier* of its subsidiary if the purchases made by its subsidiary's industry from the parent's industry represent more than 2% of the purchases made by the subsidiary industry. We classify a parent as a *major customer* of its subsidiary if the purchases made by the parent's industry from its subsidiary's industry represent more than 2% of the total output of the subsidiary industry. A subsidiary is then classified as having high *business exposure* to its parent if the parent is classified as being either a major supplier *or* a major customer of its subsidiary.

its subsidiary). This additional evidence provides reassurance that common business exposure is unlikely to be the main reason behind our findings.

7.4. Incremental Predictive Power of Group Information with Respect to Market Data

While only a small percentage of our sample subsidiaries are publicly listed entities, for listed subsidiaries market variables might subsume group financial information. To assess whether this is the case, and following the parent analysis presented in Section 5.3, we estimate two subsidiary combined models. We present the results of this analysis in Table OA-7 in the Online Appendix. The first model includes distance to default, $D2D_{p,t}$, whereas the second model includes $VOL_{p,t}$, $RSIZE_{p,t}$, and $RET_{p,t}$. $Pr(Y_{p,t+1})$ and $\overline{Pr(Y_{others,t+1})}$ remain significant as we add market information (Panel A). Most importantly, the inclusion of these variables still significantly increases the predictive ability of the combined models notwithstanding the inclusion of market information (Panel B). Taken together, these findings suggest that market information does not subsume group-level information.[32]

8. Gauging the Economic Magnitude of Our Findings

Gauging the economic magnitude of a default prediction model with a simple comparison between AUCs may be misleading given the asymmetric nature of the loss function. This is because the loss from misclassifying a distressed firm is greater than the loss of misclassifying a healthy firm. As a result, what might appear a small improvement in predictive ability could in fact represent a substantial increase in the profitability of creditors (Stein and Jordao, 2003). Bankruptcy prediction plays an important role in private (i.e., bank) lending, and, in particular, in setting lending cut-offs and interest rates. One way to assess the economic significance of an increase in AUC is thus to estimate the increase in the profitability of the loan portfolio of a medium-sized bank as a result of the use of the bankruptcy prediction model that includes group information.

Using Moody's KMV global default database, Stein and Jordao (2003) document that the use of a default prediction model with higher predictive ability on average leads to a substantial economic

[32] Note that market-based variables reflect financial statement information. Therefore, the fact that some of the accounting-based variables become insignificant as the market information is added to the model does not imply that accounting-based variables have no predictive power.

benefit for banks. In particular, they document that, by switching to a model with an *accuracy ratio* that is 0.05 higher, banks can increase the profitability of their loan portfolio by 5 basis points.[33]

Table 1, Panel B documents an increase of 0.0259 (0.7464 minus 0.7205) in the AUC as subsidiary-level information is added to the parent bankruptcy prediction model. Based on Stein and Jordao (2003) this increase, which corresponds to a 0.0518 increase in the accuracy ratio, should lead to an increase of approximately 5 basis points in the profitability of a bank's loan portfolio. Similarly, the increase of 0.0441 (0.7245 minus 0.6804) in the AUC as parent information is added to the subsidiary model (Table 3, Panel B) corresponds to an increase of approximately 9 basis points in the profitability of a bank's loan portfolio. Based on the above, we view the inclusion of group financial information in default prediction models as having a sizable impact on predictive power.

The value of the potential support that a subsidiary is expected to receive from (provide to) its parent constitutes an off-balance sheet asset (liability) for that subsidiary. We capture the extent of subsidiary off-balance sheet assets and liabilities related to potential group support by examining its effect on subsidiary leverage. Our tests build on the idea that the "true" leverage of a subsidiary may be different from its "reported" leverage precisely because of these off-balance sheet assets and liabilities. By backing out the expected increase/decrease in subsidiary leverage from the change in subsidiary default probability induced by a change in parent default risk, we are effectively able to indirectly gauge the magnitude of subsidiary off-balance sheet assets and liabilities associated with potential parent support.[34] Empirically, we find that a 1% increase (decrease) in parent default probability produces the same effect on subsidiary default probability as a 1.32% increase (decrease) in subsidiary leverage (Table 5, Panel A). The effect of potential parent support on subsidiary leverage is stronger for *integrated* subsidiaries: (i) majority owned subsidiaries (1.42% increase in leverage); and (ii) subsidiaries with interlocked boards (1.80% increase in leverage). These findings are consistent with more integrated subsidiaries being more likely to receive and provide group support.

[33] AUC=1/2 × (Accuracy Ratio + 1).

[34] We "reverse engineer" the effect of potential parent support on subsidiary leverage in two steps. First, we compute the change in subsidiary default probability induced by a 1% change in the default probability of the parent. Second, we estimate the percentage change in subsidiary leverage that would produce the exact same effect on subsidiary default probability as a 1% change in the default probability of the parent.

Next, we examine whether the "true" leverage of a subsidiary is lower (higher) than the reported leverage when a subsidiary is expected to provide (receive) group support. We expect high (low) credit-risk subsidiaries of low (high) credit-risk parents to be more likely to receive (provide) support. Accordingly, in Table 5, Panels B and C we split our sample of parent-subsidiary pairs into four sub-samples based on parent and subsidiary credit risk. We are particularly interested in the bottom-left quadrant (the *prop-down sub-sample*) and the upper-right quadrant (the *prop-up sub-sample*).We further expect parents' ability (incentives) to prop down (prop up) to be higher when subsidiaries are more integrated within the group. In order to test whether these subsidiaries have higher off-balance sheet assets (liabilities) related to group support, we add to our base model, an indicator variable capturing subsidiary integration. Using the same empirical strategy as above we find that, compared to those that are not, integrated subsidiaries in the *prop-down sub-sample* exhibit a net off-balance sheet asset, corresponding to a reduction in leverage that ranges between 82.57% (for majority owned-subsidiaries) and 87.77% (for subsidiaries with interlocked boards). Conversely, integrated subsidiaries in the *prop-up sub-sample* exhibit, compared to those that are not, a net off-balance sheet liability, corresponding to an increase in leverage that ranges between 8.95% (for subsidiaries with interlocked boards) and 48.13% (for majority owned-subsidiaries).

9. Cross-Sectional Variation in CDS Spreads

Our findings so far indicate that group information has economically-significant predictive power for parent and subsidiary default prediction. The increase in predictive power that we document is incremental to a battery of accounting and market variables. We present a graph depicting how observed subsidiary bankruptcy rates vary with parent and subsidiary estimated bankruptcy probabilities in Figure OA-3 in the Online Appendix. The average observed subsidiary bankruptcy rate is increasing in the estimated subsidiary bankruptcy probability (consistent with the default model having explanatory power). More interestingly, the average observed subsidiary bankruptcy rate is also increasing in the estimated parent bankruptcy probability which is supportive of a group-affiliation effect.

While very costly, bankruptcies are rare events. Hence, they represent “extreme observations” in the distribution of default risk. To provide further evidence on the economic significance of our findings, and to shed light on whether group affiliation matters for credit-risk assessment also along the continuum of the default-risk distribution, we examine whether the usefulness of group information extends to the pricing of credit-risk-sensitive securities. Specifically, we test whether group information explains cross-sectional variation in CDS spreads ($LN(CDS5Y_{i,t}))$. We choose to focus on CDS contracts because they are the most liquid credit-risk-sensitive securities whose availability extends to several countries in our sample. CDS contracts provide insurance against default, and thus the main determinant of CDS spreads is the bankruptcy probability of the reference obligor.[35] Our approach is similar to Bharath and Shumway (2008) who assess whether accounting- and market-based information explains default and credit spreads over and above a Merton-based distance to default. We describe our *CDS Sample* and present the results of this analysis in the Online Appendix.

Consistent with our default prediction analysis, we find that combining subsidiary information with parent-level accounting and market information improves the explanatory power of our parent credit spread models (Table OA-8, Panel A in the Online Appendix). The average subsidiary bankruptcy probability is positive and significant. The adjusted R^2 of the parent model increases from 20% to 30%, 39% to 48%, and 49% to 55% as subsidiary-level information is added to the accounting, distance to default, and market models, respectively. Subsidiary-level information accounts for 17% to 34% of the models’ explanatory power, as measured by its Shapley R^2 value.[36] This suggests that group information is not only incremental to parent-level information for default prediction, but it is also (at least in part) taken into account by credit market participants in pricing CDS contracts.[37]

Similarly, we find that parent and other subsidiary information improves the explanatory information of subsidiary CDS models (Table OA-8, Panel B in the Online Appendix). When added

[35] In fact, assuming market efficiency and risk neutrality, CDS spreads should be equal to the present value of the expected loss (the product of the default probability and loss given default).
[36] The Shapley (1953) value is typically used to decompose a regression R^2 into the contributions of individual regressors (Chevan and Sutherland, 1991; Johnson and LeBreton, 2004).
[37] The structure of our tests does not speak to differences across equity and debt market information pricing.

by itself, the parent bankruptcy probability is always positive and significant. When we add the average bankruptcy probability of the other subsidiaries, the parent bankruptcy probability becomes insignificant. As we include these two variables, the explanatory power of the accounting, distance to default, and market models increases from 15% to 32%, 30% to 45%, and 46% to 59%, respectively. The total contribution of these two variables to the models' R^2 ranges from 28% to 52%.

The fact that the results from the CDS analysis (based on 3,377 parent-year observations and 1,198 subsidiary-year observations) and the default prediction analysis (based on 310,181 parent-year observations and 823,764 subsidiary-year observations) are consistent, notwithstanding differences in sample sizes and test designs, provides further reassurance on the relevance of group information in predicting and explaining default risk, as well as on the economic significance of our findings.

10. Binary Recursive Partitioning Analysis

Our discrete hazard model analysis demonstrates the relevance of group information for default prediction. However, estimated odds ratios from hazard models do not speak to the relative importance among predictors. Moreover, our hazard model analysis may not capture potential non-linearities and interactions among default predictors. To alleviate this concern and to gauge the *relative importance* of group information for parent and subsidiary default prediction, we use the CART methodology developed by Breiman et al. (1984) and applied to the prediction of financial distress by Frydman et al. (1985).[38]

While CART estimation can accommodate potential non-linearities and better handle outliers, it might, at the same time, result in very complex decision trees which over-fit the data and may thus be highly unstable. Moreover, as previously mentioned, the AUC may be a less reliable statistic for CART than for hazard models, because it is based on a discrete number of nodes. Despite these potential limitations, CART estimation allows us to rank different bankruptcy predictors and, specifically, to infer the relative importance of group variables *vis-à-vis* traditional bankruptcy predictors used in prior studies. Most importantly, we believe the complementarity of the CART and

[38] We use the *Salford Predictive Modeler Software* developed by *Salford Systems* to perform the CART analysis.

hazard model approaches reassures us that our findings are not driven by the specificities of a particular estimation approach.

To understand the relative importance of group information for parent default prediction, we first apply this technique to all the variables in the base model, i.e., $NROAI_{p,t}$, $ROA_{p,t}$, $LTA_{p,t}$, $ETL_{p,t}$, $LN(TA_{p,t})$, and $BANKRATE_{p,t}$. We then augment this set of variables with the average bankruptcy probability of the group's subsidiaries ($\overline{Pr(Y_{s,t+1})}$) and the subsidiary bankruptcy indicator ($\bar{Y}_{s,t}$). Results of this estimation are reported in Table 6, Panel A. We find that the (out-of-sample) AUC improves, the relative error (i.e., the sum of type I and type II errors) decreases and the Hosmer-Lemeshow test-statistic[39] increases when group information is added to the base model.[40]

In order to evaluate the economic significance of subsidiary-level information for parent default prediction, we compute *variable importance scores* (Table 6, Panel B). These scores measure the improvement that can be attributed to a given variable at all tree nodes (both as a primary splitter and a surrogate or merely as a primary splitter).[41] The variable importance scores are reported on a scale of 1 to 100. Leverage is the variable with higher importance (100), followed by the average subsidiary bankruptcy probability (87.38). The importance of the average subsidiary bankruptcy probability is reduced to 11.40 when we focus solely on its role as primary splitter.

We present an example of a classification tree with potential splitting variables $NROAI_{p,t}$, $ROA_{p,t}$, $LTA_{p,t}$, $ETL_{p,t}$, $LN(TA_{p,t})$, $BANKRATE_{p,t}$, $\overline{Pr(Y_{s,t+1})}$, and $\bar{Y}_{s,t}$ in Figure OA-4 in the Online Appendix. This tree has been pruned for presentation purposes. The average subsidiary bankruptcy probability is one of the primary splitters.

[39] The Hosmer-Lemeshow test assesses the extent to which the observed default rates match expected default rates within the deciles of fitted bankruptcy probability. The Hosmer-Lemeshow test statistic is calculated as $\sum_{g=1}^{G} \frac{(O_g - E_g)^2}{N_g \pi_g (1-\pi_g)}$, where O_g, E_g, N_g and π_g are observed events, expected events, observations and predicted risk for each group g (with G equal to the number of groups).

[40] As previously mentioned, the angularity of the ROC curves, which are based on a small number of final nodes, renders the interpretation of the predictive power improvement less straightforward. In particular, because AUCs are noisier measures of predictive ability for CART than for hazard models, it becomes harder to document increases in AUC in this case.

[41] A *primary splitter* is a variable that is used to recursively split the sample data in the tree. A *surrogate* is simply a substitute for a primary splitter at a certain node. The surrogate divides the data in a similar way to the primary splitter and may thus be used to replace the primary splitter when the primary splitter is missing.

We further examine the role of group information in subsidiary default prediction using the CART methodology. Table 6, Panel C presents the results of this analysis. We find that both the (out-of-sample) AUC and the Hosmer-Lemeshow test statistic increase as information on the parent and other subsidiaries is added to the model. Furthermore, the parent bankruptcy probability ($Pr(Y_{p,t+1})$) and the average bankruptcy probability of other subsidiaries in the same group ($\overline{Pr(Y_{others,t+1})}$) have total variable importance scores of 62.71 and 84.49 (and 13.79 and 23.44 variable importance scores as primary splitters).

We present the classification tree with potential splitting variables including $NROAI_{s,t}$, $ROA_{s,t}$, $LTA_{s,t}$, $ETL_{s,t}$, $LN(TA_{s,t})$, $BANKRATE_{s,t}$,$Pr(Y_{p,t+1})$, $\overline{Pr(Y_{others,t+1})}$, $\overline{Y_{others,t}}$, and $Y_{p,t}$ in Figure OA-5 in the Online Appendix. This tree has been pruned for presentation purposes. Both the average estimated bankruptcy probability of other subsidiaries and the estimated parent bankruptcy probability are primary splitters.

Overall the results of the CART analysis are consistent with those of the hazard model tests in that group-level information has predictive power for both parent and subsidiary default. The fact that these two complementary approaches, each with relative advantages and disadvantages, yield qualitatively similar results provides support for the role (and economic significance) of group information in parent and subsidiary default prediction.

11. Conclusion

We study whether, and if so to what extent, group affiliation matters for default prediction. Prior default prediction studies (cf. Beaver et al., 2010) have typically focused on the *firm* (and its consolidated financial statements) implicitly overlooking the role of group affiliation.

We document that subsidiary default risk improves parent default prediction over and above group-level consolidated information (even when controlling for market information). This finding points at a potential loss of credit-relevant information inherent to the accounting consolidation process. Moreover, we show that the extent to which within-group information improves the predictive power of parent default prediction models is decreasing in the quality of parent-country financial reporting transparency. We also find that parent and other group-firms default risk exhibit predictive power for subsidiary default. Lastly, to gauge the relevance and the economic magnitude of within-group information, we test whether subsidiary (parent and other group firms) default risk explains cross-sectional variation in parent (subsidiary) credit spreads and find support for this conjecture. Taken together, our results are in line with the idea that default prediction improves when group information is taken into account.

Our study contributes to the default prediction literature by showing how group information improves the predictive power of traditional bankruptcy prediction models and yields important insights on the informativeness of consolidated financial statements. By showing that cross-country differences in financial infrastructures (e.g., investor protection, reporting enforcement, etc.) affect the quality of consolidated financial statements, our findings are of interest to accounting regulators, enforcement authorities and auditors. Moreover, our evidence is also relevant to credit suppliers and credit rating agencies whose current credit rating assessments incorporate group information on a highly-discretionary case-by-case basis.

While our analysis focuses on the role of business groups' *corporate* ultimate owners, future studies could examine the importance of the ultimate *natural person* "behind" a business group, whose personal wealth and default risk are likely to influence the possibility of propping distressed group firms or, conversely, of tunneling resources from the firm to meet personal debt obligations.[42]

[42] Such studies could be conducted, for example, using Danish (e.g., Nanda, 2011) or Swedish (e.g., Becker, 2006; Lundberg and Waldenstrom, 2017) personal wealth data or, instead, focusing on Finnish personal-default data (e.g., based on the *Suomen Asiaskastieto Oy* personal credit database).

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Appendix: Variable Description

Variable (*)	*Definition*
$Y_{i,t+1}$	Indicator variable set equal to one if firm i files for bankruptcy in year $t+1$, and zero otherwise (Source: Orbis).
$NROAI_{i,t}$	Indicator variable set equal to one if firm i's return on assets ($ROA_{i,t}$) in year t is negative, and zero otherwise (Source: Orbis).
$ROA_{i,t}$	Return on assets for firm i in year t, defined as net income divided by total assets at the beginning of the year (Source: Orbis).
$LTA_{i,t}$	Book leverage ratio for firm i in year t, defined as total liabilities divided by total assets (Source: Orbis).
$ETL_{i,t}$	Ratio of earnings before interest and taxes to total liabilities for firm i in year t (Source: Orbis).
$LN(TA_{i,t})$	Natural logarithm of total assets for firm i in year t (Source: Orbis).
$BANKRATE_{i,t}$	Proportion of firms filing for bankruptcy in firm i's country and one-digit SIC industry in year t (ranging from zero to 100) (Source: Orbis).
$FGDPg_{i,t}$	Forecasted GDP growth for firm i's country in year $t+1$ (Source: IMF).
$FINF_{i,t}$	Forecasted inflation for firm i's country in year $t+1$ (Source: IMF).
$\overline{Pr(Y_{s,t+1})}$	The average estimated bankruptcy probability in year $t+1$ of all subsidiaries s belonging to the same business group. The bankruptcy probability for each subsidiary s is based on the following discrete hazard model: $Pr(Y_{s,t+1}=1) = f(NROAI_{s,t}, ROA_{s,t}, LTA_{s,t}, ETL_{s,t}, LN(TA_{s,t}), BANKRATE_{s,t})$, estimated for the subsidiary-year observations within the *Estimation Sample* using an expanding window approach (Source: Orbis).
$\bar{Y}_{s,t}$	Indicator variable set equal to one if at least one of the group subsidiaries s files for bankruptcy in year t, and zero otherwise (Source: Orbis).
$\overline{Pr(Y_{stdln,t+1})}$	The average estimated bankruptcy probability of pseudo-subsidiaries $stdln$ (i.e., standalone firms) in year $t+1$. Each subsidiary s is matched to the median-sized standalone firm $stdln$ in the same country-industry. We estimate bankruptcy probabilities for each matched standalone firm based on the following discrete hazard model: $Pr(Y_{stdln,t+1}=1) = f(NROAI_{stdln,t}, ROA_{stdln,t}, LTA_{stdln,t}, ETL_{stdln,t}, LN(TA_{stdln,t}), BANKRATE_{stdln,t})$, estimated for the standalone-year observations within the *Estimation Sample* using an expanding window approach (Source: Orbis).
$\bar{Y}_{stdln,t}$	Indicator variable set equal to one if at least one of the matched standalone firms $stdln$ files for bankruptcy in year t, and zero otherwise (Source: Orbis).
$D2D_{i,t}$	Distance to default for firm i in year t, calculated following the modification of the Merton (1974) model outlined in Duan et al. (2012) (Source: NUS RMI data).
$VOL_{i,t}$	Volatility of daily equity returns for firm i in year t measured over the previous 252 days (Source: Datastream).
$RSIZE_{i,t}$	Relative size of firm i in year t, defined as the natural logarithm of the ratio of firm i's market capitalization to the total market capitalization of all listed firms in the same country and year (Source: Datastream).
$RET_{i,t}$	Cumulative abnormal returns over the previous 12 months for firm i in year t, where monthly abnormal return is defined as the difference between firm i's return and the value-weighted market return (Source: Datastream).

Appendix (continued)

Variable (*)	*Definition*
$Pr(Y_{p,t+1})$	Parent p estimated bankruptcy probability in year $t+1$. $Pr(Y_{p,t+1})$ is based on the following discrete hazard model: $Pr(Y_{p,t+1}=1)=f(NROAI_{p,t}, ROA_{p,t}, LTA_{p,t}, ETL_{p,t}, LN(TA_{p,t}), BANKRATE_{p,t})$, estimated for the parent-year observations within the *Estimation Sample* using an expanding window approach (Source: Orbis).
$\overline{Pr(Y_{others,t+1})}$	The average estimated bankruptcy probability in year $t+1$ of all other subsidiaries $others$ belonging to the same business group of the respective subsidiary. The bankruptcy probability for each subsidiary s is based on the following discrete hazard model: $Pr(Y_{s,t+1}=1)=f(NROAI_{s,t}, ROA_{s,t}, LTA_{s,t}, ETL_{s,t}, LN(TA_{s,t}), BANKRATE_{s,t})$, estimated for the subsidiary-year observations within the *Estimation Sample* using an expanding window approach (Source: Orbis).
$\overline{Y_{others,t}}$	Indicator variable set equal to one if at least one of all other subsidiaries $others$ belonging to the same business group of the respective subsidiary files for bankruptcy in year t, and zero otherwise (Source: Orbis).
$Y_{p,t}$	Indicator variable equal to one if parent p files for bankruptcy in year t, and zero otherwise (Source: Orbis).
$Pr(Y_{stdln,t+1})$	Pseudo-parent (i.e., standalone firm) $stdln$'s estimated bankruptcy probability in year $t+1$. Each parent p is matched to the median-sized standalone firm $stdln$ in the parent's country-industry. We estimate bankruptcy probabilities for each matched standalone firm based on the following discrete hazard model: $Pr(Y_{stdln,t+1}=1)=$ $f(NROAI_{stdln,t}, ROA_{stdln,t}, LTA_{stdln,t}, ETL_{stdln,t}, LN(TA_{stdln,t}), BANKRATE_{stdln,t})$, estimated for the standalone-year observations within the *Estimation Sample* using an expanding window approach (Source: Orbis).
$LN(CDS5Y_{i,t})$	Natural logarithm of firm i's spread at the end of year t for a five-year credit default swap (CDS) contract on senior unsecured debt. For U.S. firms in the *CDS Sample*, we select U.S. Dollar denominated contracts with a no-restructuring clause for months following April 2009, and contracts with a modified restructuring clause for months before April 2009. For non-U.S. firms in the *CDS Sample*, we select, for each month, the CDS contract with highest depth (Source: Markit).

(*) Variables are presented in the order in which they appear in the empirical analyses. Variables generically subscripted with an i refer to either a parent (p), a subsidiary (s) or a standalone ($stdln$) firm.

Table 1: Augmented Parent Model

Panel A: Parent Hazard Model

		Dependent variable: $Y_{p,t+1}$								
		All Groups			Consolidated			Non-Financials		
Independent variables:		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept		-5.379***	-6.023***	-5.965***	-5.725***	-6.185***	-6.056***	-5.584***	-6.248***	-6.222***
		(-19.15)	(-20.00)	(-15.93)	(-5.98)	(-6.29)	(-6.30)	(-13.08)	(-12.48)	(-12.30)
$NROAI_{p,t}$	(+)	0.315***	0.246**	0.255**	0.258*	0.289**	0.309**	0.353**	0.255*	0.255*
		(2.65)	(2.30)	(2.42)	(1.65)	(2.45)	(2.00)	(2.42)	(1.95)	(1.94)
$ROA_{p,t}$	(–)	-2.547***	-1.972***	-1.984***	-3.754**	-2.823**	-3.102***	-2.859***	-2.555***	-2.546***
		(-7.67)	(-8.23)	(-7.14)	(-2.54)	(-2.36)	(-2.83)	(-8.84)	(-11.26)	(-11.31)
$LTA_{p,t}$	(+)	1.566***	1.394***	1.446***	2.133***	2.023***	2.095***	1.782***	1.676***	1.673***
		(14.28)	(7.32)	(6.58)	(3.80)	(3.70)	(3.78)	(8.49)	(6.02)	(5.99)
$ETL_{p,t}$	(–)	-0.139	-0.111	-0.144	0.513*	0.502	0.577	-0.109	-0.118	-0.119
		(-0.95)	(-0.82)	(-0.99)	(1.91)	(1.54)	(1.24)	(-0.47)	(-0.55)	(-0.56)
$LN(TA_{p,t})$	(–)	-0.057*	-0.027	-0.039	-0.093	-0.071	-0.088	-0.049	-0.018	-0.022
		(-1.84)	(-0.90)	(-1.22)	(-1.31)	(-0.95)	(-1.18)	(-1.19)	(-0.43)	(-0.50)
$BANKRATE_{p,t}$	(+)	0.094	0.167**	0.164**	0.055	0.158***	0.150***	0.073	0.146**	0.143**
		(0.72)	(2.22)	(2.15)	(1.57)	(3.27)	(3.44)	(0.87)	(2.09)	(2.09)
$\overline{Pr(Y_{s,t+1})}$	(+)		85.473***	86.826***		58.677***	55.664***		80.086***	79.839***
			(5.20)	(4.90)		(9.40)	(9.02)		(4.85)	(4.86)
$\bar{Y}_{s,t}$	(+)			0.699***			0.808***			0.477***
				(7.56)			(4.62)			(5.93)
Marginal Effects:										
$\overline{Pr(Y_{s,t+1})}$			0.206	0.201		0.130	0.118		0.186	0.185
$\bar{Y}_{s,t}$				0.075			0.103			0.042
Obs.		350,452	310,181	276,595	90,427	73,384	66,734	206,074	163,247	163,247

Table 1 (continued)

Panel B: Predictive Ability

		All Groups			Consolidated			Non-Financials		
Model	Decile	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	0	36.03	23.46	9.19	39.14	29.98	9.35	37.65	24.66	9.05
	1	16.34	19.45	9.54	13.94	19.86	9.74	17.99	20.38	9.45
Model (1)	2	10.83	14.20	9.82	10.46	12.85	9.93	11.73	15.53	9.73
	Total	63.20	57.11	28.55	63.54	62.69	29.03	67.38	60.57	28.00
	AUC	0.7205			0.7181			0.7439		
	0	36.11	23.80	9.17	40.21	31.41	9.31	38.62	24.81	9.04
	1	17.79	19.80	9.52	13.94	19.40	9.75	17.86	21.07	9.42
Model (2)	2	9.98	14.59	9.81	10.19	13.69	9.91	10.96	15.52	9.74
	Total	63.89	58.19	28.50	64.34	64.50	28.98	67.44	61.40	28.19
	AUC	0.7464			0.7301			0.7636		
	p-value (vs. Model (1))	0.0000			0.0013			0.0000		
	0	35.87	23.49	9.19	39.14	30.50	9.34	38.94	24.60	9.04
	1	18.08	19.28	9.53	13.40	19.21	9.76	17.99	21.46	9.40
Model (3)	2	9.94	14.82	9.80	11.26	13.69	9.91	10.51	15.45	9.75
	Total	63.89	57.59	28.52	63.81	63.40	29.01	67.44	61.50	28.19
	AUC	0.7470			0.7289			0.7641		
	p-value (vs. Model (2))	0.2119			0.1847			0.3087		

This table presents the results of the parent default prediction analysis. Panel A reports coefficients and (in parentheses) z-statistics from the estimation of a discrete hazard model for the *Base Model Sample* of parent firm-years. The dependent variable is equal to one if the parent files for bankruptcy in year $t+1$, and zero otherwise. The model specification presented in Column (1) includes parent-level financial ratios only: $Pr(Y_{p,t+1}=1) = f(NROAI_{p,t}, ROA_{p,t}, LTA_{p,t}, ETL_{p,t}, LN(TA_{p,t}), BANKRATE_{p,t})$, Column (2) adds the average estimated bankruptcy probability of all group subsidiaries ($\overline{Pr(Y_{s,t+1})}$) and Column (3) adds an indicator variable ($\bar{Y}_{s,t}$) set equal to one if any of the group subsidiaries files for bankruptcy in year t, and zero otherwise. The number of observations decreases in Columns (2) and (3) due to data availability requirements on subsidiary bankruptcy information. In Columns (4) to (6) the sample is limited to parents for which consolidated financial statements are available and to subsidiaries that are consolidated, i.e., in which the parent's control rights are equal to, or higher than, 50%. In Columns (7) to (9) parents that are financial institutions are excluded. Marginal effects for group-level variables are reported as the change in estimated bankruptcy probability as each of the group-level variables increases by one standard deviation, scaled by the average estimated bankruptcy probability. Heteroskedasticity-robust standard errors are clustered at the parent-country and year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Panel B presents a comparison between the predictive power of the augmented models and that of the base model reported in Column (1) using a constant sample. Columns (1), (2) and (3) present the percentage of bankrupt years, years before bankruptcy and non-bankrupt firm-years falling in each of the top three deciles. The Area Under the Receiver Operating Characteristic Curve (AUC) is also reported for each subgroup. All variables are defined in the Appendix. The subscripts p and s are used to identify parent- and subsidiary-level variables, respectively.

Table 2: Augmented Parent Model by Financial Reporting Transparency Country Cluster

Panel A: Parent Hazard Model

		Dependent variable: $Y_{p,t+1}$			
		Financial Reporting Transparency			
		High		*Low*	
Independent variables:		(1)	(2)	(3)	(4)
Intercept		-8.321***	-9.005***	-5.595***	-6.311***
		(-8.66)	(-8.57)	(-6.27)	(-6.75)
$NROAI_{p,t}$	(+)	0.309	0.402	0.228	0.138
		(0.65)	(1.17)	(1.02)	(0.55)
$ROA_{p,t}$	(–)	-4.604**	-3.406*	-4.635***	-3.839**
		(-2.36)	(-1.86)	(-2.82)	(-2.50)
$LTA_{p,t}$	(+)	3.270***	3.228***	1.727***	1.789***
		(3.66)	(3.49)	(2.61)	(3.03)
$ETL_{p,t}$	(–)	0.196	0.086	0.256	0.289
		(1.47)	(0.40)	(0.91)	(0.91)
$LN(TA_{p,t})$	(–)	-0.000	0.040	-0.061	-0.056
		(-0.00)	(0.65)	(-0.88)	(-0.74)
$BANKRATE_{p,t}$	(+)	0.116**	0.196***	0.183*	0.556**
		(2.33)	(3.92)	(1.79)	(2.07)
$\overline{Pr(Y_{s,t+1})}$	(+)		46.376***		91.327***
			(5.55)		(8.82)
Marginal Effects:					
$\overline{Pr(Y_{s,t+1})}$			0.076		0.180
Obs.		48,907	38,526	37,590	31,960

Panel B: Predictive Ability

		Financial Reporting Transparency					
		High			*Low*		
Model	Decile	(1)	(2)	(3)	(1)	(2)	(3)
	0	51.75	39.44	9.31	37.04	22.68	9.40
	1	16.67	22.10	9.75	10.70	16.48	9.81
Model (1)	2	9.65	11.33	9.98	9.47	13.16	9.92
	Total	78.07	72.87	29.04	57.20	52.32	29.13
	AUC	0.8094			0.7196		
	0	50.88	40.56	9.29	38.27	24.67	9.33
	1	21.93	21.54	9.75	11.11	15.38	9.84
Model (2)	2	5.26	11.19	10.00	10.70	13.39	9.90
	Total	78.07	73.29	29.03	60.08	53.43	29.07
	AUC	0.8139			0.7316		
p-value (vs. Model (1))		0.2540			0.0228		

This table presents the results of the parent default prediction analysis for high and low financial reporting transparency country clusters. In this analysis, the *Base Model Sample* is limited to parents for which consolidated financial statements are available and to subsidiaries that are consolidated, i.e., in which the parent's control rights are equal to, or higher than, 50%. We classify a country as having high (low) financial reporting transparency if it falls in the Leuz (2010) institutional clusters 1 or 2 (3, 4, or 5). Panel A reports coefficients and (in parentheses) z-statistics from the estimation of the base and augmented discrete hazard models for the sub-samples of parent firms from high and low financial reporting transparency country clusters. The dependent variable is equal to one if the parent files for bankruptcy in year $t+1$, and zero otherwise. Marginal effects for group-level variables are reported as the change in estimated bankruptcy probability as each of the group-level variables increases by one standard deviation, scaled by the average estimated bankruptcy probability. Heteroskedasticity-robust standard errors are clustered at the parent-country and year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Panel B presents a comparison between the predictive power of the base and augmented models within each country cluster group. Columns (1), (2) and (3) present the percentage of bankrupt years, years before bankruptcy and non-bankrupt firm-years falling in each of the top three deciles. The Area Under the Receiver Operating Characteristic Curve (AUC) is also reported for each sample partition, as is the p-value for the increase in the AUC in the augmented model. All variables are defined in the Appendix. The subscripts p and s are used to identify parent- and subsidiary-level variables, respectively.

Table 3: Augmented Subsidiary Model

Panel A: Subsidiary Hazard Model

		Dependent variable: $Y_{s,t+1}$					
Independent variables:		(1)	(2)	(3)	(4)	(5)	(6)
Intercept		-3.995***	-4.574***	-4.975***	-4.411***	-4.948***	-3.952***
		(-7.10)	(-7.49)	(-8.85)	(-7.36)	(-8.80)	(-7.19)
$NROAI_{s,t}$	(+)	0.355***	0.284***	0.244***	0.275***	0.248***	0.329***
		(8.60)	(8.35)	(4.06)	(5.08)	(4.08)	(6.10)
$ROA_{s,t}$	(–)	-0.816***	-0.800***	-0.734***	-0.803***	-0.737***	-0.813***
		(-6.62)	(-6.00)	(-4.21)	(-5.16)	(-4.64)	(-6.36)
$LTA_{s,t}$	(+)	0.440***	0.280***	0.243**	0.292***	0.251***	0.446***
		(5.11)	(3.17)	(2.52)	(3.52)	(2.74)	(5.42)
$ETL_{s,t}$	(–)	-0.215***	-0.164***	-0.148***	-0.154***	-0.139**	-0.215***
		(-3.97)	(-3.48)	(-2.73)	(-2.79)	(-2.51)	(-3.65)
$LN(TA_{s,t})$	(–)	-0.125***	-0.091**	-0.087**	-0.109***	-0.091***	-0.128***
		(-3.61)	(-2.48)	(-2.51)	(-3.09)	(-2.68)	(-3.85)
$BANKRATE_{s,t}$	(+)	0.092	0.108*	0.107*	0.112*	0.103*	0.098
		(1.41)	(1.74)	(1.83)	(1.79)	(1.73)	(1.37)
$Pr(Y_{p,t+1})$	(+)		133.018***	87.766***	136.977***	84.110***	
			(5.58)	(6.41)	(5.21)	(5.47)	
$\overline{Pr(Y_{others,t+1})}$	(+)			109.048***		111.431***	
				(5.72)		(5.75)	
$\overline{Y_{others,t}}$	(+)				1.214***	2.017***	1.542***
					(7.77)	(5.73)	(14.99)
$Y_{p,t}$	(+)						1.190***
							(6.53)
Marginal Effects:							
$Pr(Y_{p,t+1})$			0.268	0.158	0.255	0.149	
$\overline{Pr(Y_{others,t+1})}$				0.219		0.222	
$\overline{Y_{others,t}}$					0.039	0.043	0.058
$Y_{p,t}$							0.108
Obs.		928,162	823,764	640,200	607,321	604,704	660,058

Table 3 (continued)

Panel B: Predictive Ability

Model	Decile	(1)	(2)	(3)
Model (1)	0	25.13	17.87	9.38
	1	15.86	14.68	9.67
	2	11.69	13.13	9.81
	Total	52.68	45.68	28.87
	AUC	0.6804		
Model (2)	0	24.37	18.51	9.36
	1	16.72	15.08	9.64
	2	12.46	13.11	9.80
	Total	53.55	46.69	28.80
	AUC	0.7245		
	p-value (vs. Model (1))	0.0000		
Model (3)	0	25.12	18.30	9.36
	1	16.07	15.05	9.65
	2	12.78	12.90	9.81
	Total	53.97	46.25	28.82
	AUC	0.7350		
	p-value (vs. Model (1))	0.0000		
Model (4)	0	24.76	18.44	9.36
	1	16.51	15.01	9.65
	2	12.28	13.15	9.80
	Total	53.55	46.60	28.81
	AUC	0.7264		
	p-value (vs. Model (1))	0.0000		
Model (5)	0	25.38	18.35	9.35
	1	15.93	14.91	9.66
	2	12.75	13.01	9.80
	Total	54.07	46.27	28.82
	AUC	0.7367		
	p-value (vs. Model (1))	0.0000		
Model (6)	0	25.30	17.90	9.38
	1	15.93	14.76	9.67
	2	11.77	12.97	9.82
	Total	53.00	45.62	28.87
	AUC	0.6841		
	p-value (vs. Model (1))	0.0000		

This table presents the results of the subsidiary default prediction analysis. Panels A reports coefficients and (in parentheses) z-statistics from the estimation of a discrete hazard model for the *Base Model Sample* of subsidiary firm-years in which only the parent with the highest percentage of control in each subsidiary is retained. The dependent variable is equal to one if the subsidiary files for bankruptcy in year $t+1$, and zero otherwise. The specification presented in Column (1) includes subsidiary-level financial ratios only: $Pr\left(Y_{s,t+1}=1\right) = f(NROAI_{s,t}, ROA_{s,t}, LTA_{s,t}, ETL_{s,t}, LN(TA_{s,t}), BANKRATE_{s,t})$. Column (2) adds the parent's estimated bankruptcy probability ($\mathrm{Pr}(Y_{p,t+1})$), Column (3) adds the average estimated bankruptcy probability of the other group subsidiaries ($\overline{Pr(Y_{others,t+1})}$), and Columns (4) to (6) respectively add indicators for whether the parent, or one of the other group subsidiaries, file for bankruptcy in year t ($Y_{p,t}$ and $\overline{Y_{others,t}}$). The number of observations decreases in Columns (2) to (6) due to data availability requirements on parent and other subsidiaries bankruptcy information. Marginal effects for group-level variables are reported as the change in estimated bankruptcy probability as each of the group-level variables increases by one standard deviation, scaled by the average estimated bankruptcy probability. Heteroskedasticity-robust standard errors are clustered at the subsidiary-country and year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Panel B presents a comparison between the predictive power of the augmented models and that of the base model reported in Column (1) using a constant sample. Columns (1), (2) and (3) present the percentage of bankruptcy years, years before bankruptcy and non-bankrupt firm-years falling in each of the top three deciles. The Area Under the Receiver Operating Characteristic Curve (AUC) is also reported for each subgroup. All variables are defined in the Appendix. The subscripts p and s are used to identify parent- and subsidiary-level variables, respectively.

Table 4: Augmented Subsidiary Model - Resource Sharing and Common Business Exposure

Panel A: Parent-Subsidiary Resource Sharing

		Dependent variable: $Y_{s,t+1}$							
		Subsidiary Named After Its Parent		Parent Has Specialized Knowledge		Domestic Subsidiary		Subsidiary Industry Same As Parent Industry	
		No	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Independent variables:		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept		-4.705***	-4.098***	-4.621***	-4.500***	-3.511***	-4.770***	-4.645***	-4.314***
		(-7.24)	(-10.16)	(-7.36)	(-7.72)	(-6.43)	(-7.58)	(-7.72)	(-6.85)
$NROAI_{s,t}$	(+)	0.291***	0.194	0.329***	0.202***	0.245**	0.289***	0.322***	0.123
		(7.08)	(.)	(7.45)	(4.66)	(2.19)	(8.04)	(9.23)	(1.47)
$ROA_{s,t}$	(–)	-0.846***	-0.662**	-0.770***	-0.836***	-0.134	-0.936***	-0.811***	-0.750***
		(-8.30)	(-2.06)	(-4.66)	(-4.16)	(-0.85)	(-6.27)	(-4.87)	(-6.40)
$LTA_{s,t}$	(+)	0.333***	0.030	0.300***	0.253***	0.161**	0.306***	0.303***	0.188
		(3.82)	(0.23)	(2.93)	(3.01)	(2.29)	(3.15)	(3.82)	(1.39)
$ETL_{s,t}$	(–)	-0.186***	-0.068	-0.225***	-0.089**	-0.196**	-0.163***	-0.164***	-0.168**
		(-3.47)	(-1.42)	(-3.10)	(-2.15)	(-2.16)	(-3.08)	(-4.30)	(-2.14)
$LN(TA_{s,t})$	(–)	-0.076*	-0.140***	-0.090**	-0.092***	-0.180***	-0.077**	-0.086**	-0.110***
		(-1.93)	(-7.04)	(-2.19)	(-3.19)	(-5.28)	(-1.98)	(-2.30)	(-3.45)
$BANKRATE_{s,t}$	(+)	0.115*	0.075	0.113*	0.102*	0.023	0.180***	0.105*	0.123**
		(1.89)	(1.12)	(1.68)	(1.82)	(0.53)	(2.72)	(1.67)	(2.02)
$Pr(Y_{p,t+1})$	(+)	133.169***	134.128***	131.726***	135.281***	112.727***	133.753***	133.475***	133.329***
		(5.35)	(6.05)	(5.45)	(5.60)	(3.80)	(5.28)	(5.39)	(5.98)
Marginal Effects:									
$Pr(Y_{p,t+1})$		0.268	0.270	0.266	0.271	0.197	0.271	0.263	0.289
Comp. Model		Model (1) without $Pr(Y_{p,t+1})$	Model (2) without $Pr(Y_{p,t+1})$	Model (3) without $Pr(Y_{p,t+1})$	Model (4) without $Pr(Y_{p,t+1})$	Model (5) without $Pr(Y_{p,t+1})$	Model (6) without $Pr(Y_{p,t+1})$	Model (7) without $Pr(Y_{p,t+1})$	Model (8) without $Pr(Y_{p,t+1})$
AUC		0.7223	0.7025	0.7210	0.7205	0.6714	0.7294	0.7216	0.7159
AUC (Comp. Model)		0.6791	0.6619	0.6813	0.6739	0.6518	0.6822	0.6800	0.6701
p-value (vs. Comp. Model)		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
% Top Three Deciles		53.77	53.56	54.32	53.73	50.04	54.47	54.39	51.71
% Top Three Deciles (Comp. Model)		53.47	51.40	54.12	51.88	48.97	53.75	53.82	50.98
Obs.		673,413	150,351	504,093	319,671	136,728	687,036	671,065	152,699

Table 4 (continued)

Panel B: Parent-Subsidiary Common Business Exposure

		Dependent variable: $Y_{s,t+1}$					
		Parent Major Supplier		Parent Major Customer		High Common Business Exposure	
		No	*Yes*	*No*	*Yes*	*No*	*Yes*
Independent variables:		(1)	(2)	(3)	(4)	(5)	(6)
Intercept		-4.682***	-4.416***	-4.627***	-4.466***	-4.663***	-4.456***
		(-7.22)	(-7.62)	(-6.98)	(-7.82)	(-6.90)	(-7.83)
$NROAI_{s,t}$	(+)	0.347***	0.196***	0.326***	0.212***	0.335***	0.222***
		(24.15)	(3.48)	(10.12)	(4.70)	(8.84)	(5.32)
$ROA_{s,t}$	(–)	-0.723***	-0.831***	-0.759***	-0.791***	-0.730***	-0.813***
		(-5.34)	(-5.24)	(-10.44)	(-4.69)	(-11.50)	(-4.71)
$LTA_{s,t}$	(+)	0.314***	0.217**	0.307***	0.220**	0.311***	0.228**
		(3.67)	(2.17)	(3.72)	(1.98)	(3.47)	(2.27)
$ETL_{s,t}$	(–)	-0.192***	-0.107***	-0.216***	-0.084*	-0.192***	-0.116***
		(-3.73)	(-3.11)	(-4.09)	(-1.71)	(-2.98)	(-3.44)
$LN(TA_{s,t})$	(–)	-0.079*	-0.106***	-0.087**	-0.099***	-0.082*	-0.101***
		(-1.78)	(-3.55)	(-2.00)	(-3.25)	(-1.76)	(-3.40)
$BANKRATE_{s,t}$	(+)	0.103*	0.122*	0.104	0.123**	0.099	0.124*
		(1.67)	(1.91)	(1.62)	(1.99)	(1.60)	(1.94)
$Pr(Y_{p,t+1})$	(+)	132.500***	133.336***	134.381***	131.208***	134.959***	131.130***
		(5.42)	(5.54)	(5.31)	(5.64)	(5.46)	(5.49)
Marginal Effects:							
$Pr(Y_{p,t+1})$		0.264	0.278	0.264	0.278	0.268	0.273
Comp. Model		Model (1) without $Pr(Y_{p,t+1})$	Model (2) without $Pr(Y_{p,t+1})$	Model (3) without $Pr(Y_{p,t+1})$	Model (4) without $Pr(Y_{p,t+1})$	Model (5) without $Pr(Y_{p,t+1})$	Model (6) without $Pr(Y_{p,t+1})$
AUC		0.7213	0.7158	0.7275	0.7088	0.7258	0.7128
AUC (Comp. Model)		0.6799	0.6697	0.6859	0.6625	0.6834	0.6680
p-value (vs. Comp. Model)		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
% Top Three Deciles		54.82	52.08	55.35	51.43	55.45	51.94
% Top Three Deciles (Comp. Model)		54.05	51.54	54.67	50.78	54.43	51.43
Obs.		364,459	386,442	391,930	358,971	322,989	427,912

This table presents the results of the analysis assessing the role of parent-subsidiary resource sharing and common business exposure for subsidiary default prediction. In this analysis, the *Base Model Sample* is limited to observations for which data on partitioning variables are available. Panel A presents sample partitions based on different proxies capturing the extent of parent-subsidiary resource sharing: whether the subsidiary is named after its parent (Columns (1) and (2)), whether the parent has specialized knowledge (Columns (3) and (4)), whether the subsidiary is domestic (Columns (5) and (6)), and whether the subsidiary is in the same industry as the parent (Columns (7) and (8)). A parent is classified as having specialized knowledge if it operates in industries generating specialized knowledge. Industries with a high and low degree of specialized knowledge are identified following a similar approach to Christie et al. (2003). Panel B presents sample partitions based on different proxies capturing the extent of common business exposure: whether the parent is a major supplier of its subsidiary (Columns (1) and (2)), whether the parent is a major customer of its subsidiary (Columns (3) and (4)), and whether the subsidiary has high business exposure to its parent (Columns (5) and (6)). Following Bena and Ortiz-Molina (2013), we identify major customers and suppliers using the input-output matrix. A parent is classified as a *major supplier* of its subsidiary if the purchases made by the subsidiary's industry from the parent's industry represent more than 2% of the total purchases made by the subsidiary industry. A parent is classified as a *major customer* of its subsidiary if the purchases made by the parent's industry from the subsidiary's industry represent more than 2% of the total output of the subsidiary industry. A subsidiary is classified as having high *business exposure* to its parent if the parent is classified as being either a major supplier *or* a major customer of the subsidiary. Both Panel A and B report coefficients and (in parentheses) z-statistics from the estimation of the discrete hazard model reported in Table 3, Panel A, Column (2) for the different subsidiary sub-samples. The dependent variable is equal to one if the subsidiary files for bankruptcy in year $t + 1$, and zero otherwise. Marginal effects for group-level variables are reported as the change in estimated default probability as each of the group-level variables increases by one standard deviation, scaled by the average estimated default probability. Heteroskedasticity-robust standard errors are clustered at the subsidiary-country and year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively. The table also presents a comparison between the predictive power of the models presented and that of the base model reported in Table 3, Panel A, Column (1) and re-estimated within each sub-sample. We use a constant sample for predictive power comparisons. All variables are defined in the Appendix. The subscripts p and s are used to identify parent- and subsidiary-level variables, respectively.

Table 5: Gauging the Financial Impact of Group Affiliation

Panel A: Percentage Change in Subsidiary Leverage Equivalent to 1% Change in Parent Default Probability

	Full Sample	Majority-Owned Subsidiary		Subsidiary with Interlocked Board	
		No	*Yes*	*No*	*Yes*
% Change in $LTA_{s,t}$ Equivalent to *1% Change in $Pr(Y_{p,t+1})$*	1.32%	1.05%	1.42%	0.77%	1.80%

Panel B: Majority-Owned Subsidiaries

% Change in $LTA_{s,t}$ Equivalent to Change in Subsidiary Control Rights for Different Parent-Subsidiary Credit-Risk Conditions		Parent Credit Risk: *Low*	Parent Credit Risk: *High*
Subsidiary Credit Risk	*Low*	-3.64%	48.13%
Subsidiary Credit Risk	*High*	-82.57%	-11.95%

Panel C: Subsidiaries with Interlocked Boards

% Change in $LTA_{s,t}$ Equivalent to Change in Interlocked Board for Different Parent-Subsidiary Credit-Risk Conditions		Parent Credit Risk: *Low*	Parent Credit Risk: *High*
Subsidiary Credit Risk	*Low*	-30.09%	8.95%
Subsidiary Credit Risk	*High*	-87.77%	48.94%

This table provides estimates of the relative magnitude of off-balance sheet assets and liabilities associated with group support. Panel A reports the percentage change in subsidiary leverage ($LTA_{s,t}$) that produces the same effect on the subsidiary default probability as a 1% change in the default probability of the parent ($Pr(Y_{p,t+1})$). Our estimation entails two steps. First, we compute the change in subsidiary default probability induced by a 1% change in the default probability of the parent, based on the model reported in Table 3, Panel A. Second, we estimate the percentage change in subsidiary leverage that would produce the exact same effect on subsidiary default probability as a 1% change in the default probability of the parent. Next, we examine cross-sectional variation in the magnitude of the subsidiary leverage effect based on the degree of subsidiary integration, which is measured along two dimensions: (i) whether the parent has majority ownership rights; (ii) whether parent and subsidiary boards are interlocked. In Panels B and C parent-subsidiary pairs are split into four sub-samples based on parent and subsidiary credit risk (parents/subsidiaries are classified as having high (low) credit risk if their respective leverage is above (below) the sample median). The *prop-down sub-sample* (bottom-left quadrant) comprises high credit-risk subsidiaries of low credit-risk parents and the *prop-up sub-sample* (upper-right quadrant) comprises low credit-risk subsidiaries of high credit-risk parents. Within each quadrant we report the incremental effect on leverage for integrated subsidiaries *vis-à-vis* non-integrated subsidiaries.

Table 6: Binary Recursive Partitioning Analysis

Panel A: Parent Model Predictive Ability

	Dependent variable: $Y_{p,t+1}$	
	Base Model	Augmented Model
	(1)	(2)
Independent variables:	$NROAI_{p,t}$, $ROA_{p,t}$, $LTA_{p,t}$, $ETL_{p,t}$, $LN(TA_{p,t})$, $BANKRATE_{p,t}$	$NROAI_{p,t}$, $ROA_{p,t}$, $LTA_{p,t}$, $ETL_{p,t}$, $LN(TA_{p,t})$, $BANKRATE_{p,t}$, $\overline{\Pr(Y_{s,t+1})}$, $\bar{Y}_{s,t}$
AUC (Learning sample)	0.7782	0.7793
AUC (Test sample)	0.7512	0.7525
Relative cost	0.5831	0.5817
Hosmer-Lemeshow Test-statistic (p-value)	60.77 (0.0000)	115.75 (0.0000)

Panel B: Parent Model Variable Importance (%)

	Dependent variable: $Y_{p,t+1}$			
	Base Model		Augmented Model	
	(1)		(2)	
Independent variables:	Total	Primary Splitters	Total	Primary Splitters
$NROAI_p$	43.50	5.88	42.83	6.12
$ROA_{p,t}$	85.83	97.29	85.90	100.00
$LTA_{p,t}$	100.00	38.81	100.00	42.04
$ETL_{p,t}$	54.91	4.82	54.64	4.92
$LN(TA_{p,t})$	15.41	7.73	15.46	7.61
$BANKRATE_{p,t}$	76.91	100.00	73.82	98.27
$\overline{Pr(Y_{s,t+1})}$			87.38	11.40
$\bar{Y}_{s,t}$			0.85	0.00

Table 6 (continued)

Panel C: Subsidiary Model Predictive Ability

	Dependent variable: $Y_{s,t+1}$	
	Base Model	Augmented Model
	(1)	(2)
Independent variables:	$NROAI_{s,t}$, $ROA_{s,t}$, $LTA_{s,t}$, $ETL_{s,t}$, $LN(TA_{s,t})$, $BANKRATE_{s,t}$	$NROAI_{s,t}$, $ROA_{s,t}$, $LTA_{s,t}$, $ETL_{s,t}$, $LN(TA_{s,t})$, $BANKRATE_{s,t}$, $\Pr(Y_{p,t+1})$, $\overline{\Pr(Y_{others,t+1})}$, $\overline{Y_{others,t}}$, $Y_{p,t}$
AUC (Learning sample)	0.7807	0.7848
AUC (Test sample)	0.7495	0.7510
Relative cost	0.5955	0.5956
Hosmer-Lemeshow Test-statistic (p-value)	60.77 (0.0000)	115.75 (0.0000)

Panel D: Subsidiary Model Variable Importance (%)

	Dependent variable: $Y_{s,t+1}$			
	Base Model		Augmented Model	
	(1)		(2)	
Independent variables:	Total	Primary Splitters	Total	Primary Splitters
$NROAI_{s,t}$	20.84	2.13	19.98	1.63
$ROA_{s,t}$	70.24	5.43	72.80	17.32
$LTA_{s,t}$	40.91	14.78	40.05	11.75
$ETL_{s,t}$	64.64	34.03	67.66	24.56
$LN(TA_{s,t})$	27.15	9.82	28.96	7.02
$BANKRATE_{s,t}$	100.00	100.00	100.00	100.00
$Pr(Y_{p,t+1})$			62.71	13.79
$\overline{Pr(Y_{others,t+1})}$			84.49	23.44
$\overline{Y_{others,t}}$			1.84	1.52
$Y_{p,t}$			0.93	0.00

This table reports the results of a binary recursive partitioning analysis for the one-year ahead probability of parent (Panels A and B) and subsidiary (Panels C and D) bankruptcy for the *Base Model Sample* of parent and subsidiary firm-years. We use the Classification and Regression Trees methodology (CART) (Breiman et al., 1984) to create a decision tree that classifies firm-years into bankrupt or non-bankrupt. We follow the Gini rule to choose the optimal split at each node of the tree. Based on this approach, we generate the maximal tree and a set of sub-trees. We then use 10-fold cross-validation to estimate the Area Under the Receiver Operating Characteristic Curve (AUC). Panels A and C report summary statistics for the predictive ability of the parent and subsidiary models, respectively. Relative cost is the sum of the percentage of type I and type II errors. The Hosmer-Lemeshow test statistic is calculated as $\sum_{g=1}^{G} \frac{(O_g - E_g)^2}{N_g \pi_g (1-\pi_g)}$, where O_g, E_g, N_g and π_g are observed events, expected events, observations and predicted risk for each group g (with G equal to the number of groups). Panels B and D present the importance scores for the variables included in the parent and subsidiary augmented models. These scores are calculated as the sum of the improvement that can be attributed to a given variable at each node of the tree. Total variable importance takes into account the role of the variable as a surrogate, while the column *Primary Splitters* only takes into account the role of the variable as a primary splitter.

Online Appendix for

Group Affiliation and Default Prediction

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1. Dataset Construction

We combine several vintages of Orbis data in order to maximize coverage and to accurately identify bankruptcies. These vintages, collectively labelled by BvDEP as *Orbis Historical*, reflect the content of the Orbis database at different points in time.

We start by identifying "Global Ultimate Owners" (GUOs). As discussed by Faccio and Lang (2002), the identification of ultimate owners generally proves extremely difficult. In line with the recent study by Shroff et al. (2014), we follow the Orbis criteria to identify ultimate owners. These are independent firms where no single shareholder holds more than 25% of the shares.[1, 2] For each GUO (parent company), we then obtain subsidiary information from the Orbis ownership files. We first retrieve subsidiaries that are directly held by their respective GUOs (level 1 subsidiaries), and then we iterate this process for four additional levels (level 2, 3, 4, and 5 subsidiaries) following the sequential approach used in other studies such as Shroff et al. (2014) and Beuselinck et al. (2018). For each parent-subsidiary pair, we compute control rights using the weakest link approach (La Porta et al., 1999; Claessens et al., 2000; and Nenova, 2003). We eliminate parents and subsidiaries whose Orbis legal form is labelled as "Other legal form." This effectively excludes cooperatives from the sample.[3] We further delete firms with U.S. SIC codes 8000-9999. These include industries, such as *Museums and educational services*, *Private households*, *Membership organizations* (SIC codes 8000-8999) and *Public services* (SIC codes 9000-9999). Finally, we delete firms that do not have assets and turnover of at least U.S. $10,000 for at least one of the years 2004-2012 and with missing net income or EBIT information for all of these years.

Based on historical financial data, we build an eight-year time series of bankruptcy data (2005-2012) for each parent and subsidiary in the sample, as well as for a set of standalone (i.e., non-group-

[1] Our objective is to examine whether parent (subsidiary) financial information has incremental predictive power for subsidiary (parent) default, and therefore our analysis is necessarily limited to parent firms with available financial statement information, i.e., *corporate* ultimate owners.

[2] In untabulated tests, we check the sensitivity of our findings to alternative thresholds. Specifically, we re-map our parent-subsidiary corporate ownership chains using the two alternative thresholds of 20% and 10% used in prior studies (La Porta et al. 1999; Claessens et al., 2000; Faccio and Lang, 2002; Fan and Wong, 2002). The results of these robustness tests yield qualitatively similar inferences to those presented in the paper.

[3] The drivers of the bankruptcy decision for cooperatives might be significantly different from other types of businesses.

affiliated) firms meeting similar requirements.[4] We identify bankrupt firms using the *status* variable from Orbis.[5] In particular, we classify as bankrupt firms with the following statuses: "Active (Insolvency proceedings)," "Bankruptcy," "Dissolved," "Dissolved (bankruptcy)," "Dissolved (litigation)," "In liquidation," and "Inactive (no precision)." Because insolvency procedures and bankruptcy regulations typically vary across countries, throughout the paper we use the term bankruptcy loosely and often refer to the more generic term default. We create a bankruptcy firm-year indicator equal to one if the firm goes bankrupt (as per the above definition) in a given year. Following Shumway (2001), we delete all firm-years after bankruptcy from the sample. We use the field *status date* to identify the year in which the firm becomes bankrupt. If the status date is missing, we set it equal to the first year in which the firm status changes to bankrupt.

2. Discrete Hazard Model vs. CART

The Classification and Regression Tree (CART) methodology builds classification trees which are structured as a sequence of nodes, where the data are recursively split into more homogeneous subsets using the Gini rule. The predicted classification is determined following the path down the tree to an end node, where the path depends on the values of the different predictors.

An interesting feature of the CART methodology, *vis-à-vis* discrete hazard estimation, is the possibility to directly compare the relative contribution of each default predictor. However, the CART methodology is not free of limitations, with the main flaw being its sensitivity to small changes in the learning data. The entire tree structure can in fact change if the first splitting variable and cut-point are chosen differently, and these choices strongly depend on the distribution of observations in the learning sample. Moreover, because trees have a discrete number of end nodes, the resulting Receiver Operating Characteristic (ROC) curves are typically based on a smaller number of points compared to hazard model ROC curves which are instead based on continuous bankruptcy probability estimates. As a result of the angularity of CART-based ROC curves, the resulting Area Under the Receiver Operating Characteristic Curve (AUC) may be a less reliable statistic.

[4] Because we require lagged financial ratios for our analysis, we lose observations for the year 2004.
[5] By compiling status data from several annual editions of Orbis, we effectively construct a time-series status variable starting in 2005 and ending in 2012.

3. Default Prediction Model Validation

We compare the predictive power of different default prediction models for parent, subsidiary, and standalone firms in our *Estimation Sample* (see Table OA-2, Panel A). Following Shumway (2001), we use a discrete hazard model and include three types of observations in the estimation: non-bankrupt firms, years before bankruptcy for bankrupt firms and bankruptcy year. Our dependent variable, $Y_{i,t+1}$, is equal to one if firm i files for bankruptcy within one year $(t+1)$, and zero otherwise. We retain the first bankruptcy filing and remove from the sample all years after this filing. Furthermore, to ensure that prediction is made out-of-sample, and to avoid the potential bias of ex post over-fitting the data, we estimate coefficients using an expanding window approach. We compare four model specifications:

1) *The BCM (2012) model*, augmented by the natural logarithm of the book value of assets:

   $$Pr\left(Y_{i,t+1}=1\right)=f(NROAI_{i,t},ROA_{i,t},LTA_{i,t},ETL_{i,t},LN(TA_{i,t})),\qquad \text{(OA.1)}$$

   where $Y_{i,t+1}$ is an indicator variable set equal to one if firm i files for bankruptcy in year $t+1$, and zero otherwise; $NROAI_{i,t}$ is an indicator variable set equal to one if firm i's return on assets in year t is negative, and zero otherwise; $ROA_{i,t}$ is firm i's return on assets in year t; $LTA_{i,t}$ is firm i's book leverage in year t, i.e., firm i's total liabilities scaled by total assets; $ETL_{i,t}$ is firm i's ratio of earnings before interest and taxes to total liabilities in year t; and $LN(TA_{i,t})$ is the natural logarithm of the book value of assets for firm i in year t.

2) *A country/industry/time varying baseline model* (i.e., equation (OA.1) augmented by the bankruptcy rate in firm i's country-industry in the year t, $BANKRATE_{i,t}$):

   $$Pr\left(Y_{i,t+1}=1\right)=f(NROAI_{i,t},ROA_{i,t},LTA_{i,t},ETL_{i,t},LN(TA_{i,t}),BANKRATE_{i,t}).\qquad \text{(OA.2)}$$

3) *A macro model* (i.e., equation (OA.2) augmented forecasted GDP growth and inflation for the year $t+1$):

   $$Pr\left(Y_{i,t+1}=1\right)=$$
   $$f(NROAI_{i,t},ROA_{i,t},LTA_{i,t},ETL_{i,t},LN(TA_{i,t}),BANKRATE_{i,t},FGDPg_{i,t},FINF_{i,t}),\qquad \text{(OA.3)}$$

   where $FGDPg_{i,t}$ and $FINF_{i,t}$ are the last forecasts of GDP growth and inflation for firm i's country in year $t+1$ issued in year t.

4) *A model with country and industry fixed effects* (i.e., equation (OA.1) augmented by country and one-digit SIC industry indicators):

$$Pr(Y_{i,t+1} = 1) = f(NROAI_{i,t}, ROA_{i,t}, LTA_{i,t}, ETL_{i,t}, LN(TA_{i,t}), Industry\ FE, Country\ FE), \quad \text{(OA.4)}$$

where $Industry\ FE$ and $Country\ FE$ are a series of (one-digit SIC) industry and country fixed effects.

Table OA-1, Panel A presents descriptive statistics for the variables used in these four models. Parents are on average more profitable and have lower leverage than subsidiaries (they exhibit lower incidence of losses, $NROAI_{i,t}$, higher $ROA_{i,t}$ and lower $LTA_{i,t}$ on average). Subsidiaries, despite having lower $ROA_{i,t}$ and higher $LTA_{i,t}$, have higher earnings relative to total liabilities, as measured by $ETL_{i,t}$. Standalones have on average lower book value of assets and higher $ROA_{i,t}$ and $ETL_{i,t}$ than both parents and subsidiaries. Consistent with the observed financial ratios, subsidiaries exhibit the highest bankruptcy rates out of the three groups of firms (1.17%), followed by parents (0.87%) and standalones (0.51%).

Panel B presents the coefficients from the estimation of models (OA.1) to (OA.4). These models are estimated separately for parents, subsidiaries and standalones. Across the four models, parents and subsidiaries with low profitability, losses and high leverage are more likely to file for bankruptcy in the following year. While $ETL_{i,t}$ is not significant in the parent model, it is significantly negative for subsidiaries, as expected. $LTA_{i,t}$, $ROA_{i,t}$ and $LN(TA_{i,t})$ are the main predictors of standalone bankruptcy, with size exhibiting a positive coefficient, in contrast to the coefficient documented for parents and subsidiaries. While not statistically significant, the coefficient on the country-industry bankruptcy rate is positive. Forecasted GDP growth (forecasted inflation) exhibit positive (negative) and significant associations with future parent bankruptcy but are not statistically significant for subsidiaries and standalones. We estimate the probability that each firm in the sample files for bankruptcy within the following 12 months as follows: $Pr(\widehat{Y_{i,t+1}} = 1) = \frac{exp(X_{i,t}\widehat{\beta})}{1+exp(X_{i,t}\widehat{\beta})}$.

We compare the predictive power of the models using two different approaches. First, we rank the predicted probability of bankruptcy within the parent, subsidiaries and standalones sub-samples.

We report the percentage of parents, subsidiaries and standalones in each of the top three deciles separately for three groups: (1) bankruptcy years, (2) years before bankruptcy and (3) non-bankrupt firm-years. If the models were to have no predictive power, the fraction of observations in each decile would be 10% for each of the three groups. A higher percentage of bankruptcy years in the top three deciles would be indicative of higher predictive power of the model. Second, we perform a ROC curve analysis and report the AUC, which reflects the trade-off between type 1 and type 2 classification errors. A strategy that randomly classifies firm-years as bankrupt and non-bankrupt would be represented by the diagonal of the ROC graph and have an AUC of 0.5. A perfect classification strategy would be represented by a point on the upper left corner of the ROC graph (AUC=1), while a strategy that classifies all observations as "non-bankrupt" would be represented by a point in the origin of the ROC graph, and have an AUC of zero. We use these two approaches to examine predictive power as both have advantages and disadvantages. The AUC has the advantage of providing a concise measure of the relative frequency of false positives and negatives. However, it has the disadvantage of implicitly assuming a symmetric loss function by placing equal weight on the two types of errors. The decile analysis has the advantage of illustrating these errors in more detail across the distribution of the estimated probability of bankruptcy, which is informative, given that the loss function in bankruptcy classification is likely asymmetric (Beaver et al., 2010). The disadvantage of the decile analysis, however, is that it does not provide a summary measure of predictive power across the entire distribution.

Panels C and D present the results of this analysis. Column (1) presents the percentage of bankrupt firm-years that fall within the top three deciles of the predicted probability of bankruptcy for each of the four models. Columns (2) and (3) show the percentage of years before bankruptcy and non-bankrupt firm-years falling within these deciles, respectively. The AUC of the country/industry/time varying baseline model (equation (OA.2)) is higher than that of other models for subsidiaries and standalone firms. While slightly smaller than the AUC of the macro model for parents, the difference between the two is not statistically significant (Panel D). Approximately 30% (23%) of the parent (subsidiary) bankruptcy years fall into the top decile of predicted probability of bankruptcy, and 60% (50%) fall into the top three deciles. Figure OA-1, Panels A, B and C present the ROC curves for the different models. Consistent with the reported AUC, the country/industry/time varying model appears to outperform the other three models for subsidiaries and standalone firms and the difference between that model and the other models appears negligible for parents. For the above reason, we use the country/industry/time varying baseline model (equation (OA.2)) as the main model for our analysis.

Panel E, further examines the differences in predictive power for the selected model across public and private firms. We estimate the model both within the pooled *Estimation Sample* and allowing for different coefficients for public and private firms. We find that both models have higher predictive power for public firms than for private firms, especially within subsidiaries. While we do not explore the reasons for this difference in predictive power, this could be in part due to heterogeneity in the quality of accounting information provided by public and private firms (Ball and Shivakumar (2005), for example, document that U.K. private firms exhibit lower timely loss recognition).

4. Sample Selection and Descriptive Statistics

To obtain bankruptcy probability estimates, we start from the *Estimation Sample* of parents and subsidiaries with available financial statement information (see Table OA-2: Sample Selection and Descriptive Statistics). We limit this sample to observations for which $BANKRATE_{i,t}$ is available. This requirement leaves us with 594,890 parent-year and 1,309,173 subsidiary-year observations (Table OA-1, Panel B, Columns (4) and (5)).

In order to examine the importance of group affiliation, we further limit the sample to groups with available ownership information to compute control rights. This leaves us with a final sample comprising 350,452 parent-year and 928,162 subsidiary-year observations over the period 2005-2012.[6] We refer to this sample as the *Base Model Sample* (Table OA-2, Panel A).

Table OA-2, Panel B presents the distribution of parent and subsidiary firm-year observations by country. There are 117 countries represented in the sample: France, Sweden, Spain, Italy, Russia,

[6] In line with Shroff et al. (2014) and Beuselinck et al. (2018), we choose to keep in our sample countries with very few parent and/or subsidiary firm-year observations. This is to avoid a potential "domino effect" in the sample selection procedure induced by the dropping of less populated countries (for a detailed explanation of the issue, see Beuselinck et al. (2018), footnote 13).

U.K., and Japan account for most of the parents and subsidiaries (73% and 71%, respectively).[7] Panel C (D) presents the sample distribution for the three types of firms by year (industry). Approximately 40% of the parents are in the financial industry, which suggests that many business group parents are financial holding companies. These are followed by 16% in wholesale durable goods, and 11% in services. In contrast, only 16% of subsidiaries are in the financial industry. 24% of the subsidiaries are in wholesale durable goods and 14% in services. The industry distribution of standalone firms is similar to that of subsidiaries. Panel E presents descriptive statistics for the main variables used in the default prediction model. Parents are on average more profitable and have lower leverage than subsidiaries (they exhibit lower incidence of losses, $NROAI_{i,t}$, higher $ROA_{i,t}$ and lower $LTA_{i,t}$ on average). Subsidiaries, despite having lower $ROA_{i,t}$ and higher leverage, $LTA_{i,t}$, have higher earnings before interest and tax, $ETL_{i,t}$.

5. CDS Sample

We obtain a sample of five-year credit default swap (CDS) contracts on senior unsecured debt issued by parents from Markit. We impose several data filters to ensure that we retain the most liquid CDS contract for each firm. In particular, for U.S. parents, we select U.S. Dollar denominated contracts with a no-restructuring clause for months following April 2009, and contracts with a modified restructuring clause for months before April 2009.[8] For parents in the remaining sample countries, we select the CDS contract with highest depth. This results in 3,377 parent-year observations, 3,152 (3,077) of which with available distance to default (market) information. Using similar selection criteria for the sample of subsidiaries, we obtain 1,198 subsidiary-year observations, 1,069 (509) of which have available distance to default (market) information.

[7] These cross-country differences in sample representation (which are consistent with other studies that use the Orbis database, such as Shroff et al. (2014) and Beuselinck et al. (2018)) may not only reflect differences in the number of firms in each country but also cross-country differences in reporting requirements. For example, in the U.S. only public firms are required to file their annual financial statements. To mitigate a potential concern that observations from the most represented parent and subsidiary countries in our sample may be driving our results, we conduct a battery of sensitivity tests (untabulated), where we remove parent- (subsidiary-) year observations from each of the parent (subsidiary) countries with higher sample representation both one-by-one and simultaneously. The tenor of our findings remains unchanged.

[8] A restructuring clause defines the credit events that trigger the settlement of a CDS contract. Under a modified restructuring clause, restructuring agreements count as a credit event.

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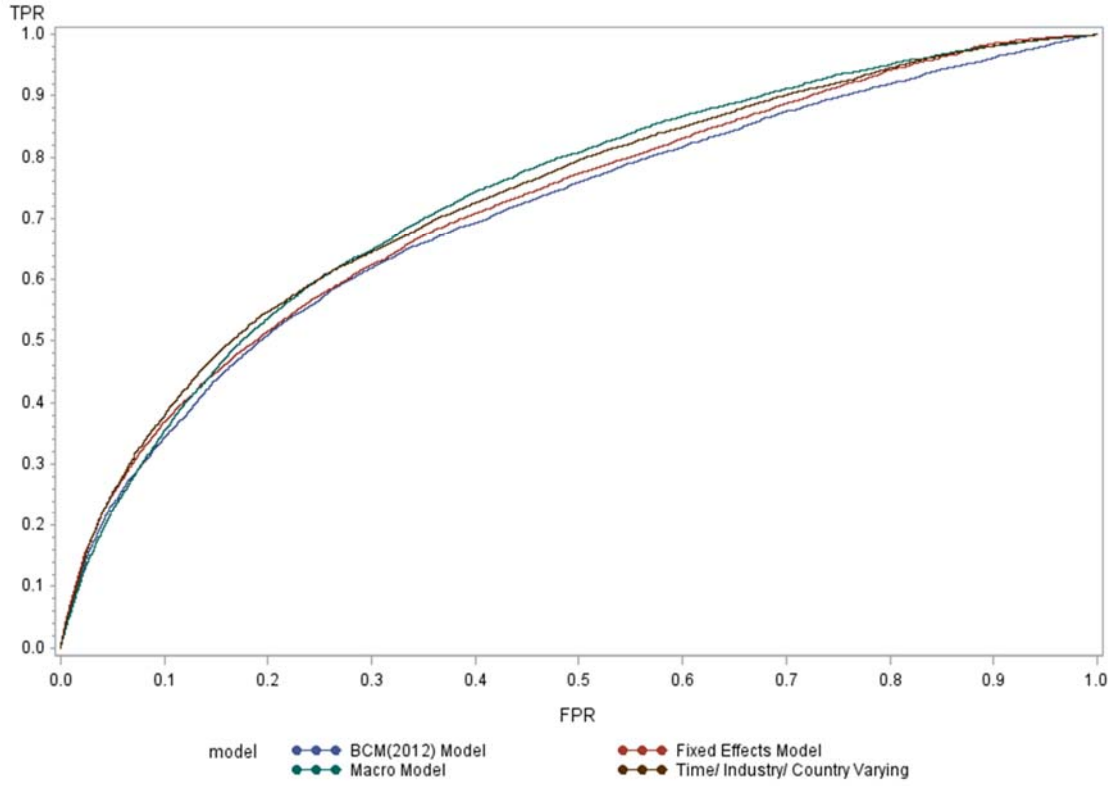
Figure OA-1: Default Prediction Model Validation - ROC Curves

Panel A: Parent ROC Curves



Panel B: Subsidiary ROC Curves

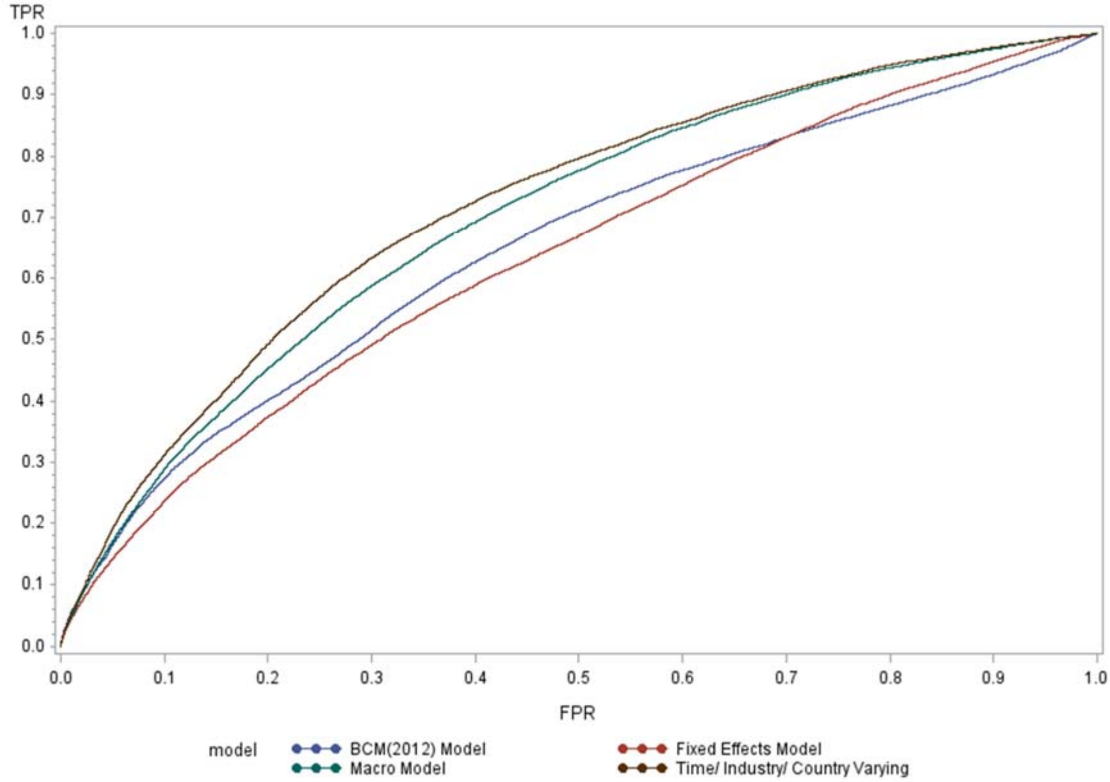
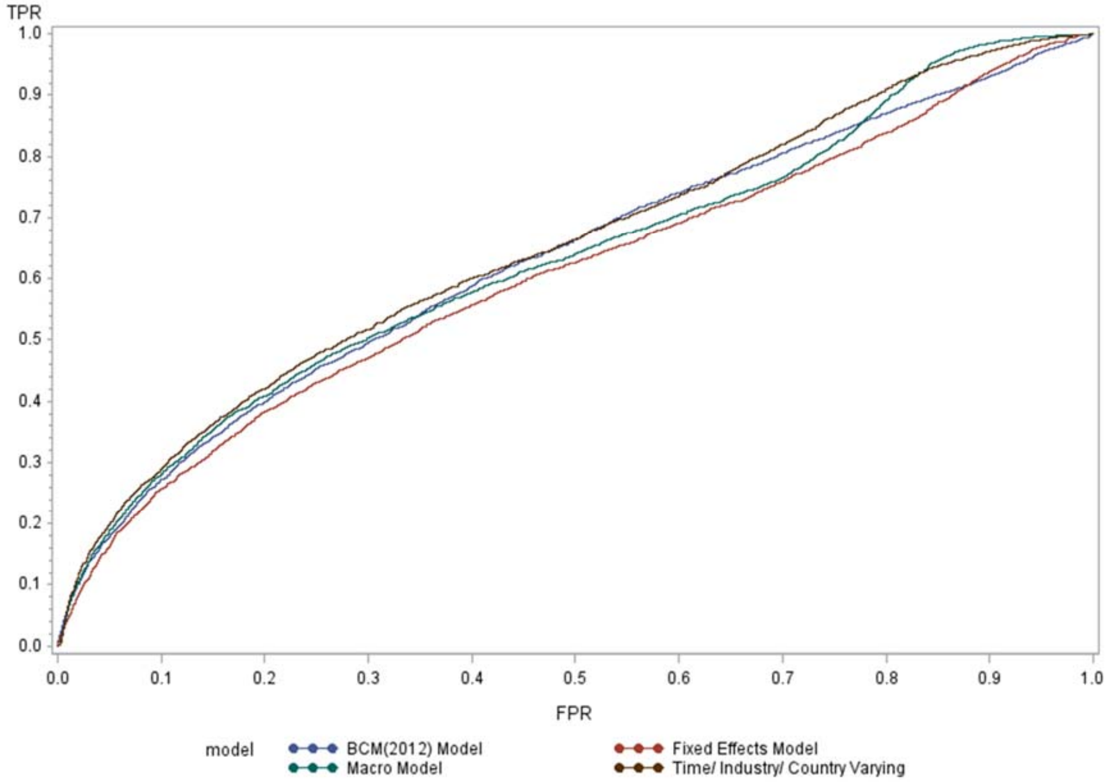


Figure OA-1 (continued)

Panel C: Standalone ROC curves

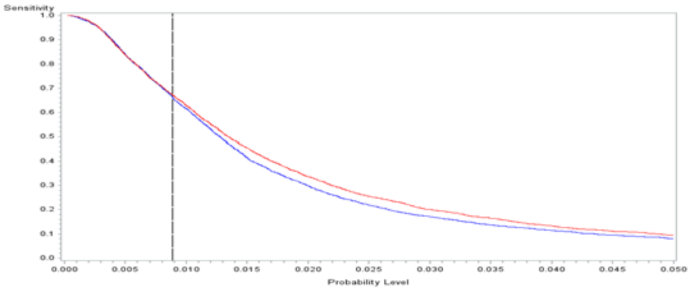


This figure shows a set of Receiver Operating Characteristic (ROC) curves. Panels A, B and C present the ROC curves for the BCM (2012) model (equation (OA.1)), the Country/Industry/Time varying baseline model (equation (OA.2)), the macro model (equation (OA.3)) and the country and year fixed effects model (equation (OA.4)), for parents, subsidiaries and standalones, respectively. FPR and TPR stand for "False Positive Rate" and "True Positive Rate," respectively.

Figure OA-2: Sensitivity and Specificity for Parent and Subsidiary Augmented Models

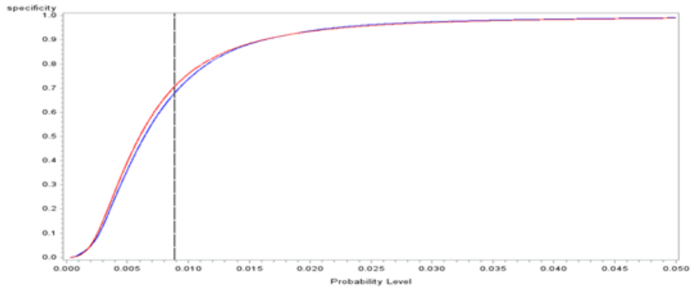
Parent Augmented Model

Sensitivity



Sensitivity base model (blue): 0.66219
Sensitivity augmented model (red): 0.67199

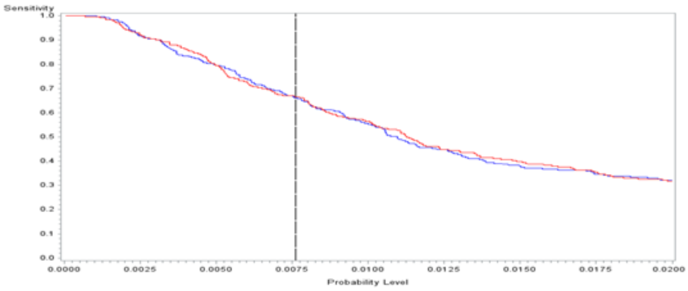
Specificity



Specificity base model (blue): 0.68044
Specificity augmented model (red): 0.70753

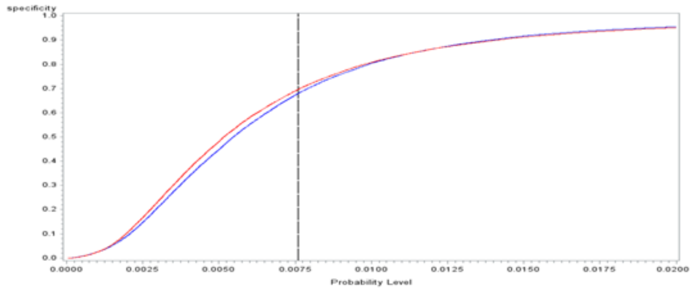
Parent Augment Model - Low Financial Reporting Quality

Sensitivity



Sensitivity base model (blue): 0.66255
Sensitivity augmented model (red): 0.66667

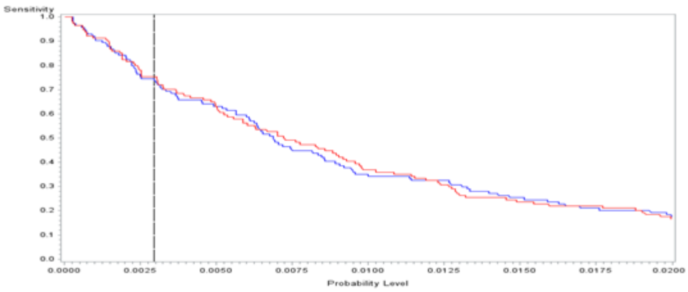
Specificity



Specificity base model (blue): 0.67957
Specificity augmented model (red): 0.69679

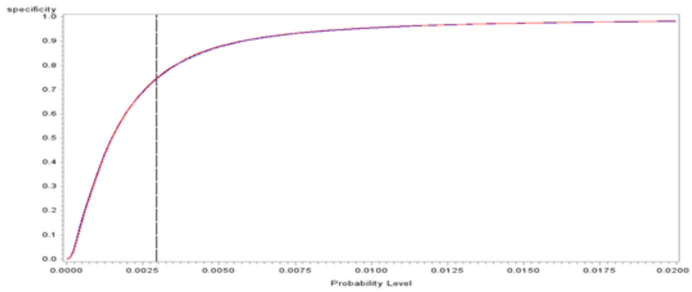
Parent Augment Model - High Financial Reporting Quality

Sensitivity



Sensitivity base model (blue): 0.73684
Sensitivity augmented model (red): 0.75439

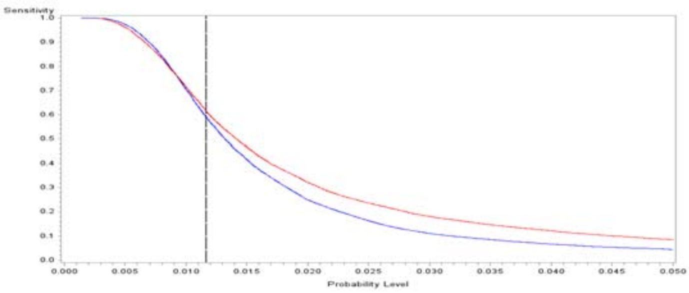
Specificity



Specificity base model (blue): 0.74508
Specificity augmented model (red): 0.74729

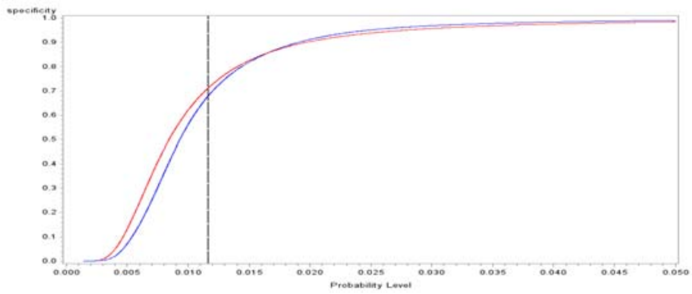
Subsidiary Augmented Model

Sensitivity



Sensitivity base model (blue): 0.73684
Sensitivity augmented model (red): 0.75439

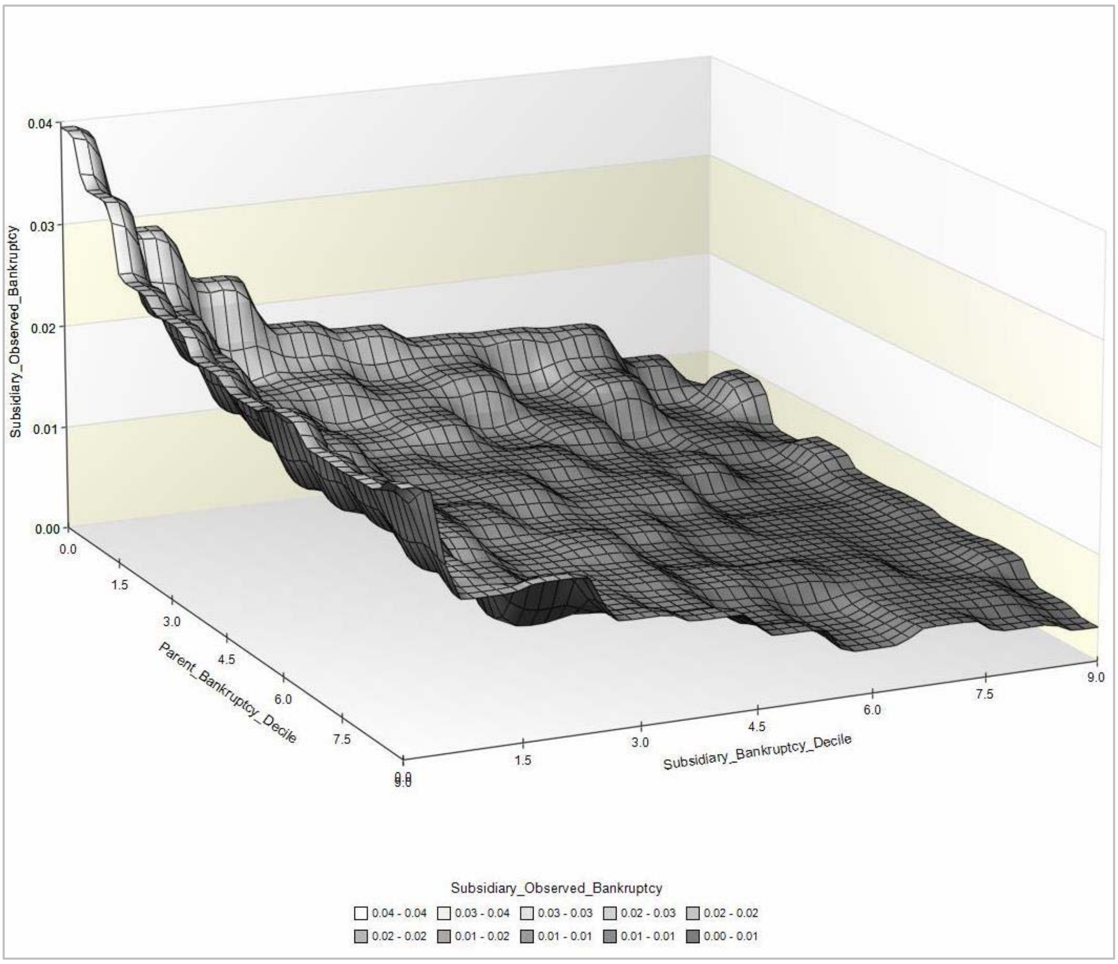
Specificity



Specificity base model (blue): 0.74508
Specificity augmented model (red): 0.74729

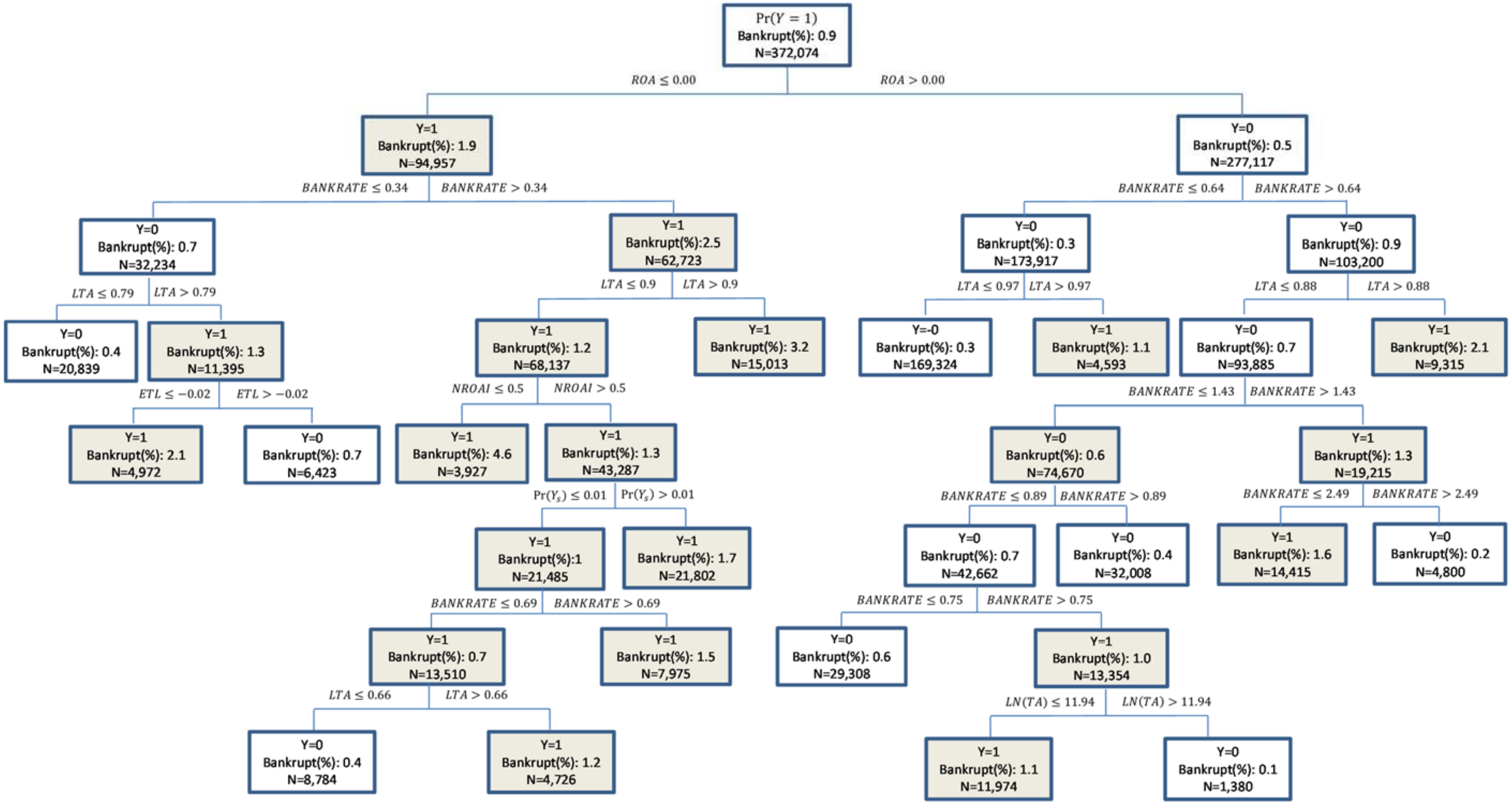
This figure presents the sensitivity and specificity of the base (blue lines) and augmented (red lines) default prediction models for parents and subsidiaries at different probability thresholds. The parent base model as presented in Table 1, Panel A, Column (1) in the paper is estimated as follows: $Pr(Y_{p,t+1} = 1) = f(NROAI_{p,t}, ROA_{p,t}, LTA_{p,t}, ETL_{p,t}, LN(TA_{p,t}), BANKRATE_{p,t})$. The parent augmented model adds the average estimated bankruptcy probability of all group subsidiaries ($\overline{Pr(Y_{s,t+1}}$)) to the parent base model (Table 1, Panel A, Column (2) in the paper). The subsidiary base model as presented in Table 3, Panel A, Column (1) in the paper is estimated as follows: $Pr(Y_{s,t+1} = 1) = f(NROAI_{s,t}, ROA_{s,t}, LTA_{s,t}, ETL_{s,t}, LN(TA_{s,t}), BANKRATE_{s,t})$. The subsidiary augmented model adds the estimated bankruptcy probability of the parent (($Pr(Y_{p,t+1}$)) to the subsidiary base model (Table 3, Panel A, Column (2) in the paper).

Figure OA-3: Average Subsidiary Bankruptcy Rates by Decile of Subsidiary and Parent Bankruptcy Probability



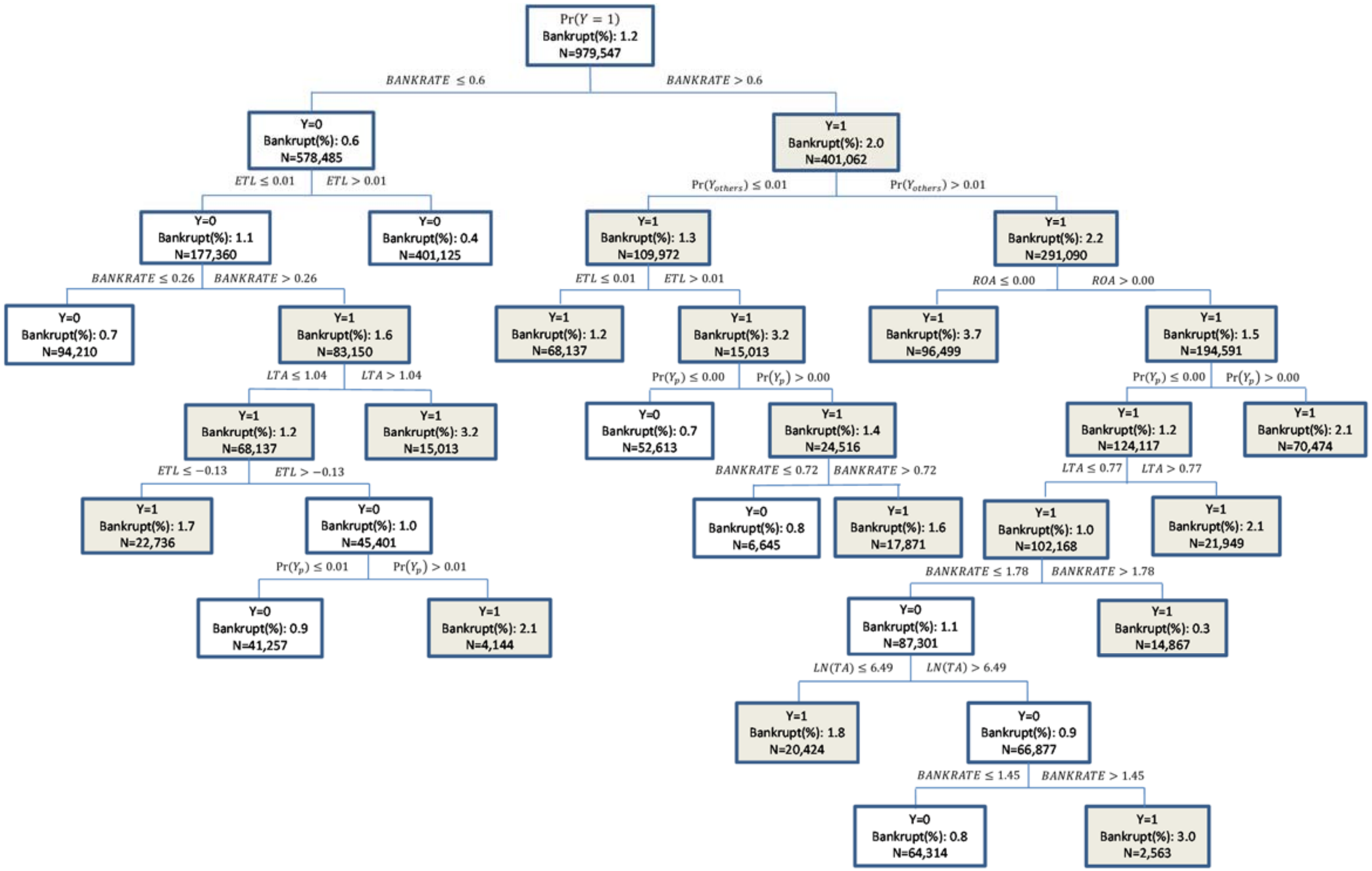
This figure depicts the association between parent and subsidiary estimated bankruptcy probabilities. Each year, we sort subsidiaries into deciles based on their estimated bankruptcy probability ($Pr(Y_{s,t+1})$) and on their parents' estimated bankruptcy probability ($Pr(Y_{p,t+1})$). These sorts are independent given that our sorting variables are correlated. We then plot the mean observed subsidiary bankruptcy rate in year $t+1$ across the resulting 100 cells.

Figure OA-4: Example of Binary Recursive Partitioning for Parents



This figure presents the Classification and Regression Tree (CART) for the parent augmented model that includes $NROAI_{p,t}$, $ROA_{p,t}$, $LTA_{p,t}$, $ETL_{p,t}$, $LN(TA_{p,t})$, $BANKRATE_{p,t}$, $\overline{Pr(Y_{s,t+1})}$, and $\bar{Y}_{s,t}$ (Table 6, Panel A, Column (2) in the paper). The tree is pruned for presentation purposes.

Figure OA-5: Example of Binary Recursive Partitioning for Subsidiaries



This figure presents the Classification and Regression Tree (CART) for the subsidiary augmented model that includes $NROAI_{s,t}$, $ROA_{s,t}$, $LTA_{s,t}$, $ETL_{s,t}$, $LN(TA_{s,t})$, $BANKRATE_{s,t}$, $Pr(Y_{p,t+1})$, $\overline{Pr(Y_{others,t+1})}$, $\overline{Y_{others,t}}$, and $Y_{p,t}$ (Table 6, Panel C, Column (2) in the paper).The tree is pruned for presentation purposes.

Table OA-1: Default Prediction Model Validation

Panel A: Descriptive Statistics

		Mean	*Std. Dev.*	*P25*	*Median*	*P75*
Parents	$Y_{i,t+1}$	0.0086	0.0921	0.0000	0.0000	0.0000
	$NROAI_{i,t}$	0.2554	0.4361	0.0000	0.0000	1.0000
	$ROA_{i,t}$	0.0468	0.1817	-0.0034	0.0267	0.0937
	$LTA_{i,t}$	0.5478	0.3223	0.2929	0.5547	0.7802
	$ETL_{i,t}$	0.0456	0.7074	-0.0143	0.0520	0.1825
	$LN(TA_{i,t})$	8.5727	2.3704	6.8985	8.3305	9.9882
	$BANKRATE_{i,t}$	0.5861	0.9667	0.1104	0.4249	0.7619
	$FGDPg_{i,t}$	0.0220	0.0169	0.0117	0.0200	0.0280
	$FINF_{i,t}$	0.0260	0.0242	0.0159	0.0190	0.0268
Subsidiaries	$Y_{i,t+1}$	0.0117	0.1074	0.0000	0.0000	0.0000
	$NROAI_{i,t}$	0.2720	0.4450	0.0000	0.0000	1.0000
	$ROA_{i,t}$	0.0378	0.1775	-0.0075	0.0250	0.0926
	$LTA_{i,t}$	0.6798	0.3841	0.4360	0.6851	0.8821
	$ETL_{i,t}$	0.1441	0.4701	-0.0063	0.0614	0.2140
	$LN(TA_{i,t})$	8.4468	2.2784	6.8741	8.3305	9.9087
	$BANKRATE_{i,t}$	0.6433	1.1398	0.1642	0.4249	0.8230
	$FGDPg_{i,t}$	0.0202	0.0160	0.0112	0.0182	0.0270
	$FINF_{i,t}$	0.0250	0.0971	0.0159	0.0190	0.0259
Standalones	$Y_{i,t+1}$	0.0051	0.0713	0.0000	0.0000	0.0000
	$NROAI_{i,t}$	0.2728	0.4454	0.0000	0.0000	1.0000
	$ROA_{i,t}$	0.0541	0.2075	-0.0054	0.0194	0.0880
	$LTA_{i,t}$	0.6491	0.3867	0.3662	0.6658	0.8923
	$ETL_{i,t}$	0.2618	0.8952	-0.0001	0.0628	0.2355
	$LN(TA_{i,t})$	6.4664	1.8788	5.2721	6.5972	7.7619
	$BANKRATE_{i,t}$	0.6943	1.8002	0.1040	0.4108	0.7977
	$FGDPg_{i,t}$	0.0247	0.0220	0.0091	0.0200	0.0408
	$FINF_{i,t}$	0.0363	0.0311	0.0169	0.0217	0.0400

Table OA-1 (continued)

Panel B: Coefficients

	Dependent variable: $Y_{i,t+1}$											
	BCM (2012) Model			Country/Industry/Time varying baseline			Macro Model			Fixed Effects Model		
	Parents	*Subsidiaries*	*Standalones*	*Parents*	*Subsidiaries*	*Standalones*	*Parents*	*Subsidiaries*	*Standalones*	*Parents*	*Subsidiaries*	*Standalones*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	-5.322***	-4.083***	-7.203***	-5.507***	-3.990***	-7.794***	-5.358***	-3.973***	-7.456***	-5.451***	-4.009***	-7.209***
	(-21.33)	(-7.68)	(-9.08)	(-19.42)	(-7.88)	(-9.35)	(-18.79)	(-10.76)	(-14.80)	(-21.62)	(-8.43)	(-7.68)
$NROAI_{i,t}$	0.446***	0.266***	0.047	0.459***	0.279***	0.054	0.397***	0.277***	0.034	0.461***	0.258***	0.110
	(3.72)	(4.09)	(0.18)	(4.03)	(5.13)	(0.17)	(3.88)	(7.44)	(0.11)	(3.98)	(3.41)	(0.49)
$ROA_{i,t}$	-0.845***	-0.787***	-1.275***	-0.943***	-0.837***	-1.522***	-1.016***	-0.838***	-1.550***	-0.996***	-0.818***	-1.274**
	(-3.02)	(-7.46)	(-2.66)	(-3.26)	(-7.21)	(-3.08)	(-3.84)	(-7.07)	(-2.91)	(-3.43)	(-10.56)	(-2.56)
$LTA_{i,t}$	1.390***	0.393***	1.059***	1.455***	0.396***	1.178***	1.409***	0.394***	1.188***	1.355***	0.388***	1.042**
	(11.25)	(4.48)	(2.64)	(10.86)	(4.60)	(2.66)	(10.65)	(4.66)	(2.62)	(10.78)	(4.26)	(2.34)
$ETL_{i,t}$	0.009	-0.241***	0.018	0.028	-0.211***	0.050	0.021	-0.210***	0.082	-0.041	-0.235***	0.043
	(0.11)	(-3.82)	(0.12)	(0.34)	(-4.25)	(0.26)	(0.27)	(-5.07)	(0.54)	(-0.48)	(-3.73)	(0.30)
$LN(TA_{i,t})$	-0.056**	-0.088***	0.171**	-0.050*	-0.111***	0.221***	-0.041	-0.111***	0.209***	-0.054**	-0.087***	0.142*
	(-2.16)	(-2.65)	(2.36)	(-1.75)	(-4.42)	(2.89)	(-1.40)	(-4.63)	(3.22)	(-2.02)	(-3.04)	(1.93)
$BANKRATE_{i,t}$				0.088	0.067	0.025	0.080	0.066	0.016			
				(0.83)	(1.23)	(1.46)	(0.73)	(1.20)	(1.31)			
$FGDPg_{i,t}$							-23.653***	-0.920	-5.779			
							(-2.58)	(-0.11)	(-0.55)			
$FINF_{i,t}$							10.122***	0.042	-4.616			
							(2.91)	(0.42)	(-0.44)			
Country FE	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Industry FE	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Obs.	640,627	1,412,890	614,178	594,890	1,309,173	560,166	592,809	1,307,415	560,137	638,531	1,407,529	607,352

Table OA-1 (continued)

Panel C: Predictive Power

Model	Decile	*Parents (N=527,063)* (1)	(2)	(3)	*Subsidiaries (N=1,165,149)* (1)	(2)	(3)	*Standalones (N=499,171)* (1)	(2)	(3)
BCM (2012) Model	0	29.80	16.47	9.51	23.12	15.01	9.52	28.06	25.77	9.66
	1	17.12	16.20	9.64	15.35	13.80	9.70	14.03	16.26	9.88
	2	12.61	13.71	9.80	10.93	11.58	9.89	11.48	13.35	9.94
	Total	59.53	46.38	28.95	49.40	40.39	29.11	53.57	55.38	29.48
	AUC	0.7055			0.6485			0.6309		
Country/Industry/Time varying baseline	0	30.36	17.02	9.48	23.44	16.03	9.45	27.66	27.44	9.64
	1	17.45	15.72	9.66	15.38	13.89	9.69	14.23	16.59	9.88
	2	11.84	13.55	9.82	11.25	12.66	9.82	11.08	12.03	9.96
	Total	59.65	46.29	28.96	50.07	42.58	28.96	52.97	56.06	29.47
	AUC	0.7330			0.7185			0.6487		
Macro Model	0	32.81	19.00	9.36	22.67	16.47	9.43	27.38	28.25	9.62
	1	17.49	17.07	9.60	14.65	14.30	9.68	14.47	17.32	9.86
	2	12.42	13.45	9.82	11.02	12.13	9.86	9.92	12.49	9.96
	Total	62.72	49.52	28.78	48.34	42.91	28.97	51.77	58.06	29.45
	AUC	0.7355			0.6998			0.6310		
Fixed Effects Model	0	31.93	18.48	9.39	22.38	14.92	9.53	27.54	23.46	9.70
	1	16.77	17.25	9.60	14.82	13.39	9.73	12.40	15.09	9.91
	2	12.50	14.29	9.78	12.00	11.62	9.87	9.96	11.44	9.98
	Total	61.19	50.03	28.77	49.20	39.92	29.14	49.90	49.99	29.58
	AUC	0.7193			0.6330			0.6054		

Panel D: Significance of AUC differences

	p-values Parents	Subsidiaries	Standalones
BCM (2012) Model vs. Country/Industry/Time varying baseline	0.0000	0.0000	0.0000
Macro Model vs. Country/Industry/Time varying baseline	0.2871	0.0000	0.0000
Fixed Effects Model vs. Country/Industry/Time varying baseline	0.0000	0.0000	0.0000

Table OA-1 (continued)

Panel E: Predictive Power Public vs. Private

		Parents						Subsidiaries					
		Private			*Public*			*Private*			*Public*		
		(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Country/Industry/Time varying baseline Pooled estimation	0	29.31	16.27	9.47	32.23	18.25	9.50	23.46	15.98	9.45	26.63	17.08	9.48
	1	16.1	14.99	9.68	18.97	17.94	9.61	15.51	13.52	9.71	15.00	15.37	9.68
	2	12.36	12.89	9.83	11.31	14.56	9.81	11.12	12.47	9.83	11.50	12.88	9.84
	Total	57.77	44.15	28.98	62.51	50.75	28.92	50.09	41.97	28.99	53.13	45.33	29.00
	AUC	0.7193			0.7496			0.7142			0.7511		
Country/Industry/Time varying baseline Public vs. Private partition-specific coefficients	0	30.46	16.21	9.46	33.40	21.54	9.36	23.09	15.43	9.49	27.52	18.33	9.40
	1	15.86	14.89	9.69	17.48	16.19	9.70	15.33	13.66	9.70	14.05	14.47	9.74
	2	11.55	12.55	9.85	12.35	14.75	9.79	11.12	12.03	9.86	11.34	12.2	9.88
	Total	57.87	43.65	29.00	63.23	52.48	28.85	49.54	41.12	29.05	52.91	45.00	29.02
	AUC	0.7188			0.7541			0.7126			0.7460		

Panel A presents descriptive statistics for the variables included in the default prediction models estimated using the *Estimation Sample* (see Table OA-2, Panel A). Panel B reports coefficients and (in parentheses) z-statistics from the estimation of four different discrete hazard models. The dependent variable is equal to one if firm i (parent, subsidiary, or standalone) files for bankruptcy in year $t+1$, and zero otherwise. Heteroskedasticity-robust standard errors are clustered at the country and year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Panel C presents a comparison between the predictive ability of the four models estimated out-of-sample. Column (1) reports the percentage of bankrupt firm-years that fall in each of the top three deciles of the predicted bankruptcy probability, Column (2) reports the percentage of years before bankruptcy, and Column (3) reports the percentage of non-bankrupt years. The Area Under the Receiver Operating Curve (AUC) is also reported. Panel D reports the p-values for the comparison of the AUC of the different models. Panel E compares the predictive ability of the Country/Industry/Time varying baseline model for public and private firms. We first estimate a single set of coefficients based on the pooled *Estimation Sample* and then estimate separate sets of coefficients for private and public firms. All variables are defined in the paper Appendix. The subscript i refers to parent, subsidiary, or standalone firms.

Table OA-2: Sample Selection and Descriptive Statistics

Panel A: Sample Selection Criteria

Estimation Sample

This sample comprises parents (ultimate owners), subsidiaries (levels 1 to 5) and standalone firms with total assets and sales greater than U.S. $10,000, excluding *Other legal form* entities, *Museums and educational services*, *Private households*, *Membership organizations* (SIC codes 8000-8999) and *Public services* (SIC code 9000-9999). This sample includes three types of observations: non-bankrupt firms, years before bankruptcy for bankrupt firms and bankruptcy year.

	Unique Obs.	*Firm-Year Obs.*
- Parents	105,999	640,627
- Subsidiaries	237,319	1,412,890
- Standalones	117,764	614,178

Base Model Sample

This sample limits the *Estimation Sample* to the subset of business group firms (parents and subsidiaries) for which ownership information to compute control rights is available. In the *Base Model Sample* of subsidiary firm-years, only the parent with the highest percentage of control in each subsidiary is retained.

	Firm-Year Obs.
- Parents	350,452
- Subsidiaries	928,162

Placebo Test Sample

This sample limits the *Base-Model Sample* to the subset of parents and subsidiaries for which a successful match with pseudo-parents and pseudo-subsidiaries obtains. Pseudo-parents and pseudo-subsidiaries are, respectively, median-sized standalone firms from the same country-industry of parents and subsidiaries.

	Firm-Year Obs.
- Parents (and matched pseudo-parents)	255,102
- Subsidiaries (and matched pseudo-subsidiaries)	510,581
- All standalones used in the placebo tests	544,704

Combined Model Sample

This sample limits the *Base Model Sample* to the subset of publicly-listed parents and subsidiaries with available data to compute market variables.

	Firm-Year Obs.
- Parents	31,051
- Subsidiaries	23,422

CDS Sample

This sample limits the *Base Model Sample* to the subset of parents and subsidiaries with available 5-year CDS contract data.

	Firm-Year Obs.
- Parents	3,377
- Subsidiaries	1,198

Table OA-2 (continued)

Panel B: Sample Composition by Country

Country	Parents		Subsidiaries		Standalones	
	Obs.	%	Obs.	%	Obs.	%
Algeria	0	0.00	21	0.00	0	0.00
Argentina	58	0.02	505	0.05	0	0.00
Australia	787	0.22	977	0.11	255	0.05
Austria	384	0.11	2,138	0.23	578	0.11
Bahamas	8	0.00	0	0.00	0	0.00
Bahrain	11	0.00	17	0.00	0	0.00
Bangladesh	3	0.00	10	0.00	0	0.00
Barbados	5	0.00	16	0.00	0	0.00
Belgium	7,835	2.24	27,911	3.01	1,245	0.23
Bermuda	151	0.04	189	0.02	0	0.00
Bolivia	0	0.00	7	0.00	0	0.00
Bosnia and Herzegovina	251	0.07	1,113	0.12	9,414	1.73
Botswana	6	0.00	13	0.00	0	0.00
Brazil	375	0.11	1,462	0.16	37	0.01
Bulgaria	1,259	0.36	3,654	0.39	2,883	0.53
Burkina Faso	0	0.00	1	0.00	0	0.00
Canada	785	0.22	934	0.10	1,046	0.19
Cayman Islands	69	0.02	178	0.02	7	0.00
Chile	67	0.02	156	0.02	0	0.00
China	1,366	0.39	2,503	0.27	2,183	0.40
Colombia	902	0.26	2,217	0.24	5,393	0.99
Costa Rica	0	0.00	6	0.00	0	0.00
Côte d’Ivoire	3	0.00	24	0.00	0	0.00
Croatia	1,346	0.38	3,656	0.39	618	0.11
Curaçao	12	0.00	6	0.00	0	0.00
Cyprus	96	0.03	140	0.02	36	0.01
Czech Republic	5,454	1.56	14,368	1.55	10,930	2.01
Denmark	3,820	1.09	7,600	0.82	213	0.04
Dominica	0	0.00	5	0.00	0	0.00
Ecuador	10	0.00	17	0.00	8	0.00
Egypt	43	0.01	102	0.01	18	0.00
El Salvador	0	0.00	9	0.00	0	0.00
Estonia	1,228	0.35	5,020	0.54	2,237	0.41
Fiji	6	0.00	6	0.00	0	0.00
Finland	10,996	3.14	25,143	2.71	1,347	0.25
France	89,242	25.46	208,946	22.51	40,810	7.49
Gabon	0	0.00	7	0.00	0	0.00
Germany	3,558	1.02	17,313	1.87	5,106	0.94
Ghana	0	0.00	14	0.00	0	0.00
Gibraltar	10	0.00			0	0.00
Greece	1,305	0.37	4,552	0.49	3,165	0.58
Guatemala	2	0.00	5	0.00	0	0.00
Guyana	0	0.00	6	0.00	0	0.00
Hong Kong	53	0.02	82	0.01	0	0.00
Hungary	132	0.04	304	0.03	95	0.02
Iceland	585	0.17	1,130	0.12	1,422	0.26
India	1,999	0.57	7,242	0.78	3,983	0.73
Indonesia	52	0.01	183	0.02	0	0.00
Iran	0	0.00	1	0.00	0	0.00
Ireland	357	0.10	798	0.09	1,732	0.32

(continued)

Table OA-2 (continued)

(continued)

Country	Parents		Subsidiaries		Standalones	
	Obs.	%	Obs.	%	Obs.	%
Israel	259	0.07	241	0.03	36	0.01
Italy	21,580	6.16	78,920	8.50	130,649	23.99
Jamaica	18	0.01	17	0.00	0	0.00
Japan	11,980	3.42	47,637	5.13	1,029	0.19
Jordan	124	0.04	311	0.03	30	0.01
Kazakhstan	9	0.00	31	0.00	9	0.00
Kenya	9	0.00	39	0.00	0	0.00
Korea	1,798	0.51	5,885	0.63	19,238	3.53
Kuwait	142	0.04	242	0.03	10	0.00
Latvia	355	0.10	737	0.08	477	0.09
Liberia	4	0.00	7	0.00	0	0.00
Lithuania	240	0.07	1,282	0.14	598	0.11
Luxembourg	607	0.17	1,574	0.17	222	0.04
Macedonia	12	0.00	17	0.00	0	0.00
Malaysia	302	0.09	425	0.05	3,966	0.73
Malta	151	0.04	397	0.04	20	0.00
Marshall Islands	12	0.00	3	0.00	0	0.00
Mauritius	22	0.01	28	0.00	2	0.00
Mexico	220	0.06	923	0.10	0	0.00
Moldova	26	0.01	50	0.01	23	0.00
Monaco	0	0.00	6	0.00	0	0.00
Montenegro	7	0.00	34	0.00	0	0.00
Morocco	1	0.00	32	0.00	3	0.00
Namibia	0	0.00	2	0.00	0	0.00
Nepal	0	0.00	8	0.00	0	0.00
Netherlands	6,626	1.89	12,414	1.34	238	0.04
New Zealand	20	0.01	362	0.04	7	0.00
Nigeria	12	0.00	88	0.01	0	0.00
Norway	5,457	1.56	29,760	3.21	16,903	3.10
Oman	42	0.01	84	0.01	0	0.00
Pakistan	66	0.02	172	0.02	152	0.03
Palestine	12	0.00	60	0.01	0	0.00
Panama	5	0.00	6	0.00	0	0.00
Paraguay	0	0.00	4	0.00	0	0.00
Peru	21	0.01	71	0.01	0	0.00
Philippines	19	0.01	102	0.01	0	0.00
Poland	3,526	1.01	15,784	1.70	6,991	1.28
Portugal	10,131	2.89	30,152	3.25	43,787	8.04
Qatar	6	0.00	13	0.00	0	0.00
Romania	1,101	0.31	6,341	0.68	9,797	1.80
Russia	12,300	3.51	30,456	3.28	96,136	17.65
Saudi Arabia	68	0.02	72	0.01	1	0.00
Serbia	471	0.13	3,018	0.33	2,323	0.43
Singapore	202	0.06	287	0.03	7	0.00
Slovakia	827	0.24	2,911	0.31	2,295	0.42
Slovenia	603	0.17	2,680	0.29	2,418	0.44
South Africa	139	0.04	122	0.01	0	0.00
Spain	48,606	13.87	124,552	13.42	61,073	11.21
Sri Lanka	90	0.03	261	0.03	0	0.00
Sweden	57,859	16.51	112,223	12.09	1,415	0.26

(continued)

Table OA-2 (continued)

(continued)

Country	Parents		Subsidiaries		Standalones	
	Obs.	%	Obs.	%	Obs.	%
Switzerland	634	0.18	527	0.06	74	0.01
Taiwan	2,338	0.67	3,379	0.36	151	0.03
Tanzania	0	0.00	7	0.00	0	0.00
Thailand	144	0.04	359	0.04	2,130	0.39
Trinidad and Tobago	4	0.00	12	0.00	0	0.00
Tunisia	0	0.00	14	0.00	0	0.00
Turkey	196	0.06	700	0.08	237	0.04
Ukraine	8,483	2.42	15,146	1.63	8,358	1.53
United Arab Emirates	19	0.01	10	0.00	0	0.00
United Kingdom	13,081	3.73	55,422	5.97	38,279	7.03
United States	4,748	1.35	865	0.09	795	0.15
Uruguay	0	0.00	2	0.00	0	0.00
Venezuela	11	0.00	19	0.00	0	0.00
Vietnam	53	0.02	114	0.01	64	0.01
Virgin Islands	23	0.01	24	0.00	0	0.00
Zambia	0	0.00	7	0.00	0	0.00
Zimbabwe	0	0.00	5	0.00	0	0.00
Total	350,452	100.00	928,162	100.00	544,704	100.00

Panel C: Firm-Year Observations by Year

Year	Parents		Subsidiaries		Standalones	
	Obs.	%	Obs.	%	Obs.	%
2006	34,369	9.81	88,812	9.57	59,739	10.97
2007	39,941	11.40	104,156	11.22	69,859	12.82
2008	45,176	12.89	118,558	12.77	74,771	13.73
2009	50,265	14.34	133,848	14.42	82,105	15.07
2010	57,040	16.28	151,614	16.33	84,731	15.56
2011	60,467	17.25	161,420	17.39	85,213	15.64
2012	63,194	18.03	169,754	18.29	88,293	16.21
Total	350,452	100.00	928,162	100.00	544,711	100.00

Panel D: Firm-Year Observations by Industry

One-Digit SIC Code	Parents		Subsidiaries		Standalones	
	Obs.	%	Obs.	%	Obs.	%
0: Agriculture, forestry and fishery	6,897	1.97	18,679	2.01	21,382	3.93
1: Mining and construction	32,315	9.22	113,172	12.19	78,551	14.42
2: Light manufactured products	22,745	6.49	81,063	8.73	48,151	8.84
3: Heavy manufactured products	31,453	8.97	115,724	12.47	60,257	11.06
4: Transportation, communications, electric, gas and sanitary services	18,779	5.36	91,950	9.91	32,346	5.94
5: Wholesale and retail trade	55,107	15.72	224,341	24.17	140,756	25.84
6: Finance, insurance and real estate	144,378	41.20	151,693	16.34	94,742	17.39
7: Services	38,778	11.07	131,540	14.17	68,526	12.58
Total	350,452	100.00	928,162	100.00	544,711	100.00

Table OA-2 (continued)

Panel E: Descriptive Statistics for Variables Used in the Main Models

	Obs.	Mean	Std. Dev.	P25	Median	P75
<u>*Parent-level variables*</u>:						
$Y_{p,t+1}$	350,452	0.0085	0.0920	0.0000	0.0000	0.0000
$NROAI_{p,t}$	350,452	0.2359	0.4245	0.0000	0.0000	0.0000
$ROA_{p,t}$	350,452	0.0569	0.1452	0.0000	0.0281	0.0925
$LTA_{p,t}$	350,452	0.5272	0.3076	0.2783	0.5382	0.7610
$ETL_{p,t}$	350,452	0.0962	0.4863	-0.0096	0.0493	0.1685
$LN(TA_{p,t})$	350,452	8.6888	2.3676	7.0139	8.3974	10.0180
$BANKRATE_{p,t}$	350,452	0.6208	0.9153	0.1831	0.5005	0.8163
$\overline{Pr(Y_{s,t+1})}$	310,181	0.0051	0.0034	0.0028	0.0045	0.0064
$\bar{Y}_{s,t}$	302,462	0.0162	0.1262	0.0000	0.0000	0.0000
$D2D_{p,t}$	29,342	3.9704	2.4709	2.1811	3.5769	5.2768
$VOL_{p,t}$	31,773	0.4397	0.2248	0.2902	0.3910	0.5344
$RSIZE_{p,t}$	31,365	-8.7569	2.2121	-10.3367	-8.9025	-7.2893
$RET_{p,t}$	31,774	-0.1450	0.4046	-0.3927	-0.1594	0.0560
$\overline{Pr(Y_{stdln,t+1})}$	287,274	0.0030	0.0019	0.0016	0.0029	0.0041
$\bar{Y}_{stdln,t}$	278,919	0.0109	0.1038	0.0000	0.0000	0.0000
<u>*Subsidiary-level variables*</u>:						
$Y_{s,t+1}$	928,162	0.0115	0.1066	0.0000	0.0000	0.0000
$NROAI_{s,t}$	928,162	0.2807	0.4494	0.0000	0.0000	1.0000
$ROA_{s,t}$	928,162	0.0323	0.1698	-0.0091	0.0216	0.0841
$LTA_{s,t}$	928,162	0.6827	0.3868	0.4414	0.6888	0.8841
$ETL_{s,t}$	928,162	0.1271	0.4588	-0.0083	0.0559	0.1972
$LN(TA_{s,t})$	928,162	8.2471	2.1952	6.7499	8.1411	9.6525
$BANKRATE_{s,t}$	928,162	0.6433	1.0310	0.1791	0.4648	0.8597
$Pr(Y_{p,t+1})$	823,764	0.0030	0.0026	0.0013	0.0024	0.0039
$\overline{Pr(Y_{others,t+1})}$	650,943	0.0046	0.0027	0.0025	0.0044	0.0060
$Y_{p,t}$	855,821	0.0039	0.0622	0.0000	0.0000	0.0000
$\overline{Y}_{others,t}$	660,058	0.0059	0.0448	0.0000	0.0000	0.0000
$D2D_{p,t}$	23,422	3.6421	2.3208	1.9693	3.2660	4.8975
$VOL_{p,t}$	25,773	0.4887	0.2800	0.3096	0.4240	0.5827
$RSIZE_{p,t}$	15,653	-7.7777	2.4532	-9.6165	-7.9934	-6.1811
$RET_{p,t}$	25,754	-0.1138	0.4407	-0.3908	-0.1597	0.0776
$Pr(Y_{stdln,t+1})$	673,764	0.0032	0.0020	0.0018	0.0030	0.0042
$\bar{Y}_{stdln,t}$	694,606	0.0063	0.0790	0.0000	0.0000	0.0000

This table presents sample selection criteria, sample composition and descriptive statistics for the sample of parent, subsidiary and standalone firm-year observations. Panel A presents the sample selection criteria. We build five different samples: (1) the *Estimation Sample* of parent, subsidiary and standalone firm-year observations; (2) the *Base Model Sample*; (3) the *Placebo Test Sample*; (4) the *Combined Model Sample*; and (5) the *CDS Sample*. Panels B, C and D respectively present the distribution of observations by country, year and industry for the *Base Model Sample* containing the subset of observations from the *Estimation Sample* (Table OA-1) for which ownership information to compute control rights is available. Panel E presents descriptive statistics for the variables used in the main default prediction models. All variables are defined in the paper Appendix. The subscripts p, s, and *stdln* are used to identify parent-, subsidiary-, and standalone-level variables, respectively.

Table OA-3: Placebo Test - Parent Model

		Dependent variable: $Y_{p,t+1}$	
Independent variables:		(1)	(2)
Intercept		-5.642***	-5.647***
		(-12.74)	(-12.74)
$NROAI_{p,t}$	(+)	0.288***	0.288***
		(2.78)	(2.78)
$ROA_{p,t}$	(–)	-2.563***	-2.564***
		(-8.99)	(-9.03)
$LTA_{p,t}$	(+)	1.690***	1.689***
		(9.12)	(9.12)
$ETL_{p,t}$	(–)	-0.193	-0.193
		(-1.41)	(-1.41)
$LN(TA_{p,t})$	(–)	-0.067**	-0.067**
		(-2.04)	(-2.04)
$BANKRATE_{p,t}$	(+)	0.154*	0.156*
		(1.79)	(1.83)
$\overline{Pr(Y_{stdln,t+1})}$	(NS)	104.566	104.734
		(1.48)	(1.49)
$\bar{Y}_{stdln,t}$	(NS)		-0.214
			(-0.55)
Comp. Model		Model (1) without $\overline{Pr(Y_{stdln,t+1})}$	Model (1) without $\overline{Pr(Y_{stdln,t+1})}$ and $\bar{Y}_{stdln,t}$
AUC		0.7404	0.7404
AUC (Comp. Model)		0.7511	0.7511
p-value (vs. Comp. Model)		0.0000	0.0000
% Top Three Deciles		64.17	63.91
% Top Three Deciles (Comp. Model)		64.64	64.64
Obs.		255,102	255,102

This table reports the results of a placebo test in which each subsidiary is replaced by the median-sized standalone firm in the same country-industry. The sample is limited to observations for which a successful match with standalone firms from the same country-industry obtains (*Placebo Test Sample*). All variables are defined in the paper Appendix. Heteroskedasticity-robust standard errors are clustered at the parent-country and year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively. The subscripts p and $stdln$ are used to identify parent- and standalone-level variables, respectively.

Table OA-4: Augmented Parent Combined Model

Panel A: Parent Hazard Model

		Dependent variable: $Y_{p,t+1}$			
Independent variables:		(1)	(2)	(3)	(4)
Intercept		-4.519***	-5.889***	-8.282***	-9.652***
		(-4.80)	(-4.77)	(-4.22)	(-4.59)
$NROAI_{p,t}$	(+)	-0.535	-0.559	-0.403	-0.372
		(-1.15)	(-1.17)	(-0.65)	(-0.59)
$ROA_{p,t}$	(–)	-9.213***	-8.513***	-8.461***	-6.972***
		(-4.90)	(-4.57)	(-4.70)	(-3.60)
$LTA_{p,t}$	(+)	1.160*	1.215*	2.006***	2.069***
		(1.70)	(1.96)	(4.51)	(4.71)
$ETL_{p,t}$	(–)	0.871**	1.076**	0.902**	0.907**
		(2.12)	(2.02)	(2.39)	(2.13)
$LN(TA_{p,t})$	(–)	-0.075	-0.010	-0.002	0.068
		(-0.77)	(-0.09)	(-0.01)	(0.49)
$BANKRATE_{p,t}$		0.083***	0.090***	0.100**	0.139***
		(3.20)	(4.49)	(2.42)	(3.06)
$D2D_{p,t}$	(–)	-0.474***	-0.451***		
		(-2.99)	(-3.06)		
$VOL_{p,t}$				1.556***	1.519***
				(3.59)	(4.19)
$RSIZE_{p,t}$				0.006	-0.001
				(0.08)	(-0.01)
$RET_{p,t}$	(+)			-0.852*	-0.954*
				(-1.73)	(-1.75)
$\overline{Pr(Y_{s,t+1})}$	(+)		106.950***		96.918***
			(5.23)		(3.98)
Marginal effects:					
$\overline{Pr(Y_{s,t+1})}$			0.108		0.1386
Obs.		29,342	26,047	31,051	27,488

Table OA-4 (continued)

Panel B: Predictive Ability

Model	Decile	(1)	(2)	(3)
Model (1)	0	70.15	39.59	9.47
	1	5.97	16.38	9.93
	2	2.99	8.19	10.04
	Total	79.10	64.16	29.45
	AUC	0.8377		
Model (2)	0	70.15	37.20	9.50
	1	7.46	15.70	9.94
	2	4.48	11.26	10.00
	Total	82.09	64.16	29.44
	AUC	0.8552		
	p-value (vs. Model (1))	0.0783		
Model (3)	0	63.77	39.63	9.47
	1	11.59	12.38	9.97
	2	7.25	9.91	10.01
	Total	82.61	61.92	29.45
	AUC	0.8483		
Model (4)	0	75.36	36.84	9.48
	1	2.90	11.15	10.01
	2	5.80	9.60	10.02
	Total	84.06	57.59	29.50
	AUC	0.8761		
	p-value (vs. Model (3))	0.0215		

This table presents the results of the parent default prediction analysis for the *Combined Model Sample* (see Table OA-2, Panel A) of publicly listed parent firms using a model that combines accounting and market data. The number of observations decreases with respect to the specification presented in Table 1, Panel A in the paper, due to data availability requirements on distance to default and remaining market variables. Panel A reports coefficients and (in parentheses) z-statistics from the estimation of a discrete hazard model. The dependent variable is equal to one if the parent files for bankruptcy in year $t+1$, and zero otherwise. The specification presented in Column (1) includes parent-level financial ratios and parent-level distance to default only: $Pr(Y_{p,t+1}=1)=f(NROAI_{p,t}, ROA_{p,t}, LTA_{p,t}, ETL_{p,t}, LN(TA_{p,t}), D2D_{p,t}, BANKRATE_{p,t})$. Column (2) adds the average estimated bankruptcy probability of all group subsidiaries ($\overline{\Pr(Y_{s,t+1})}$). In Column (3) the distance to default measure ($D2D_{p,t}$) is replaced by the volatility of the parent's returns ($VOL_{p,t}$), the parent's market capitalization relative to its country total market capitalization ($RSIZE_{p,t}$), and the parent's returns over the previous year ($RET_{p,t}$). Column (4) adds the average estimated bankruptcy probability of all group subsidiaries ($\overline{Pr(Y_{s,t+1})}$) to the specification presented in Column (3). Marginal effects for group-level variables are reported as the change in estimated bankruptcy probability as each of the group-level variables increases by one standard deviation, scaled by the average estimated bankruptcy probability. Heteroskedasticity-robust standard errors are clustered at the parent-country and year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Panel B presents a comparison between the predictive power of the augmented models and that of the base models reported in Columns (1) and (3) using constant samples. Columns (1), (2) and (3) present the percentage of bankrupt years, years before bankruptcy and non-bankrupt firm-years falling in each of the top three deciles. The Area Under the Receiver Operating Characteristic Curve (AUC) is also reported for each subgroup. All variables are defined in the paper Appendix. The subscripts p and s are used to identify parent- and subsidiary-level variables, respectively.

Table OA-5: Augmented Parent Model by Capital Market Development, Rule of Law and Financial Reporting Transparency

Panel A: Augmented Parent Model by Parent-Country Capital Market Development and Financial Reporting Transparency

	Parent-Country Capital Market Development			
	Weak		*Strong*	
	Financial Reporting Transparency		Financial Reporting Transparency	
	Low	*High*	*Low*	*High*
	(1)	(2)	(3)	(4)
Model	$Pr(Y_{p,t+1} = 1) = f\left(NROAI_{p,t}, ROA_{p,t}, LTA_{p,t}, ETL_{p,t}, LN(TA_{p,t}), BANKRATE_{p,t}, \overline{Pr(Y_{s,t+1})}\right)$			
Comp. Model	Model (1) without $\overline{Pr(Y_{s,t+1})}$	Model (2) without $\overline{Pr(Y_{s,t+1})}$	Model (3) without $\overline{Pr(Y_{s,t+1})}$	Model (4) without $\overline{Pr(Y_{s,t+1})}$
AUC	0.7337	0.7856	0.6741	0.8373
AUC (Comp. Model)	0.7158	0.7821	0.6631	0.8407
p-value (vs. Comp. Model)	0.0000	0.1469	0.0109	0.1069
% Top Three Deciles	66.43	80.00	52.00	81.88
% Top Three Deciles (Comp. Model)	61.54	78.57	52.00	79.55

Panel B: Augmented Parent Model by Parent-Country Rule of Law and Financial Reporting Transparency

	Parent-Country Rule of Law			
	Weak		*Strong*	
	Financial Reporting Transparency		Financial Reporting Transparency	
	Low	*High*	*Low*	*High*
	(1)	(2)	(3)	(4)
Model	$Pr(Y_{p,t+1} = 1) = f\left(NROAI_{p,t}, ROA_{p,t}, LTA_{p,t}, ETL_{p,t}, LN(TA_{p,t}), BANKRATE_{p,t}, \overline{Pr(Y_{s,t+1})}\right)$			
Comp. Model	Model (5) without $\overline{Pr(Y_{s,t+1})}$	Model (6) without $\overline{Pr(Y_{s,t+1})}$	Model (7) without $\overline{Pr(Y_{s,t+1})}$	Model (8) without $\overline{Pr(Y_{s,t+1})}$
AUC	0.6422	0.7818	0.7392	0.8126
AUC (Comp. Model)	0.6206	0.7809	0.7319	0.8132
p-value (vs. Comp. Model)	0.0159	0.6929	0.0000	0.1586
% Top Three Deciles	80.00	66.43	81.88	52.00
% Top Three Deciles (Comp. Model)	78.57	61.54	79.55	52.00

This table presents the results of an additional analysis based on the tests shown in Table 2 of the paper. Specifically, Panels A and B present sample partitions based on capital market development (computed as ratio of total market capitalization of all firms in a country to the country's GDP. Source: World Bank) and rule of law (Kaufmann et al., 2009), respectively. In this analysis, the *Base Model Sample* (see Table OA-2, Panel A) is limited to parents for which consolidated financial statements are available and to subsidiaries that are consolidated, i.e., in which the parent's control rights are equal to, or higher than, 50%. We classify a country as having high (low) financial reporting transparency if it falls in the Leuz (2010) institutional clusters 1 or 2 (3, 4, or 5). A parent country is classified as having strong (weak) capital market development and rule of law if the country's capital market development and rule of law indices are above (below) the respective sample medians. The dependent variable is equal to one if the parent files for bankruptcy in year $t + 1$, and zero otherwise. The Area Under the Receiver Operating Characteristic Curve (AUC) and the percentage of bankrupt years in the top three deciles are reported for each sample partition, as is the p-value for the increase in the AUC in the augmented model. Heteroskedasticity-robust standard errors are clustered at the parent-country and year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively. All variables are defined in the paper Appendix. The subscripts p and s are used to identify parent- and subsidiary-level variables, respectively.

Table OA-6: Placebo Test - Subsidiary Model

		Dependent variable: $Y_{s,t+1}$			
Independent variables:		(2)	(3)	(4)	(5)
Intercept		-4.124***	-5.039***	-4.129***	-5.040***
		(-6.78)	(-8.75)	(-6.93)	(-8.85)
$NROAI_{s,t}$	(+)	0.322***	0.256***	0.318***	0.254***
		(6.93)	(4.32)	(6.72)	(4.23)
$ROA_{s,t}$	(–)	-0.785***	-0.716***	-0.807***	-0.733***
		(-4.52)	(-3.74)	(-5.23)	(-4.10)
$LTA_{s,t}$	(+)	0.440***	0.320***	0.448***	0.323***
		(4.63)	(3.15)	(4.95)	(3.37)
$ETL_{s,t}$	(–)	-0.206***	-0.172***	-0.197***	-0.162***
		(-5.13)	(-4.25)	(-4.70)	(-3.80)
$LN(TA_{s,t})$	(–)	-0.133***	-0.087**	-0.132***	-0.088**
		(-3.38)	(-2.30)	(-3.47)	(-2.37)
$BANKRATE_{s,t}$	(+)	0.126**	0.120**	0.116*	0.109*
		(1.98)	(2.05)	(1.76)	(1.82)
$Pr(Y_{stdln,t+1})$	(NS)	80.708	25.969	79.915	26.686
		(1.48)	(0.73)	(1.49)	(0.78)
$\overline{Pr(Y_{others,t+1})}$	(+)		151.786***		152.722***
			(7.18)		(7.02)
$\overline{Y_{others,t}}$	(+)			1.686***	2.408***
				(15.45)	(8.94)
Comp. Model		Model (2) without $Pr(Y_{stdln,t+1})$	Model (3) without $Pr(Y_{stdln,t+1})$	Model (4) without $Pr(Y_{stdln,t+1})$	Model (5) without $Pr(Y_{stdln,t+1})$
AUC		0.6989	0.7064	0.7007	0.7082
AUC (Comp. Model)		0.7152	0.7162	0.7170	0.7181
p-value (vs. Comp. Model)		0.0000	0.0000	0.0000	0.0000
% Top Three Deciles		50.55	51.96	50.88	52.13
% Top Three Deciles (Comp. Model)		51.15	52.99	51.75	53.07
Obs.		510,581	510,581	484,321	481,807

This table reports the results of a placebo test in which each parent is replaced by the median-sized standalone firm in the same country-industry. The sample is limited to observations for which a successful match with standalone firms from the same country-industry obtains (*Placebo Test Sample*). All variables are defined in the paper Appendix. Heteroskedasticity-robust standard errors are clustered at the subsidiary-country and year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively. The subscripts s and $stdln$ are used to identify subsidiary- and standalone-level variables, respectively.

Table OA-7: Augmented Subsidiary Combined Model

Panel A: Subsidiary Hazard Model

		Dependent variable: $Y_{s,t+1}$					
Independent variables:		(1)	(2)	(3)	(4)	(5)	(6)
Intercept		-6.345***	-8.446***	-8.692***	-7.125	-7.877	-10.100**
		(-6.59)	(-9.08)	(-9.80)	(-1.64)	(-1.53)	(-2.12)
$NROAI_{s,t}$	(+)	0.022	-0.056	-0.085	-0.065	-0.206	-0.196
		(0.18)	(-0.37)	(-0.40)	(-0.23)	(-0.75)	(-0.66)
$ROA_{s,t}$	(–)	-3.923***	-3.947***	-3.518***	-3.545***	-3.567***	-3.285***
		(-5.15)	(-5.71)	(-4.20)	(-5.74)	(-4.45)	(-3.52)
$LTA_{s,t}$	(+)	0.480	0.543*	0.775**	0.653**	0.538*	0.749
		(1.53)	(1.79)	(2.14)	(2.40)	(1.88)	(1.51)
$ETL_{s,t}$	(–)	0.091	0.053	0.040	0.155	0.115	0.268
		(0.21)	(0.10)	(0.06)	(0.71)	(0.43)	(0.88)
$LN(TA_{s,t})$	(–)	0.118	0.221***	0.220***	0.060	0.098	0.175
		(1.54)	(2.71)	(2.88)	(0.22)	(0.31)	(0.62)
$BANKRATE_{s,t}$	(+)	0.036**	0.078***	0.068***	0.047	0.077	0.086*
		(2.27)	(3.27)	(2.90)	(1.37)	(1.33)	(1.66)
$D2D_{s,t}$		-0.412***	-0.320***	-0.333***			
		(-4.02)	(-3.28)	(-2.60)			
$VOL_{s,t}$					0.613	0.272	-0.220
					(1.26)	(0.41)	(-0.24)
$RSIZE_{s,t}$					0.025	0.019	-0.089
					(0.17)	(0.12)	(-0.73)
$RET_{s,t}$					-0.556**	-0.551*	-0.565*
					(-2.20)	(-1.96)	(-1.95)
$Pr(Y_{p,t+1})$	(+)		234.288***	155.592***		220.323***	119.168**
			(45.05)	(8.41)		(5.71)	(2.55)
$\overline{Pr(Y_{others,t+1})}$	(+)			97.710**			183.728***
				(2.20)			(2.97)
Marginal Effects:							
$Pr(Y_{p,t+1})$			0.209	0.138		0.290	0.143
$\overline{Pr(Y_{others,t+1})}$				0.107			0.282
Obs.		23,422	20,815	18,250	15,429	13,059	11,101

Table OA-7 (continued)

Panel B: Predictive Ability

Model	Decile	(1)	(2)	(3)
Model (1)	0	43.84	33.92	9.45
	1	16.44	16.25	9.88
	2	4.11	9.19	10.04
	Total	64.38	59.36	29.37
	AUC	0.7523		
Model (2)	0	41.10	40.28	9.35
	1	15.07	11.66	9.96
	2	12.33	9.19	10.01
	Total	68.49	61.13	29.32
	AUC	0.7894		
	p-value (vs. Model (1))	0.0110		
Model (3)	0	41.10	38.87	9.38
	1	15.07	13.07	9.93
	2	12.33	8.13	10.03
	Total	68.49	60.07	29.34
	AUC	0.7965		
	p-value (vs. Model (1))	0.0016		
Model (4)	0	35.90	28.71	9.71
	1	10.26	11.88	9.98
	2	5.13	7.92	10.05
	Total	51.28	48.51	29.73
	AUC	0.6609		
Model (5)	0	30.77	27.72	9.74
	1	5.13	14.85	9.97
	2	23.08	9.90	9.97
	Total	58.97	52.48	29.67
	AUC	0.7606		
	p-value (vs. Model (4))	0.0060		
Model (6)	0	33.33	30.69	9.70
	1	15.38	15.84	9.92
	2	2.56	6.93	10.07
	Total	51.28	53.47	29.69
	AUC	0.7859		
	p-value (vs. Model (4))	0.0012		

This table presents the results of the subsidiary default prediction analysis for the *Combined Model Sample* (see Table OA-2, Panel A) of publicly listed subsidiary firms using a model that combines accounting and market data. The number of observations decreases with respect to the specification presented in Table 5, Panel A, due to data availability requirements on distance to default and remaining market variables. Panel A reports coefficients and (in parentheses) z-statistics from the estimation of a discrete hazard model. The dependent variable is equal to one if the subsidiary files for bankruptcy in year $t+1$, and zero otherwise. The specification presented in Column (1) includes subsidiary-level financial ratios and distance to default only: $Pr(Y_{s,t+1}=1) = f(NROAI_{s,t}, ROA_{s,t}, LTA_{s,t}, ETL_{s,t}, LN(TA_{s,t}), BANKRATE_{s,t}, D2D_{s,t})$, Column (2) adds the parent estimated bankruptcy probability ($\overline{\Pr(Y_{p,t+1}=1)}$) and Column (3) the average estimated bankruptcy probability of other subsidiaries in the group (($Pr(Y_{others,t+1}$)). In Column (4) the distance to default measure ($D2D_{s,t}$) is replaced by the volatility of the subsidiary's returns ($VOL_{s,t}$), the subsidiary's market capitalization relative to its country's total market capitalization ($RSIZE_{s,t}$), and the subsidiary's returns over the previous year ($RET_{s,t}$). Columns (5) and (6) add the parent estimated bankruptcy probability ($\overline{Pr(Y_{p,t+1}=1)}$) and the average bankruptcy probability of other subsidiaries in the group ($Pr(Y_{others,t+1})$) to the specification presented in Column (4). Marginal effects for group-level variables are reported as the change in estimated bankruptcy probability as each of the group-level variables increases by one standard deviation, scaled by the average estimated bankruptcy probability. Heteroskedasticity-robust standard errors are clustered at the parent-country and year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively. Panel B presents a comparison between the predictive power of the augmented models and that of the base models reported in Columns (1) and (4) using constant samples. Columns (1), (2) and (3) present the percentage of bankrupt years, years before bankruptcy and non-bankrupt firm-years falling in each of the top three deciles. The Area Under the Receiver Operating Characteristic Curve (AUC) is also reported for each subgroup. All variables are defined in the paper Appendix. The subscripts p, and s are used to identify parent- and subsidiary-level variables, respectively.

Table OA-8: Cross-Sectional Variation in CDS Spreads

Panel A: Parent CDS Spreads

		Dependent variable: $LN(CDS5Y_{p,t})$					
Independent variables:		(1)	(2)	(3)	(4)	(5)	(6)
Intercept		-3.584***	-4.095***	-3.473***	-3.954***	-5.381***	-5.686***
		(-4.81)	(-6.52)	(-4.36)	(-5.75)	(-5.30)	(-6.44)
$NROAI_{p,t}$	(+)	0.643***	0.666***	0.511**	0.539***	0.282	0.285
		(2.90)	(3.02)	(2.58)	(2.73)	(1.38)	(1.33)
$ROA_{p,t}$	(–)	-2.934	-2.706	-0.683	-0.487	1.078	0.910
		(-1.25)	(-0.93)	(-0.42)	(-0.23)	(0.58)	(0.45)
$LTA_{p,t}$	(+)	1.734***	1.764***	1.003***	1.047***	1.410***	1.410***
		(5.19)	(5.31)	(3.87)	(4.97)	(5.70)	(6.03)
$ETL_{p,t}$	(–)	0.225	0.454	1.383**	1.544**	-0.405	-0.259
		(0.23)	(0.46)	(2.32)	(2.06)	(-0.78)	(-0.45)
$LN(TA_{p,t})$	(–)	-0.140***	-0.149***	-0.064	-0.076*	-0.114***	-0.117***
		(-3.65)	(-4.01)	(-1.45)	(-1.79)	(-2.69)	(-2.94)
$BANKRATE_{p,t}$	(+)	0.115	0.050*	0.100	0.041*	0.694***	0.328***
		(1.48)	(1.94)	(1.54)	(1.73)	(2.83)	(2.68)
$D2D_{p,t}$	(–)			-0.248***	-0.238***		
				(-5.90)	(-4.85)		
$VOL_{p,t}$	(+)					4.024***	3.792***
						(8.28)	(15.43)
$RSIZE_{p,t}$	(–)					0.029	0.033
						(0.89)	(0.88)
$RET_{p,t}$	(–)					-0.545***	-0.625***
						(-3.88)	(-4.51)
$\overline{Pr(Y_{s,t+1})}$	(+)		185.957**		182.074***		165.862***
			(2.40)		(3.31)		(4.29)
Obs.		3,377	3,377	3,152	3,152	3,077	3,077
R^2		0.204	0.300	0.387	0.476	0.488	0.552
Shapley R^2 (%) for $\overline{Pr(Y_{s,t+1})}$			33.7725		21.4178		16.6921

Table OA-8 (continued)

Panel B: Subsidiary CDS Spreads

Independent variables:		Dependent variable: $LN(CDS5Y_{s,t})$ (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept		-4.350***	-4.508***	-4.391***	-3.736***	-3.824***	-3.569***	-2.641**	-1.665	-1.965
		(-5.73)	(-6.72)	(-7.68)	(-4.91)	(-5.09)	(-5.83)	(-2.15)	(-1.05)	(-1.27)
$NROAI_{s,t}$	(+)	0.776***	0.848***	0.810***	0.766***	0.834***	0.838***	0.612*	0.587*	0.546*
		(2.84)	(2.98)	(3.08)	(3.04)	(3.22)	(3.48)	(1.83)	(1.77)	(1.92)
$ROA_{s,t}$	(–)	-0.709	0.998	1.129	1.525	3.385*	3.740**	1.236	2.933**	3.051***
		(-0.58)	(0.47)	(0.53)	(1.20)	(1.93)	(2.06)	(0.83)	(2.19)	(2.72)
$LTA_{s,t}$	(+)	1.873***	1.898***	2.045***	1.198***	1.197***	1.246***	1.534***	1.586***	1.635***
		(5.16)	(5.18)	(6.98)	(3.04)	(3.16)	(3.98)	(7.66)	(6.42)	(6.73)
$ETL_{s,t}$	(–)	0.378	0.324	0.002	1.693*	1.500	1.114	-0.157	-0.633	-0.873*
		(0.69)	(0.67)	(0.00)	(1.69)	(1.39)	(1.05)	(-0.48)	(-1.20)	(-1.83)
$LN(TA_{s,t})$	(–)	-0.102**	-0.125***	-0.161***	-0.063*	-0.088**	-0.133***	-0.258***	-0.324***	-0.326***
		(-2.48)	(-3.03)	(-4.10)	(-1.83)	(-2.56)	(-4.02)	(-2.97)	(-3.31)	(-3.54)
$BANKRATE_{s,t}$	(+)	0.079*	0.051***	0.013***	0.068*	0.044***	0.009	0.539	0.167	0.031
		(1.83)	(3.13)	(2.95)	(1.76)	(2.61)	(1.26)	(1.55)	(1.29)	(0.32)
$D2D_{s,t}$	(–)				-0.257***	-0.252***	-0.235***			
					(-4.46)	(-3.17)	(-2.84)			
$VOL_{s,t}$	(+)							5.111***	4.757***	4.490***
								(8.91)	(5.44)	(4.93)
$RSIZE_{s,t}$	(–)							0.181***	0.224***	0.206***
								(3.03)	(3.62)	(3.37)
$RET_{s,t}$	(–)							-0.448**	-0.544***	-0.632***
								(-2.29)	(-2.80)	(-3.34)
$Pr(Y_{p,t+1})$	(+)		252.338**	-36.130		243.852***	-30.633		253.852***	46.508
			(2.03)	(-0.36)		(2.70)	(-0.52)		(2.74)	(0.95)
$\overline{Pr(Y_{others,t+1})}$	(+)			298.672***			287.752***			237.526***
				(3.57)			(3.89)			(3.89)
Obs.		1,198	1,198	1,167	1,069	1,069	1,044	509	509	497
R^2		0.147	0.248	0.322	0.297	0.389	0.454	0.458	0.546	0.594
Shapley R^2 (%) for $Pr(Y_{p,t+1})$			41.0401	16.6173		24.2991	11.0303		18.4935	9.4582
Shapley R^2 (%) for $\overline{Pr(Y_{others,t+1})}$				35.7715			25.3073			19.0053
Total R^2 contribution of group variables (%)				52.3888			36.3376			28.4635

This table reports the results of the analysis that examines the association between group-level variables and cross-sectional variation in parent and subsidiary credit default swap (CDS) spreads for the *CDS Sample* (see Table OA-2, Panel A) of parent and subsidiary firm-years. The number of observations decreases with respect to the specification presented in Table 1, Panel A of the paper due to data availability requirements on 5-year CDS spreads (Columns (1) and (2)), distance to default (Columns (3) and (4)) and market variables (Columns (5) and (6)). Panel A reports OLS coefficient estimates and (in parentheses) t-statistics for the sample of parent firms 5-year CDS contracts, where the dependent variable is equal to the natural logarithm of the spread at the end of year t. Panel B presents a similar analysis for a sample of subsidiary firms 5-year CDS contracts. Panel A (Panel B) reports the Shapley values assessing the marginal contribution of $\overline{Pr(Y_{s,t+1})}$ ($Pr(Y_{p,t+1})$ and $\overline{Pr(Y_{others,t+1})}$) to the R^2 of the respective model. In Panel A (Panel B) heteroskedasticity-robust standard errors are clustered at the parent (subsidiary) and year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively. All variables are defined in the paper Appendix. The subscripts p, and s are used to identify parent- and subsidiary-level variables, respectively.