Default Prediction Around the World: The Effect of Constraints on Pessimistic Trading

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Abstract
Research examining cross-country differences in the ability of market participants to accurately assess a firm's likelihood of default using publicly available sources of information is virtually non-existent. This paper examines one potential source of such variation, constraints on pessimistic trading (i.e., trades made in anticipation of future price declines). On average, predictive accuracy is significantly greater in countries where pessimistic trading is less constrained. This relation is further identified using time-series variation in restrictions on short selling and the introduction of put option trading. Consistent with trading constraints limiting the extent to which prices reflect publicly available default risk information, the direct incorporation of accounting information in the default prediction model leads to a larger improvement in accuracy where pessimistic trading is limited. Finally, although fewer constraints consistently lead to more accurate identification of actual defaults, during periods of heightened macroeconomic uncertainty, default prediction models in countries with fewer pessimistic trading constraints inaccurately classify a greater proportion of non-default observations.

Keywords: Default prediction; short selling constraints; financial reporting transparency
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1. Introduction

In this paper, we examine cross-country variation in the ability of market participants to accurately assess a firm's likelihood of default using publicly available sources of information. Although some lenders have access to private information, for other market participants, such as equity and public debt holders, public sources of information are critical for assessing default risk. A vast prior literature has extensively investigated the most accurate publicly available predictors of default in a U.S. setting.[1] As this stream of research has evolved, a general consensus has emerged that equity market-based sources of information, such as size, stock return and stock volatility, are the most informative predictors of default likelihood. An implication of this finding is that the speed and accuracy with which these predictors reflect default risk-relevant information is likely to have a large impact on assessments of financial distress. In particular, prior literature suggests that the efficiency of prices with respect to negative information is especially important for assessing default risk (e.g., Merton 1974; Black 1976).[2] Although this work is informative with respect to the role of equity prices in default prediction in a relatively efficient capital market, it provides little insight into how country-level aspects of firms' information environments affect assessments of default likelihood.

Internationally, there exists substantial variation in the institutions that determine the informational efficiency of equity prices, particularly with respect to constraints on market participants' ability to trade in anticipation of future price declines (e.g., Bris et al. 2007; Jain et al. 2013). However, research examining how these factors affect the accuracy of default

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[1] See for example: Beaver 1966; Altman 1968; Ohlson 1980; Shumway 2001; Chava and Jarrow 2004; Hillegeist et al. 2004; Duffie et al. 2007; Bharath and Shumway 2008; Campbell et al. 2008; Duan et al. 2012.

[2] Merton (1974) demonstrates that a firm's likelihood of default is increasing in the volatility of firm value. An extensive prior literature further shows that volatility of firm value is more sensitive to bad than good news, because, for example, of the presence of volatility feedback which amplifies the effect of bad news on stock returns (e.g. Campbell and Hentschel 1992).

prediction is virtually non-existent. In this paper, we use an international database of defaults covering 28 countries over a period of 20 years to help fill this gap in the literature.

Prior research suggests two potential effects of pessimistic trading constraints on default prediction. On the one hand, pessimistic trading constraints could decrease predictive accuracy by making prices less efficient. For example, constraints, such as short selling restrictions, can lead to a delay in the speed with which prices reflect negative publicly available information or can reduce (or eliminate altogether) the incentive to acquire private information (Diamond and Verrecchia 1987).[3] Primarily focusing on the effect of short selling on price informativeness, a large body of empirical research supports this prediction (e.g., Jones and Lamont 2002; Bris et al. 2007; Chang et al. 2007; Saffi and Sigurdsson 2011; Boehmer and Wu 2012; Kaplan et al. 2013).

On the other hand, pessimistic trading constraints may *increase* predictive accuracy by limiting speculative, non-fundamentals-based trading. Trades based on anticipated future price declines, rather than firm economics, can cause prices to behave as if default risk has increased (e.g., through negative returns) without a corresponding decline in firm financial health. For example, Brunnermeier and Pedersen (2005) demonstrate that predictable trading behavior by large institutional investors creates the incentive for speculative traders to short sell in anticipation of large liquidations. Coval and Stafford (2007) provide empirical support for this notion by demonstrating that the predictability of asset fire sales by mutual fund investors leads to front-running and significant (temporary) price pressure, whereby speculators profit from a trading strategy that sells short the stocks most likely to be subject to institutional forced selling.

[3] It is important to note that the theory on short selling constraints does not suggest that a given piece of negative information is *never* incorporated into price, but rather that it is incorporated with a delay. Although this delay may be temporary, the arrival of public information on an ongoing basis can still create persistent differences in the average informativeness of equity prices. If trading constraints prevent negative information from being profitably exploited, the delay in the revelation of private information could be indefinite.

Moreover, often citing fears over the potential for downward spirals in equity prices, since the financial crisis in 2008, stock exchange regulators around the world have placed numerous restrictions on pessimistic trading and continue to contemplate others.[4] These arguments suggest that speculative pessimistic trading has the potential to decrease predictive accuracy by creating a disconnect between market-based default predictors and firm fundamentals.

Even if pessimistic trading constraints do reduce the extent to which prices efficiently reflect default risk-relevant information, because equity markets are not the only source of such information, it is not clear ex ante that overall predictive accuracy will suffer. For example, the most commonly employed class of default prediction models also directly incorporates financial statement information, the usefulness of which is unlikely to be affected by pessimistic trading constraints. Conditional on this information being widely available and of relatively high quality, accounting information has the potential to serve as an alternative source of default risk information, (partially) offsetting any loss in predictive accuracy caused by a decrease in the informativeness of market-based variables in the presence of constraints on pessimistic trading.

We empirically assess model predictive accuracy using areas under receiver operating characteristic curves ("ROC curves") (e.g., Chava and Jarrow 2004). To estimate default probabilities, we use a model that combines both market (relative size, prior return and return volatility) and financial statement (return-on-assets and leverage) inputs following the reduced-form approach suggested in Shumway (2001), as well as several additional variables (distance-

[4] Many such regulators have taken the view that constraints on pessimistic trading have the potential to reduce "selling pressures or unusual volatility causing significant downward spirals [in equity prices]" (ESMA 2012/715). For example, on November 1st, 2012 Spanish securities market regulators, with the backing of the European Securities and Market Authority (ESMA), announced their intention to introduce emergency measures to ban short sales given "certain adverse situations… exist[ing] at present that constitute a serious threat to the financial stability of, and confidence in, the financial market in Spain (ESMA 2012/715)."

to-default and the country-year specific risk-free rate) suggested by the structural model of Duffie et al. (2007).

Because there is little extant cross-country research on default prediction, we begin by descriptively documenting the performance of the model for each of our sample countries. Not surprisingly, we find substantial cross-country heterogeneity in predictive accuracy. This variation provides an initial indication that country-specific institutions create meaningful differences in predictive accuracy.

Next, we turn to our primary research question and investigate the extent to which the observed cross-country heterogeneity in default model predictive accuracy can be explained by constraints on pessimistic trading. We employ three alternative proxies for pessimistic trading constraints based on the extent to which short selling is practiced in a particular country. Our first measure is an indicator of the legal permissibility and practitioner-assessed feasibility of short selling from Bris et al. (2007). Our second measure is the country-level scaled borrowing ratio from Jain et al. (2013), which measures the extent of share borrowing as a proportion of market capitalization. Our third measure is a proxy for the availability of borrowable shares based on country-level institutional ownership (e.g. Nagel 2005).

Using each of these measures of short selling constraints, we document that both the explanatory power of market-based default predictors and default model predictive accuracy are greater in those countries where short selling is more actively practiced. We further confirm that the negative relation between predictive accuracy and pessimistic trading constraints is robust to the inclusion of industry fixed effects and the exclusion of observations from the U.S. in the default model. Taken together, the results from our initial analyses provide evidence that constraints on pessimistic trading reduce default model predictive accuracy by limiting the extent to which equity prices reflect default risk-relevant information.

We conduct several additional analyses to address the possibility that other unmodeled country-level attributes are an alternative explanation for our findings. In these analyses we attempt to hold constant static aspects of the institutional infrastructure and specifically examine how default model predictive accuracy varies with changes in pessimistic trading constraints. First, we repeat our main analysis with country-fixed effects and a firm-level measure of trading constraints. These analyses similarly indicate that firms with greater pessimistic trading constraints have lower default model predictive accuracy *within* a given country. Second, we exploit time-series variation in short selling constraints. Although the majority of the countries in our sample have no clearly identifiable periods of variation in short selling constraints, Malaysia experienced prolonged periods where short selling was allowed, constrained, and then allowed once again. Again, we document a negative association between default model predictive accuracy and the extent of short selling practice. Third, we examine settings where the pessimistic trading constraints created by short selling restrictions were mitigated through the introduction of exchange-traded put options (e.g., Diamond and Verrecchia 1987). Specifically, we exploit the fact that, during our sample period, two countries identified as non-short sale practicing countries reduced restrictions on pessimistic trading by introducing put option trading. We find that in those countries with significant short selling constraints, the introduction of exchange-traded put options significantly increases default model predictive accuracy.

Next, we investigate the role of alternative, non-market-based, sources of default risk information in mitigating the decrease in default model predictive accuracy created by pessimistic trading constraints. Intuitively, if equity prices are less informative in the presence of such constraints, consideration of alternative sources of publicly available information may become more important for default prediction. Consistent with this notion, we document that, in those countries where pessimistic trading is constrained, the inclusion of accounting variables in the default prediction model increases overall predictive accuracy significantly more than in countries without pessimistic trading constraints.[5] Further, we find that the incremental contribution of accounting variables is larger in those countries where financial reporting is relatively more transparent. This analysis further indicates that pessimistic trading constraints have a direct effect on the accuracy of default prediction by providing evidence consistent with these constraints limiting the extent to which prices reflect *publicly available* default risk information.

Finally, to provide a more complete picture of their effect on predictive accuracy, we examine how constraints on pessimistic trading separately affect the proportion of correctly identified default and non-default observations. Consistent with our prior analyses, we document that, on average, countries with fewer pessimistic trading constraints perform better on both dimensions of predictive accuracy. However, given that much of the regulatory and political concern over short selling relates to the potential for increased speculative trading and downward spirals in equity prices during periods of heightened financial instability, we further examine differences in default model predictive accuracy across partitions based on short selling practice during periods of high and low macroeconomic uncertainty. We find that, while the proportion of actual default observations that are accurately classified during high uncertainty periods is larger across both partitions of short selling practice, the proportion of inaccurately classified *non-*

[5] Accounting variables represent only one potential source of non-market-based default risk information. Other potential sources include, for example, information produced by analysts or the news media. We investigate the substitutive role of accounting information because it is included most default prediction models employed in prior research (e.g., Shumway 2001).

default observations increases by significantly more in countries where short selling is more actively practiced. These findings suggest a higher proportion of inaccurately classified non-default observations during periods of high macroeconomic uncertainty as a potential tradeoff of having relatively fewer restrictions on pessimistic trading.

Our findings make several contributions to the existing literature. Foremost, ours is the first paper (of which we are aware) to examine the economic drivers of market participants' ability to accurately assess a firm's likelihood of default using publicly available information in an international context. The vast majority of the prior literature on default prediction has focused on model predictive accuracy in the context of U.S. markets without considering how country-level aspects of the informational infrastructure affect predictive accuracy. Our analysis identifies constraints on pessimistic trading as one aspect of a firm's institutional environment that significantly affects market participants' ability to assess its likelihood of default.

Second, prior literature generally concludes that the inclusion of market-based variables renders other publicly available sources of information relatively unimportant for default prediction (e.g., Chava and Jarrow 2004; Hillegeist et al. 2004). In contrast, our results indicate a significant role for non-market based sources of default risk information in settings where equity prices are relatively less informationally efficient. In addition, our findings suggest that the incremental contribution of accounting information to default model predictive accuracy is greater where financial reporting transparency is high, highlighting an additional capital market benefit of greater corporate transparency.

Third, our results contribute to the literature on the economic effects of constraints on pessimistic trading by documenting a significant decrease in default prediction accuracy as a novel consequence of such constraints. Our analysis also indicates a higher proportion of inaccurately classified non-default observations during high uncertainty periods as a potential cost of having fewer constraints. Given the ongoing debate in the European Union and elsewhere over the merits of constraints on pessimistic trading, these results are relevant for policy makers and regulators.

The remainder of the paper proceeds as follows. In Section 2 we describe our research design; in Section 3 we provide a description of our data sources and sample selection criteria; in Sections 4 and 5, we present our empirical results; in Section 6 we conclude.

2. Research Design

2.1. Measures of constraints on pessimistic trading

We consider three alternative proxies for constraints on pessimistic trading based on country-level short selling practices.[6] Prior research demonstrates, both theoretically (e.g., Diamond and Verrecchia 1987) and empirically (e.g., Boehmer and Wu 2012), that constraints on short selling are a significant impediment to the flow of negative information into stock price.

Our first measure is constructed following Bris et al. (2007) and provides an indicator of the extent to which short-selling is actively practiced in a particular country. An important aspect of the dataset gathered by Bris et al. (2007) is that it is compiled based on data collected from practitioners and regulators and focuses on the prevalence of short selling from the perspective of investors (e.g., Morgan Stanley and Goldman Sachs), rather than solely on the explicit regulations regarding the legality of short selling. This distinction is important because, as pointed out by Bris et al. (2007), although short-selling is *legally permitted* (in some form) in most countries, it is *commonly practiced* in significantly fewer. It is only with widespread

[6] Other potential proxies for pessimistic trading constraints include the availability of exchange traded put options and credit default swaps. As a practical matter, empirical measures of variation in short selling are more widely available. In additional analyses, we also consider country-level variation in the availability of put options as an alternative measure.

practice that we expect short selling to have a meaningful impact on the informativeness of equity prices for default prediction. Based on the data in Bris et al. (2007), we classify each of our sample countries as either *ShortPract* = "No" or *ShortPract* = "Yes."

Our second measure is the country-level scaled borrowing ratio (*SBRatio*) from Jain et al. (2013) which is calculated as a country's daily average outstanding dollar share borrowing divided by the country's total stock market capitalization. The proportion of shares on loan provides a direct measure of the extent of short selling. We classify each of our sample countries into one of three partitions: *SBRatio* = {"Low", "Medium", "High"} based on country-level sample terciles.

Our third measure is based on country-level institutional ownership data from Ferreira and Matos (2008) which is computed as the U.S. dollar value of total institutional ownership as a percentage of stock market capitalization (*InstOwn*). In order to sell a stock short, shares must be available for borrowing. Nagel (2005) shows that because institutions are the primary lenders of shares, institutional ownership is a proxy for the ability to short sell. We classify each of our sample countries into one of three partitions: *InstOwn* = {"Low", "Medium", "High"} based on country-level sample terciles.[7] Table 1 reports each sample country's partition classification for each of the three measures of short selling practice.

2.2. Estimating the likelihood of default

Prior literature suggests two primary approaches for empirically estimating a firm's likelihood of default using publicly available information — a reduced-form and a structural approach. In the reduced-form modeling of defaults, it has become common practice to assess a company's likelihood of default using a multi-period logit model that includes a combination of

[7] If one of our sample countries is not covered in Ferreira and Matos (2008), we classify that country as having "low" institutional ownership.

both market- and accounting-based measures (e.g., Shumway 2001; Chava and Jarrow 2004; Campbell et al. 2008; Beaver 2012). The structural approach, as exemplified in Duffie et al. (2007), develops a time series model of the covariates expected to affect a firm's likelihood of default and then specifies a particular parameterization of these covariates to explain actual incidences of default. The structural approach in Duffie et al. (2007) suggests the inclusion of both a variety of dynamic firm-specific and macroeconomic covariates.

We follow the reduced form multi-period logit approach of Shumway (2001), supplemented by the additional variables suggested by the structural approach in Duffie et al. (2007).[8] Specifically, we estimate the following logistic regression where the probability of default for firm *i* in year *t* is estimated:

$$P(DEFAULT_{i,t+1}=1)=\frac{1}{1+e^{-z}}, \tag{1}$$

$$\begin{aligned} z = {} & \alpha_0+\alpha_1 LERET_{i,t}+\alpha_2 LSIGMA_{i,t}+\alpha_3 LRSIZE_{i,t}+\alpha_4 ROA_{i,t}+\alpha_5 LTA_{i,t} \\ & +\alpha_6 DTD_{i,t}+\alpha_7 RFRATE1YR_{i,t}. \end{aligned}$$

DEFAULT is an indicator variable that equals one if the firm defaults in year *t*+1 and equals 0 otherwise. The firm-year predictive variables are measured at the end of year *t*, where year *t* is the most recently available data prior to *t+1*. Under this dynamic methodology, Shumway (2001) recommends using a multiperiod logit model, where each year a firm survives is included as a non-failure observation and default observations are included as a failure observation only in the year of failure. Accordingly, *DEFAULT* = 0 includes all firm-year observations for firms that never default, as well as all firm-year observations for defaulted firms in years prior to the year

[8] Our objective is not to identify the "best" empirical default prediction model, but rather to explore cross-sectional variation in the general performance of default models based on public information across countries and, to the extent that such variation exists, examine the role of constraints on pessimistic trading in determining those differences. To this end, we employ a model that includes the two most commonly used and widely available public sources of default risk information (i.e., equity markets and financial reports) and is extensively used in the prior empirical literature.

immediately preceding their default.[9] We delete all firm-years of data for defaulted firms after their default year. We cluster standard errors at the firm level to account for the lack of independence between firm-year observations.

LERET, *LSIGMA*, and *LRSIZE* are market-based predictive variables, where *LERET* is lagged twelve-month cumulative abnormal stock return (i.e., firm return less the market index return), *LSIGMA* is lagged twelve-month return volatility, and *LRSIZE* is the logarithm of a firm's market capitalization relative to the aggregate sample market capitalization. We use market data as of the end of the month following the month of financial statement data availability to allow time for the market time to incorporate this information.[10] *ROA* and *LTA* are accounting-based predictive variables, where *ROA* is a measure of profitability (return-on-assets), and *LTA* is a measure of leverage (total liabilities divided by total assets). *DTD*, distance-to-default, is a default risk measure generated from the theoretical underpinnings of the Black-Scholes-Merton structural model of default probabilities using both accounting and market data. *RFRATE1YR* is the interest rate in percent of the firm's country's one-year government treasury security. All variables are discussed in further detail in the Appendix.

2.3. Assessing model predictive accuracy

Conceptually, two aspects of default model predictive accuracy are of interest — sensitivity (i.e., how well a model identifies actual incidences of default) and specificity (i.e., how well a model identifies actual incidences of non-default). We assess model predictive accuracy based on the area under receiver operating characteristic curves (*ROCArea*), which

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[9] We follow the prior literature (e.g., Shumway 2001, Chava and Jarrow 2004, Campbell et al. 2008) and assume that any censoring (i.e., firms that leave the sample for reasons other than default) is non-informative. While this may not be strictly true, for censoring to be a source of bias in our study it would have to differ systematically across our sample partitions, which is less plausible. Moreover, Duffie et al. (2007) show that the effect of censoring is minimal on one-year ahead default prediction, which is the focus of our study. Nonetheless, we repeat our analyses after excluding all firms that are censored and find very similar results.

[10] For example, if financial statement data are available 04/17/2004, we use market data as of 05/31/2004.

simultaneously capture both aspects of predictive accuracy (e.g., Chava and Jarrow 2004). ROC curves are cumulative probability curves across the entire sample population (ordered by estimated default probability) that simultaneously consider how a model performs in terms of both sensitivity and specificity, where the area under the curve is increasing in overall predictive accuracy. The area under an ROC curve is generally expressed relative to the unit square area, where a value of 0.5 reflects a random model with no predictive ability and a value of 1.0 indicates perfect predictive ability. The total area under the ROC curve reflects the tradeoff between increasing sensitivity and decreasing specificity.

3. Data and sample selection

3.1. NUS Credit Research Initiative

Our firm-level default data comes from the Risk Management Institute (RMI) at the National University of Singapore. In July 2009, RMI launched the non-profit Credit Research Initiative (CRI) to promote independent transparent research in the credit risk arena. The foundation of the CRI is a database of over 53,000 publicly-listed firms from 46 countries across the Asian-Pacific, North American, Western European and Latin American regions. The proprietary database that underlies this output includes extensive panel data on firm stock price, financial statement data, and events of default from 1990 to the present categorized by default class. It is this underlying proprietary database from which we draw our sample. [11]

The CRI research team collects default events from numerous sources, including Bloomberg, Compustat, CRSP, Moody's, exchange web sites and media outlets. Because definitions of credit default can vary across national jurisdictions and between data sources, CRI continuously attempts to normalize to a common set of default definitions. In the version of the

[11] For more information on the CRI, refer to http://rmicri.org/home/. For an extensive discussion of the default dataset construction process, as well as a 3,000 firm sample of the data, refer to http://rmicri.org/data/document. This data source has also been used in prior published work by Duan et al. 2012.

dataset we use, default events recognized by CRI include "1) bankruptcy filing, receivership, administration, liquidation, or any other legal impasse to the timely settlement of interest and/or principal payments; 2) a missed or delayed payment of interest and/or principal, excluding delayed payments made within a grace period; 3) debt restructuring/distressed exchange." Delistings or "other exits" are not considered as defaults initially, but are reclassified as defaults if a firm experiences a default within one year of the delisting. Technical defaults (i.e., covenant violations) are not included in the definition of default. In addition to these general categories, CRI separately examines cases that require special attention to determine whether a default event has actually occurred.

Our objective is to focus on the economic condition of default, defined as an inability to pay one's debts when contractually due. This fundamental notion of financial distress transcends bankruptcy or any other specific legal default resolution mechanism and conceptually applies to a firm operating in any institutional environment. RMI’s extensive efforts to normalize their default data to capture an economic default help to mitigate concerns about the comparability of our default observations across country.[12]

3.2. Sample selection and descriptive statistics

To construct our sample of default observations, we begin with the initial default occurrences for all firms in the CRI default database. We next delete banks and utilities, and attempt to supplement any missing CRI financial statement data with Worldscope data, where we merge the CRI data with Worldscope based on ISIN. [13] As discussed above, we use three market-

[12] Despite these efforts, country-specific aspects of firms’ financing environments might lead to differences in the extent to which firms ever experience financial distress or a missed payment. In order to facilitate identification of the direct effects of pessimistic trading constraints, in Section 4.3, we conduct an extensive set of analyses to control for such country-level differences.
[13] Supplementation with data from Worldscope/Datastream adds very few additional observations to the sample, which provides comfort that the CRI data are fairly comprehensive.

based measures in the prediction models. For excess firm return (*LERET*) and return volatility (*LSIGMA*), our primary data source is the CRI 'pd' dataset, which contains data on closing monthly stock price. For the third market variable, *LRSIZE*, our primary data source is Datastream, because the use of Datastream allows us to directly obtain market capitalization in a common currency (i.e., U.S. dollars) across all sample observations. Distance-to-default (*DTD*) and the one-year government risk free rate (*RFRATE1YR*) are likewise obtained directly from the CRI database.[14]

We delete all observations with missing values for any of our predictive variables, and likewise delete observations where *LSIGMA* equals zero (i.e., firms with no price change over the prior twelve months), as well as all observations from countries with no defaults in the dataset. These deletions result in a final sample of 335,231 firm-year observations comprised of 2,153 default-year observations and 333,078 non-default-year observations from fiscal years 1989 through 2012.[15] The defaults that underlie the default-year observations span the years 1991 through 2012. Finally, to control for extreme observations, we Winsorize financial statement variables at the upper and lower 2.5%, and Winsorize *LERET* and *LSIGMA* at the upper 2.5% only, because these variables have natural lower bounds.

Table 1 presents the total number of sample observations and number of sample default observations by country. The United States has both the largest total number of observations (24.94%) and default observations (43.33%). Asia-Pacific nations are also well represented in the sample.[16] Figure 1 presents our sample default frequency by year. As expected, our sample

[14] For a detailed description of RMI's firm-specific distance-to-default calculation method, see http://rmicri.org/data/document. For further conceptual background on this approach, see Duan et al. 2012.
[15] We eliminate 985 default observations without sufficient data to calculate our primary predictive variables.
[16] It is likely that RMI's default data search efforts are biased toward Asian-Pacific countries. However, we have no reason to suspect that these search efforts are likely to be correlated with pessimistic trading constraints. As an initial indication of this, we note that Asian-Pacific countries appear in both the relatively active and inactive short selling

exhibits pronounced spikes in default frequency in the years surrounding 2000 and 2008, which roughly coincide with the aftermath of the Asian financial crisis, the 2001 recession and the 2008 financial crisis. Table 2 presents aggregate sample descriptive statistics. The overall distributional characteristics of the accounting and market-based predictor variables are consistent with those reported in prior studies (e.g., Shumway 2001).

4. Empirical results

4.1. Baseline default model estimation

We begin by estimating variants of Eq. (1) that mirror the individual specifications used in Shumway (2001) and Duffie et al. (2007), with results presented in columns (1) and (2) of Table 3, respectively. The signs of the estimated coefficients on the predictive variables are consistent with prior literature that estimates similar models using U.S. data. We next estimate the Eq. (1) default prediction model using our pooled global sample, with results presented in column (3) of Table 3. Firms that have higher lagged abnormal stock returns (*LERET*), a larger relative size (*LRSIZE*), a greater return-on-assets (*ROA*), and a larger distance to default (*DTD*) are less likely to default, whereas firms with higher return volatility (*LSIGMA*) and greater leverage (*LTA*) are more likely to default.

Table 3 also reports the area under receiver operating characteristic curves (*ROCArea*), our summary measure of model accuracy. Focusing on column (3), *ROCArea* is 0.841. Intuitively, an *ROCArea* of 0.841 can be interpreted as the percentage of instances (in this case 84.1%), in repeated randomly drawn pairs of actual default and non-default observations, that the default observation has a higher estimated default probability than the non-default observation.

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practice partitions. Nonetheless, in Sections 4.3 and 4.4 we conduct a series of within-country analyses to ensure this search bias does not drive our inferences.

Table 4 presents results from separate estimation of Eq. (1) for each sample country having greater than ten default observations. Generally speaking, the relations between the model predictive variables and default incidence are consistent in sign and significance across the country-level estimations. For example, four of the predictive variables never enter a country-level regression with a statistically significant sign that is opposite to the predicted sign (we do not have a prediction for the sign of *RFRATE1YR*). In general, the average accuracy (*ROCArea*) across the individual countries is consistent with the results from our pooled estimation in Table 3 (0.859 and 0.841, respectively). However, we note wide variation in predictive accuracy among countries, ranging from 0.754 in China to 0.955 in Denmark. The remainder of our analysis focuses on understanding the extent to which pessimistic trading constraints contribute to these observed differences in predictive accuracy.

4.2 Pessimistic trading constraints and predictive accuracy

Table 5 presents regression statistics from estimation of Eq. (1) separately for observations in countries with and without significant short-selling restrictions, based on the country-level short selling practice measure from Bris et al. (2007). Specifically, we identify those countries where short selling is relatively less (*ShortPract* = No) and more actively practiced (*ShortPract* = Yes), and estimate Eq. (1) separately for each partition. Column (3) indicates significant differences in the predictive variable coefficient magnitudes across partitions. The magnitude of the coefficients on the market-based variables (e.g., *LERET*, *LSIGMA*, *LRSIZE*) are smaller in countries with relatively greater short selling constraints, consistent with these constraints impeding the informational efficiency of the market-based variables. Interestingly, the coefficient magnitudes on the accounting variables (e.g. *ROA*, *LTA*) are larger for these same countries, which provides an initial indication that accounting inputs may take on increased direct predictive importance in the presence of short selling constraints (we explore this insight further in section 4.5).

The bottom section of Table 5 presents the difference in model predictive accuracy across partitions based on the areas under the ROC curves. *ROCArea* is over 12% larger in countries where short-selling is more actively practiced (0.871 vs. 0.775). Figure 2 depicts this result graphically.

Panels A and B of Table 6 present results based on our two alternative country-level measures of short selling constraints. In Panel A, we estimate the default prediction model separately for sample terciles based on the country-level scaled-borrowing ratio (*SBRatio*), where a lower ratio suggests less short selling. Consistent with the results in Table 5, predictive accuracy is monotonically increasing with the scaled-borrowing ratio, with an *ROCArea* of 0.800, 0.830, and 0.871 in the low, medium, and high *SBRatio* terciles, respectively. Further, the difference in *ROCArea* both between the medium and low partitions (one-tailed) and between the high and medium partitions are statistically significant. This result is depicted graphically in Figure 3.

In Panel B of Table 6, we estimate the default prediction model separately for sample terciles based on country-level institutional ownership (*InstOwn*), where lower institutional ownership is a proxy for a less active share lending market. Consistent with our previous results, predictive accuracy is monotonically increasing with country-level institutional ownership, with *ROCArea* of 0.781, 0.843, and 0.876 in the low, medium, and high *InstOwn* terciles, respectively. Further, the difference in *ROCArea* both between the medium and low partitions and between the high and medium partitions are statistically significant. This result is depicted graphically in Figure 4.

In Panel C of Table 6, rather than using a country-level measure of short selling constraints, we estimate our default prediction model separately for sample terciles based on a *firm-year* measure of short selling constraints. Specifically, for each firm-year observation we calculate *InstOwnResid* as the residual from a regression firm *i*'s year *t* mutual fund ownership as a percentage of firm *i*'s shares outstanding on country-year fixed effects, where we obtain mutual fund ownership data from Factset. Accordingly, the sample terciles reflect a firm's effective short selling constraints relative to all other firms in the same country in the same year, and thus provide a very strict test of our predicted effects. Consistent with our previous findings, predictive accuracy is monotonically increasing with firm *i*'s institutional ownership within a country-year, with *ROCArea* of 0.808, 0.848, and 0.895 in the low, medium, and high *InstOwnResid* terciles, respectively, where the differences between terciles are highly significant.

Overall, the results from our initial analyses suggest that constraints on pessimistic trading reduce default model predictive accuracy by limiting the extent to which equity prices reflect default risk-relevant information. Next, we conduct several additional analyses to increase our confidence in the interpretation of these findings.

4.3 Additional analyses

4.3.1. Fixed effects

Panel A of Table 7 presents results across *ShortPract* partitions using Eq. (1) with the addition of industry fixed effects to account for potential differences across industries in the performance of the default prediction model (e.g., Chava and Jarrow 2004). The predictive accuracy difference across short sale partitions remains statistically significant (*ROCArea* difference of 0.097; $p < 0.01$).

Panel B presents results across *ShortPract* partitions using Eq. (1) with the addition of country fixed effects to control for unmodeled cross-country differences in default model predictive ability. This approach provides a very strict test of the effects of our short selling practice measure by controlling for all static country-level determinants of default within each partition not perfectly correlated with our short selling practice measure. A potential disadvantage is that, because our empirical proxies for pessimistic trading constraints are measured with error, the country fixed effects also likely absorb some of the variation in predictive accuracy related to the pessimistic trading constraints themselves. Despite this loss in power, the inferences from this analysis are similar to those reported previously, although the magnitude of the differences in predictive accuracy across constraint partitions is smaller (*ROCArea* area difference of 0.0351 vs. 0.0960 in the model without country fixed effects).

4.3.2. Sample composition

As discussed previously and reported in Table 1, our sample is weighted towards observations from the U.S. Although the observed heterogeneity in predictive accuracy from the by-country results in Table 4 suggest that our key inferences are not driven by any single country, in Panel C of Table 7 we present formal results from Eq. (1) estimated across *ShortPract* partitions after excluding all observations from the U.S. Consistent with our primary inferences, we continue to find that model predictive accuracy is significantly higher in non-U.S. countries where short selling is relatively more actively practiced (difference of 0.083; $p < 0.01$).

4.4. Time-series variation in country-level constraints on pessimistic trading

In this section, we exploit time-series variation in country-level constraints on pessimistic trading to further investigate their effect on default model predictive accuracy.

4.4.1. Within-country changes in short selling constraints

Among our sample countries, Malaysia provides a unique setting with relatively extensive variation in legal restrictions on short selling. Specifically, although short selling was prohibited in Malaysia from 1998-2006, it was permitted before 1998 and after 2006. This time-series variation in short selling restrictions provides an opportunity to strengthen our identification of the effect of pessimistic trading constraints by assessing whether default model predictive accuracy varies predictably with changes in short selling regulations.

Panel A of Table 8 presents results from estimating Eq. (1) for our sample of observations from Malaysia across the three within-country short selling regimes. Consistent with a direct effect of short selling constraints on predictive accuracy, moving from the pre-1998 period to the 1998-2006 period there is a statistically significant decrease in *ROCArea* (from 0.937 to 0.867), followed by a significant increase in *ROCArea* (to 0.921) in the post-2006 period relative to the 1998-2006 period.

4.4.2. Put option introduction in the face of short selling constraints

Diamond and Verrecchia (1987) demonstrate that, because put options can be used to mimic a short position in a stock, time-series variation in put option availability can be used to as an additional means of identifying the effect of short selling constraints. In this section, we exploit this dynamic as a further attempt to enhance the identification of the effect of pessimistic trading constraints on default model predictive accuracy. In our sample, there exist two countries, Malaysia and South Korea, where short selling is practiced relatively less extensively, but which introduced exchange-traded put options during our sample period, December 2000 and January 2002, respectively (Charoenrook and Daouk 2005). To test this dynamic, we estimate Eq. (1) for Malaysia and South Korea separately for the pre-put option period (*PostPut* = 0) and post-put option period (*PostPut* = 1). Results in Panel B of Table 8 indicate that the performance of the default prediction model improves significantly in the *PostPut* = 1 period (*ROCArea* difference of 0.055; p-value 0.06).

To provide some assurance that this result does not merely reflect a general increase in predictive accuracy over time, we repeat this analysis for the four countries in our sample that do not allow short selling and never introduce put options (China, Philippines, Taiwan, and Thailand) and again for the remainder of sample countries where short selling is practiced and put options are traded throughout our sample period. For this analysis, we choose June 2001, the mid-point between the dates when put options were introduced in Malaysia and South Korea, as the line of delineation for a *PseudoPostPut* partitioning variable. Results presented in the second and third rows of Panel B of Table 8 show no significant differences in model predictive accuracy in these countries across the pre- versus post-June 2001 periods, indicating that the improvement in predictive accuracy upon put option introduction in Malaysia and South Korea is not indicative of a general trend.

4.4.3. Within-country changes in short selling constraints and put option trading

The various combinations of short selling and put option regimes in Malaysia present an opportunity for an even finer partitioning of time-series variation in country-level pessimistic trading constraints. In Malaysia, there are four distinct regimes of pessimistic trading constraints: (1) pre-1998 when Malaysia allowed short selling but not put option trading, (2) 1998-2000 when Malaysia did not permit short selling and there was no put option trading, (3) 2000-2006 when short selling was not permitted but put options were traded, and (4) post-2006 when short sales were permitted, and put options traded.

Panel C of Table 8 presents *ROCArea* for separate estimations of Eq. (1) in Malaysia during each of these four time periods. Although the differences in predictive accuracy are generally statistically insignificant (possibly because of the reduced number of observations in each partition), the pattern in *ROCArea* is striking. Beginning with a relatively high *ROCArea* pre-1998 (0.937) when short selling was permitted, *ROCArea* decreases significantly during 1998-2000 (0.853) when it was subsequently restricted. *ROCArea* then increases during the 2000-2006 period (0.890) when exchange-traded put options were introduced, and increases once again after 2006 (0.921) when both short selling and put option trading were possible.

Overall, by exploiting time-series variation in pessimistic trading constraints, the results in this section abstract from cross-sectional country-level differences and facilitate a more direct investigation of how changes in the existence and severity of these constraints within a particular country affect default model predictive accuracy. The evidence is consistent with a direct link between pessimistic trading constraints and a reduction the ability to accurately assess a firm's likelihood of default.

4.5 The role of accounting information and corporate transparency

In this section, we investigate the role of alternative, non-market-based sources of default risk information in mitigating the negative relation between default model predictive accuracy and pessimistic trading constraints. Recall that Table 5 shows that the magnitudes of the coefficient estimates on the two accounting-based predictors (*ROA* and *LTA*) are actually *larger* in the presence of pessimistic trading constraints. One potential interpretation of this finding is that the consideration of alternative sources of publicly available default risk information becomes more important in the presence of trading constraints.[17]

[17] Beaver et al. (2012) shows that the ability to accurately assess a firm's likelihood of default is increasing in the quality of accounting information. Batta and Wongsunwai (2012) show that the relative accuracy of accounting-based default prediction models is increasing in the extent of equity "misvaluation."

To test this conjecture, we estimate both the full Eq. (1) specification and a version of Eq. (1) excluding the accounting-based default predictors (*LTA*, *ROA*, and *DTD*).[18] We then interpret the differential predictive accuracy of the full Eq. (1) specification, compared to the model including only market-based inputs, as a measure of the incremental contribution of the accounting-based predictors (hereafter, the "accounting increment"). Results in Panel A of Table 9 indicate that, in those countries where pessimistic trading is more constrained, the inclusion of accounting variables increases overall predictive accuracy by 18 percent (*ROCArea* increases from 0.66 to 0.77), whereas the corresponding increase where pessimistic trading is less constrained is only 8 percent (i.e. *ROCArea* increases from 0.81 to 0.87). This difference is highly statistically significant (p-value < 0.01), suggesting that alternative, non-market-based, sources of default risk information play a more direct role in default prediction where pessimistic trading constraints are more pronounced.[19]

To further assess the role of alternative, non-market-based, sources of default risk information, we next examine variation in the accounting increment based on country-level differences in corporate transparency. Prior research examining the effects of corporate financial reporting transparency suggests that an institutional infrastructure that supports relatively transparent financial reporting enhances the incremental effect of accounting information (e.g. Lang and Maffett 2012). To measure the extent to which a country's institutional infrastructure supports transparent financial reporting, we use the Leuz (2010) country-level institutional cluster categorizations. Leuz (2010) bases these factors on both the capital market demand for transparent financial reporting and the enforcement mechanisms in place that support such

[18] The Merton (1974)-style *DTD* measure is calculated using both market-based volatility and accounting-based leverage inputs. In this analysis, we remove *DTD* in order to focus directly on the explanatory power of the market-based variables. Results are similar if we exclude *DTD* from this analysis altogether.

[19] The incremental contribution to predictive accuracy of the accounting variables in the *ShortPract*=Yes partition suggests the presence of other, albeit less pervasive, market frictions in these settings.

reporting. We classify a country as having institutions that support relatively high (low) transparency financial reporting if it falls in Leuz (2010) cluster 1 or 2 (3, 4, or 5). Table 1 reports the low versus high transparency categorization by sample country.

To test the interactive effect of corporate transparency and short sale constraints on predictive accuracy, we estimate default models separately for low and high corporate transparency partitions within each of the *ShortPract* subsamples. Panel B (Panel C) of Table 9 presents the results within the *ShortPract* = *No* (*ShortPract* = *Yes*) sample partition. Holding the *ShortPract* partition fixed, the accounting increment is larger where corporate reporting transparency is relatively high, but only significantly so where short selling is relatively constrained. For example, in the sample partition where short selling is restricted, the accounting increment is 0.131 where *FRTransp* is high, but only 0.085 where *FRTransp* is low (difference of 0.046; p-value 0.01).

Overall, the results in this section provide further support for a direct effect of pessimistic trading constraints on the accuracy of default prediction. In an efficient capital market, prices reflect all value relevant publicly available information. The fact that the incremental contribution of *publicly available* accounting information is greater in in the *ShortPract=0* partition suggests pessimistic trading constraints decrease the efficiency with which equity markets reflect information. It is difficult to envision an alternative explanation, other than the presence of a significant market friction, for the observed higher incremental explanatory power of accounting information. Also consistent with an enhanced role for non-market based default risk information in the presence of pessimistic trading constraints, these results suggest that the direct contribution of accounting information is larger where this information is more transparent.

4.6. *Sensitivity, specificity, and macroeconomic uncertainty*

In this section, to provide a more complete picture of their effect on predictive accuracy, we examine how constraints on pessimistic trading separately affect model sensitivity (i.e., the proportion of correctly identified default observations) and specificity (i.e., the proportion of correctly identified non-default observations).

Model sensitivity and specificity cannot be interpreted in an absolute sense, but rather must be evaluated with respect to a particular default probability threshold. The area under an ROC curve is a comprehensive measure of predictive accuracy that plots the range of both model sensitivity and specificity across the entire distribution of default probabilities. To directly compare the sensitivity (specificity) of one model versus another, a (arbitrary) threshold above which an observation will be classified as a predicted "default" and below which it will be classified as a predicted "non-default" must be specified. Model sensitivity and specificity can then be evaluated relative to the predetermined threshold. Because much of the prior literature (e.g., Beaver et al. 2005, 2012) focuses on the third decile of estimated default probability to assess predictive accuracy, we assess differences in model sensitivity and specificity using the estimated default probability that underlies the 70th percentile of estimated default probabilities when Eq. (1) is estimated for our pooled sample (Table 3 column (3)). This estimated default probability is 0.74% (i.e., a firm has a 0.74% chance of defaulting within the next year).

Panel A of Table 10 presents sensitivity and specificity at the estimated default probability threshold of 0.74% separately for *ShortPract* partitions. On average, model sensitivity, the proportion of total actual default observations with a default probability higher than the 0.74% threshold, is significantly larger in countries with fewer pessimistic trading constraints (81.0 vs. 57.8). Alternatively, model specificity, the proportion of non-default observations below the 0.74% threshold, is similar across partitions, indicating that the previously documented greater default model predictive accuracy in settings where pessimistic trading is relatively more actively practiced is driven primarily by higher sensitivity.

As discussed previously, the conceptual possibility that pessimistic trading constraints *increase* predictive accuracy centers on the potential for such constraints to enhance price efficiency by reducing speculative trading. The potential for anticipatory speculative trading to create deviations in price from firm economics has been empirically documented by academics (e.g., Coval and Stafford 2007) and espoused by regulators and politicians (e.g., SEC 2008-211). An explicit (or implicit) aspect of many of these arguments is that restrictions on pessimistic trading are necessary only during periods of heightened financial turmoil.[20] To explicitly examine this conjecture, we next separately examine differences in default model sensitivity and specificity across partitions based on short selling practice during periods of high and low macroeconomic uncertainty.

We proxy for macroeconomic uncertainty using country-level index return volatility during the twelve month period over which we measure the market-based predictive variables (σ*IndexRet*), where we obtain index return data from RMI. For each country, we rank σ*IndexRet* into terciles and classify the top tercile as high macroeconomic uncertainty (*MacroUncert* = "high"), and the bottom tercile as low macroeconomic uncertainty (*MacroUncert* = "low").

We present results from this analysis in Panel B of Table 10. Compared to periods of low macroeconomic uncertainty, during high uncertainty periods, model *sensitivity* is significantly larger in both partitions of short selling practice. For example, where short selling is relatively unconstrained, model sensitivity increases from 66.8 to 85.7 when macroeconomic uncertainty is

[20] For example, during the 2008 financial crisis SEC Chairman Christopher Cox noted that while an "emergency order temporarily banning short selling [would] restore equilibrium to markets" such an extraordinary action "would not be necessary in a well-functioning market" and accordingly would be "temporary in nature (SEC 2008-211)."

high. However, during periods of high macroeconomic uncertainty, model *specificity* decreases significantly in countries where short selling is relatively unconstrained (from 88.1 to 74.1). In fact, model specificity is actually significantly lower during these periods than in those settings where short selling is relatively more constrained (difference of 4.3; p-value 0.05).

Overall, consistent with our prior analyses, the results from this section suggest that a benefit of more actively practiced pessimistic trading is that, on average, in countries with fewer constraints, default prediction models accurately classify a higher proportion of actual default observations. However, the results in this section also suggest a higher proportion of inaccurately classified non-default observations during periods of high macroeconomic uncertainty as a potential cost of unconstrained pessimistic trading. Although these findings might be relevant to policy makers and regulators considering the merits of constraints on pessimistic trading such as short selling restrictions, our analysis does not have a clear normative implication. Rather, it indicates that the decision to adopt such constraints requires a consideration of the tradeoff between the potential for less accurate classifications of actual defaults versus overestimation of the likelihood of default for non-defaulting firms.

5. Conclusion

We examine cross-country variation in the ability to accurately assess a firm's likelihood of default using publicly available sources of information. Most prior studies examine defaults only in the relatively informationally efficient capital markets of the U.S. However, internationally, there exists substantial variation in the institutional infrastructures that determine the informational efficiency of equity prices, particularly with respect to constraints on pessimistic trading.

On average, we find that predictive accuracy is significantly greater in countries where pessimistic trading is less constrained. This relation is further identified using time-series variation in restrictions on short selling and the introduction of exchange-traded put options. We also document that the direct incorporation of accounting information in the default prediction model leads to a larger improvement in accuracy in the presence of limitations on pessimistic trading. Finally, although fewer trading constraints consistently lead to more accurate identification of actual defaults, we find that during periods of heightened macroeconomic uncertainty, default prediction models in countries with fewer pessimistic trading constraints inaccurately classify a greater proportion of non-default observations.

These results make three distinct contributions to the extant literature. First, our analysis identifies constraints on pessimistic trading as an important determinant of the ability to accurately assess a firm's likelihood of default. Second, our findings suggest that the incremental contribution of accounting information to default model predictive accuracy is greater where financial reporting transparency is high and, thus, highlight an additional capital market benefit of greater corporate transparency. Third, our results contribute to the literature on the economic effects of constraints on pessimistic trading by documenting both a significant cost (i.e., a decrease in overall default prediction accuracy) and a potential benefit (i.e., a lower proportion of inaccurately classified non-default observations during periods of significant macroeconomic uncertainty) of these constraints.

Our study is subject to several limitations. First, our analysis does not speak to the potential default risk information content of other publicly available sources of information, such as credit reports or data compiled by analysts and the news media. Our objective instead is to understand how country-level aspects of firms' information environments affect assessments of default likelihood using equity prices and accounting reports, the most frequently used and readily available sources of default risk information. Although the inclusion of additional sources of public information might lead to incremental improvements in default prediction accuracy over those documented here, pessimistic trading constraints also limit the incentive to acquire private information and thus likely lead to persistently lower price efficiency.

Finally, pessimistic trading constraints are only one potential source of cross-country variation in market participants' ability to accurately assess a firm's likelihood of default. Other potential drivers of this heterogeneity, such as variation in the availability of information created by differences in, for example, accounting quality, insider trading laws and the level of institutional ownership, also likely contribute to differences in accuracy. Our analysis attempts to hold constant the general availability of information and focus on variation in price efficiency, leaving the investigation of other factors to future research.

Appendix
Variable definitions

Subscripts *i* and *t* refer to a particular firm and fiscal year, respectively. Subscript *c* refers to a country.

$DEFAULT_{i,t}$	An indicator variable that equals one if firm *i* has a default event in year *t*, and equals zero otherwise, where default events are identified from the RMI data from National University of Singapore.
$DTD_{i,t}$	Firm *i*'s distance to default; from the NUS RMI data.
$FRTransp_c$	Country *c*'s corporate transparency, based on institutional clusters from Leuz (2010). Specifically, we classify a country as having high (low) corporate transparency if it falls in Leuz (2010) cluster 1 or 2 (3, 4, or 5).
$INDEXRET_{i,t}$	Twelve month cumulative return on the market index for firm *i*; calculated from the NUS RMI price data file.
$LERET_{i,t}$	Twelve month cumulative excess stock return (over the market index return) for firm *i* ending in the month following firm *i*'s financial statement availability for fiscal year *t*; calculated from the NUS RMI price data file.
$LRET_{i,t}$	Twelve month cumulative stock return for firm *i* ending in the month following firm *i*'s financial statement availability for fiscal year *t*; calculated from the NUS RMI price data file.
$LRSIZE_{i,t}$	The natural logarithm of firm *i*'s relative size, computed at the end of the month following firm *i*'s fiscal year *t* financial statement data availability; relative size is computed as firm *i*'s stock market capitalization (in U.S. dollars) divided by the aggregate sample market capitalization (in U.S. dollars), where stock market capitalization is obtained from Datastream.
$LSIGMA_{i,t}$	Standard deviation of firm *i's* monthly stock return for the twelve months ending in the month following firm *i*'s financial statement availability for fiscal year *t*; calculated from the NUS RMI price data file.
$LTA_{i,t}$	Leverage ratio for firm *i* in year *t*; calculated from the RMI data as total liabilities divided by total assets.
$InstOwn_c$	Country *c*'s institutional ownership; computed in Ferreira and Matos (2008) as the dollar value of total institutional ownership as a percentage of stock market capitalization. We classify each of our sample countries into one of three partitions - $InstOwn_c$ = {"Low", "Medium", "High"} based on country-level sample terciles.
$InstOwnResid_{fy}$	Firm-year difference from the country-year mean level of mutual fund ownership (in country *c* in year *t*), computed as the residual from a regression of firm *i*'s year *t* mutual fund ownership as percent of shares outstanding (data obtained from Factset) on country-year fixed effects.

MacroUncert$_{i,t}$	Macroeconomic uncertainty in firm *i*'s country for the twelve month period ending with the month following firm *i*'s fiscal year *t* financial statement data availability. We first compute the standard deviation of twelve monthly country-level index returns (*σIndexRet*), and rank *σIndexRet* into terciles by country. Observations in the top tercile are classified as *MacroUncert* = "high", and observations in the bottom tercile are classified as *MacroUncert* = "low".
PostPut$_{i,t}$	For firms in Malaysia and South Korea, an indicator variable that equals one if firm *i*'s year *t* observation is after the introduction of put options in firm *i*'s country, and equals zero otherwise; put options were introduced in Malaysia on 12/01/2000, and introduced in South Korea on 01/28/2002 (Charoenrook and Daouk 2005).
PseudoPostPut$_{i,t}$	An indicator variable applicable to all countries that either had put options traded throughout our sample period, or never had put options traded during our sample period (i.e., all sample countries other than Malaysia and South Korea); equals one if firm *i*'s year *t* observation is after 06/01/2001, and equals zero otherwise.
RFRATE1YR$_{i,t}$	The interest rate on a one-year government debt security in firm *i*'s country; from the NUS RMI data.
ROA$_{i,t}$	Return on assets for firm *i* in year *t*; calculated from the RMI data as net income divided by lagged total assets.
ROCArea	The area under a receiver operating characteristic curve, which is a summary measure of model predictive accuracy. This measure generally ranges between 0.5 and 1.0, where a value of 0.5 reflects that a model has no discrimination ability, and a value of 1.0 implies perfect discrimination ability.
SBRatio$_c$	Country *c*'s scaled borrowing ratio, which is computed in Jain et al. (2013) as a country's daily average outstanding dollar share borrowing divided by the country's total stock market capitalization. We classify each of our sample countries into one of three partitions - *SBRatio* = {"Low", "Medium", "High"} based on country-level sample terciles.
ShortPract$_c$	An indicator variable that equals one if short-selling is allowed/practiced in country *c* and equals zero otherwise, where the coding is done based on the analysis in Bris et al. (2007).

REFERENCES

Altman, E., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance 23, 598–609.

Batta, G., Wongsunwai, W., 2012. Equity misevaluation and corporate bankruptcy prediction. Working paper.

Beaver, W., 1966. Financial ratios as predictors of failure. Journal of Accounting Research 4, 71–111.

Beaver, W., Correia, M., McNichols, M., 2012. Do differences in financial reporting attributes impair the predictive ability of financial ratios for bankruptcy? Review of Accounting Studies 17, 969-1010.

Beaver, W., McNichols, M., Rhie, J., 2005. Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy. Review of Accounting Studies 10, 93–122.

Bharath, S., Shumway, T., 2008. Forecasting default with the Merton distance to default model. Review of Financial Studies 21, 1339–1369.

Black, F., 1976. Studies of stock price volatility changes, in: *Proceedings of the 1976 Meetings of the Business and Economics Statistics Section*, American Statistical Association, 177-181.

Boehmer, E., Wu, J., 2012. Short selling and the price discovery process. Review of Financial Studies 26, 287-322.

Bris, A., Goetzmann, W., Zhu, N., 2007. Efficiency and the bear: short sales and markets around the world. The Journal of Finance 62, 1029-1079.

Brunnermeier, M., Pedersen, L., 2005. Predatory trading. The Journal of Finance 60, 1825-1863.

Campbell, J., Hentschel, L., 1992. No news is good news: An asymmetric model of changing volatility in stock returns. Journal of Financial Economics 31, 281-318.

Campbell, J., Hilscher, J., Szilagyi, J., 2008. In search of distress risk. The Journal of Finance 63, 2899-2939.

Charoenrook, A., Daouk, H., 2005. A study of market-wide short-selling restrictions. Working paper.

Chang, E., Cheng, J., Yinghui, Y., 2007. Short-sales constraints and price discovery: evidence from the Hong Kong market. The Journal of Finance 62, 2097-2122.

Chava, S., Jarrow, R., 2004. Bankruptcy prediction with industry effects. Review of Finance 8, 537–569.

Coval, J., Stafford, E., 2007. Asset fire sales (and purchases) in equity markets. Journal of Financial Economics 86, 479-512.

Diamond, D., Verrecchia, R., 1987. Constraints on short-selling and asset price adjustment to private information. Journal of Financial Economics 18, 277-311.

Duan, J., Sun, J., Wang, T., 2012. Multiperiod corporate default prediction—a forward intensity approach. Journal of Econometrics 170, 191-209.

Duffie, D., Saita, L., Wang, K., 2007. Multi-period corporate default prediction with stochastic covariates. Journal of Financial Economics 83, 635-665.

Ferreira, M., Matos, P., 2008. The colors of investors' money: The role of institutional investors around the world. Journal of Financial Economics 88, 499-533.

Hillegeist, S., Keating, E., Cram, D., Lundstedt, K., 2004. Assessing the probability of bankruptcy. Review of Accounting Studies 9, 5–34.

Jain, A., Jain, P., McInish, T., McKenzie, M., 2013. Worldwide reach of short selling regulations. Journal of Financial Economics 109, 177-197.

Jones, C., Lamont, O., 2002. Short-sale constraints and stock returns. Journal of Financial Economics 66, 207–239.

Kaplan, S., Moskowitz, T., Sensoy, B., 2013. The effects of stock lending on security prices: an experiment. National Bureau of Economic Research, Working Paper.

Lang, M., Maffett, M., 2011. Transparency and liquidity uncertainty in crisis periods. Journal of Accounting and Economics 52, 101-125.

Leuz, C., 2010. Different approaches to corporate reporting regulation: how jurisdictions differ and why. Accounting and Business Research 40, 229-256.

Merton, R., 1974. On the pricing of corporate debt: the risk structure of interest rates. The Journal of Finance 29, 449–470.

Nagel, S., 2005. Short sales, institutional investors and the cross-section of stock returns. Journal of Financial Economics 78, 277-309.

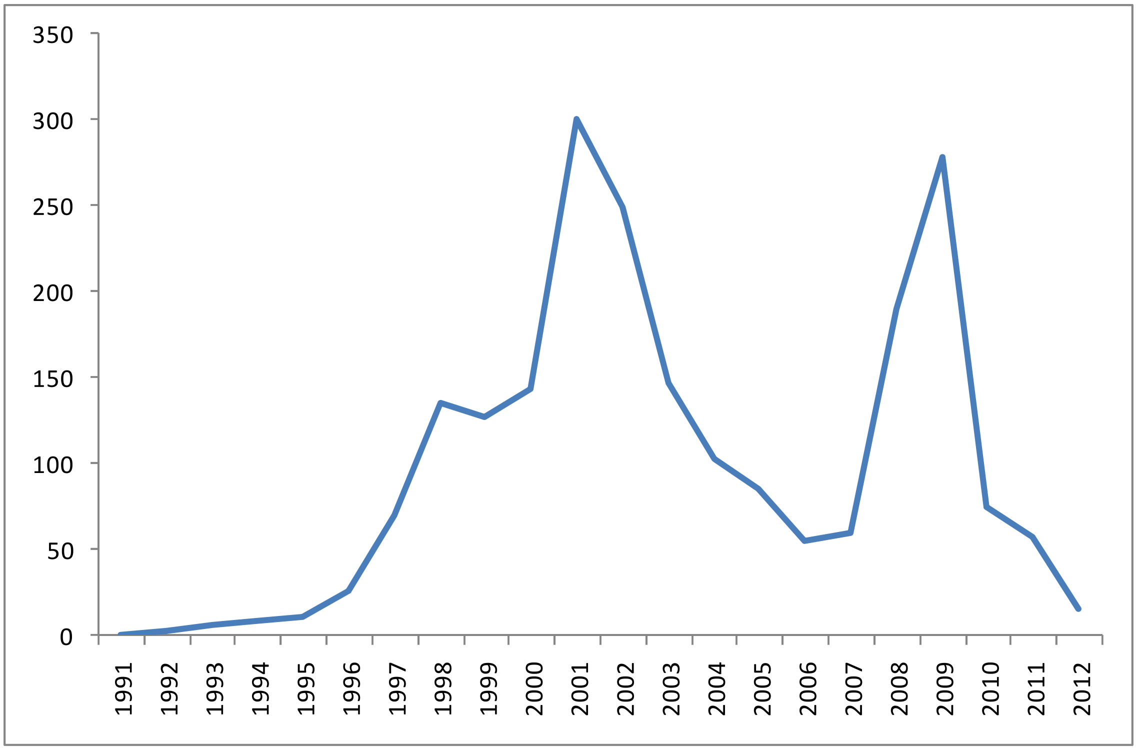
Ohlson, J.,1980. Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research 18, 109-131.

Saffi, P., Sigurdsson, K., 2011. Price efficiency and short selling. Review of Financial Studies 24, 821-852.

Securities and Exchange Commission, 2008. SEC halts short selling of financial stocks to protect investors and markets. http://www.sec.gov/news/press/2008/2008-211.htm.

Shumway, T., 2001. Forecasting bankruptcy more accurately: a simple hazard model. The Journal of Business 74, 101–124.

Figure 1
Sample defaults by year
Figure 1 presents calendar-year frequency of the 2,153 default observations in our sample.



Year	Frequency	Percent	Year	Frequency	Percent
1991	1	0.05	**2002**	249	11.57
1992	3	0.14	**2003**	147	6.83
1993	7	0.33	**2004**	103	4.78
1994	9	0.42	**2005**	86	3.99
1995	11	0.51	**2006**	56	2.60
1996	27	1.25	**2007**	60	2.79
1997	71	3.30	**2008**	190	8.82
1998	136	6.32	**2009**	278	12.91
1999	127	5.90	**2010**	75	3.48
2000	143	6.64	**2011**	58	2.69
2001	300	13.93	**2012**	16	0.74
			Total	**2,153**	**100.00**

Figure 2

ROC curves corresponding to the Table 5 analysis

Figure 2 plots curves from a receiver operating characteristic analysis across sample partitions based on the existence of country-level short-selling practice (*ShortPract*). The 45-degree line represents an ROC curve for a random model with no predictive ability. A larger area under the curve reflects a model with greater predictive accuracy.

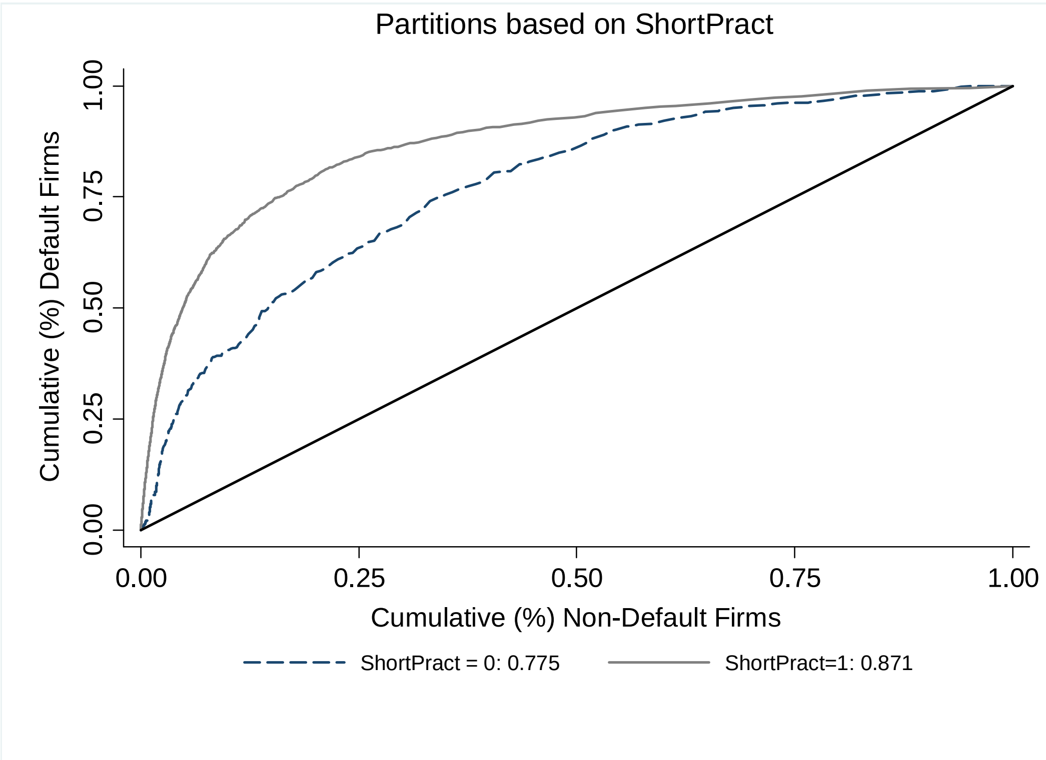


Figure 3

ROC curves corresponding to the analysis in Table 6 Panel A

Figure 3 plots curves from a receiver operating characteristic curve analysis across sample partitions based on country-level short borrowing ratios. The 45-degree line represents an ROC curve for a random model with no predictive ability. A larger area under the curve reflects a model with greater predictive accuracy.

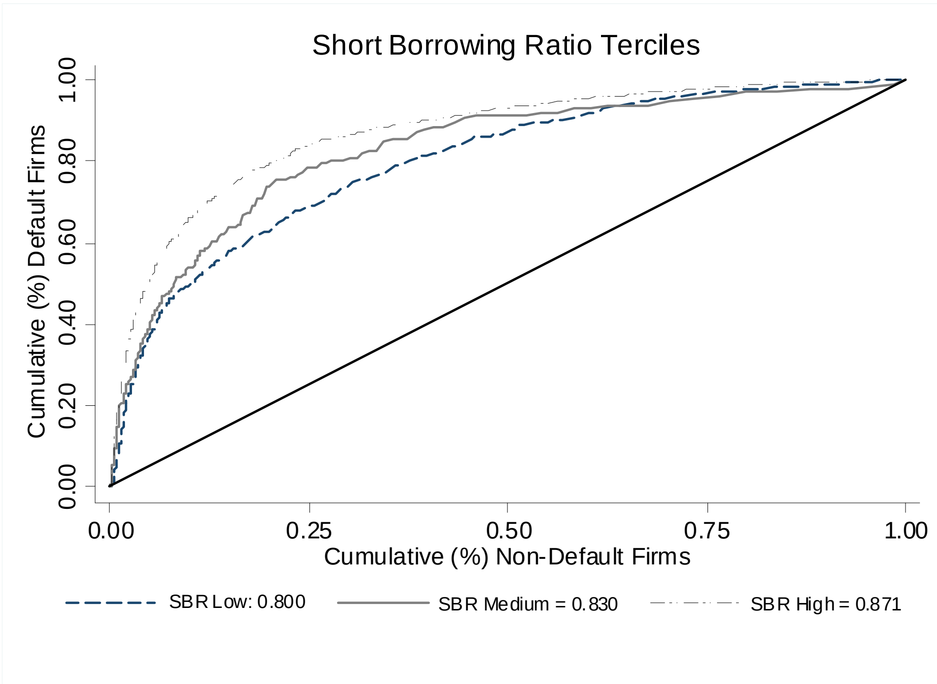


Figure 4

ROC curves corresponding to the analyses in Table 6 Panel B

Figure 4 plots curves from a receiver operating characteristic curve analysis across sample partitions based on country-level institutional ownership. The 45-degree line represents an ROC curve for a random model with no predictive ability. A larger area under the curve reflects a model with greater predictive accuracy.

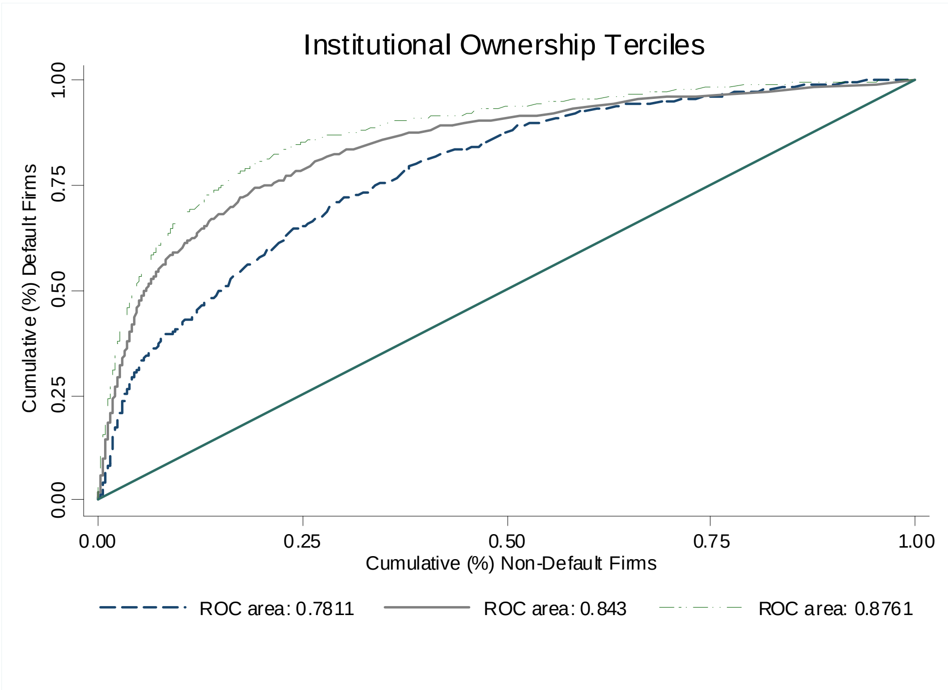


Table 1
Defaults by country

Table 1 presents the number of firm-year observations for both the total sample and the default sample, by country. Table 1 also presents information on whether short selling is practiced within the country (*ShortPract*), and country-level measures of the scaled borrowing ratio (*SBRatio*), institutional ownership (*InstOwn*), and financial reporting transparency (*FRTransp*). All variables are further defined in the Appendix.

	Total Obs.		**Default Obs.**					
Country	**Freq**	**%**	**Freq**	**%**	***ShortPract***	***SBRatio***	***InstOwn***	***FRTransp***
Australia	17,145	5.11	96	4.46	Yes	High	Med	High
Austria	1,200	0.36	5	0.23	Yes	Med	Med	Low
Belgium	1,781	0.53	6	0.28	Yes	Med	Med	High
Canada	10,384	3.10	66	3.07	Yes	High	High	High
China	13,688	4.08	155	7.20	No	Low	Low	Low
Denmark	2,214	0.66	11	0.51	Yes	Med	High	Low
Finland	1,822	0.54	4	0.19	No	High	High	High
France	9,835	2.93	43	2.00	Yes	High	High	Low
Germany	10,835	3.23	116	5.39	Yes	High	High	Low
Hong Kong	12,621	3.76	38	1.76	Yes	Low	Med	High
India	18,494	5.52	26	1.21	No	Low	Med	High
Indonesia	2,965	0.88	28	1.30	No	Low	Low	Low
Italy	3,276	0.98	14	0.65	Yes	High	Med	High
Japan	50,551	15.08	165	7.66	Yes	Low	Med	High
Malaysia	11,922	3.56	66	3.07	No	Low	Low	High
Netherlands	2,508	0.75	18	0.84	Yes	High	High	High
Norway	2,256	0.67	11	0.51	Yes	Med	High	Low
Philippines	1,870	0.56	19	0.88	No	Low	Low	Low
Portugal	722	0.22	1	0.05	Yes	Med	Low	Low
Singapore	7,086	2.11	26	1.21	Yes	Med	Med	High
South Korea	17,006	5.07	77	3.58	No	Low	Low	High
Spain	1,732	0.52	5	0.23	No	Med	Med	Low
Sweden	4,803	1.43	16	0.74	Yes	Med	High	Low
Switzerland	2,862	0.85	6	0.28	Yes	High	High	Low
Taiwan	12,601	3.76	29	1.35	No	Low	Low	High
Thailand	5,295	1.58	72	3.34	No	Low	Low	Low
UK	24,151	7.20	101	4.69	Yes	Med	Med	High
US	83,606	24.94	933	43.33	Yes	High	High	High
Total	**335,231**	**100.00**	**2,153**	**100.00**				

Table 2
Descriptive statistics for default predictors

Table 2 presents descriptive statistics for the independent variables used in our default prediction model, where our sample size for all variables is 335,231 firm-year observations. *LERET*, *LRET*, and *INDEXRET* are market-based measures of cumulative annual firm excess return, firm return, and the return on the market index, respectively. *LSIGMA* and *LRSIZE* are market-based measures of return volatility and relative market capitalization, respectively. *ROA* and *LTA* are accounting-based measures of return-on-assets and leverage, respectively. *DTD* is distance to default. *RFRATE1YR* is the one year government bond rate. All variables are further defined in the Appendix.

Variable	**Mean**	**Std**	**P25**	**P50**	**P75**
LERET	0.020	0.610	-0.324	-0.077	0.205
LRET	0.099	0.662	-0.297	-0.026	0.304
INDEXRET	0.077	0.247	-0.081	0.086	0.221
LSIGMA	0.151	0.110	0.080	0.122	0.187
LRSIZE	-10.544	2.325	-12.175	-10.689	-9.072
ROA	-0.003	0.175	-0.013	0.026	0.072
LTA	0.500	0.242	0.317	0.505	0.671
DTD	3.306	2.682	1.312	2.854	4.843
RFRATE1YR	3.461	2.769	1.062	3.533	5.080

Table 3
Default prediction using the pooled global sample

Table 3 presents results of the maximum likelihood estimation of the multiperiod logit model in Eq. (1) using 335,231 firm-year observations. *DEFAULT* is an indicator variable that equals one if a firm-year observation is a default-year observation, and equals zero otherwise. *LERET*, *LSIGMA*, and *LRSIZE* are market-based measures of firms' cumulative annual excess return, return volatility, and relative market capitalization, respectively. *ROA* and *LTA* are accounting-based measures of return-on-assets and leverage, respectively. *DTD* is distance to default from the NUS RMI data. *RFRATE1YR* is the country-specific one-year risk-free rate. *LRET* is firm-specific cumulative annual total return, and *INDEXRET* is the corresponding country-specific cumulative annual index return. *ROCArea* is the area under the receiver operating characteristic curve, a measure of model predictive accuracy. All variables are further defined in the Appendix. Robust standard errors clustered by firm are reported in parentheses. *, **, and *** indicate significance (two-sided) at the 10%, 5% and 1% levels, respectively.

Model:		**1**	**2**	**Combined**
Dep. Var.:		***DEFAULT***	***DEFAULT***	***DEFAULT***
Column:	**Pred. Sign**	**(1)**	**(2)**	**(3)**
Intercept		-8.548***	-4.146***	-6.490***
		(0.118)	(0.055)	(0.148)
LERET	–	-1.191***		-0.759***
		(0.059)		(0.058)
LSIGMA	+	2.870***		1.790***
		(0.133)		(0.141)
LRSIZE	–	-0.098***		-0.035***
		(0.010)		(0.011)
ROA	–	-1.209***		-1.287***
		(0.079)		(0.077)
LTA	+	2.772***		2.091***
		(0.081)		(0.087)
DTD	–		-0.577***	-0.377***
			(0.024)	(0.022)
RFRATE1YR	?		0.001	-0.013**
			(0.006)	(0.006)
LRET	–		-0.742***	
			(0.089)	
INDEXRET	?		0.497***	
			(0.093)	
N		335,231	335,231	335,231
Pseudo-R^2		0.136	0.119	0.158
ROCArea		0.833	0.810	0.841

Table 4

By-country default prediction model estimation

Table 4 presents results of the maximum likelihood estimation of the multiperiod logit model in Eq. (1) estimated by country, for each country having greater than ten default observations. The dependent variable *DEFAULT* is an indicator variable that equals one if a firm-year observation is a default-year observation, and equals zero otherwise. *ROA*, *LTA*, and *ETL* are return-on-assets, leverage, and cash flow-to-liabilities, respectively. *LERET*, *LSIGMA*, and *LRSIZE* are market-based measures of firms' cumulative annual excess return, return volatility, and relative market capitalization, respectively. *ROA* and *LTA* are accounting-based measures of return-on-assets and leverage, respectively. *DTD* is distance to default from the NUS RMI data. *RFRATE1YR* is the country-specific one-year risk-free rate. *ROCArea* is the area under receiver operating characteristic curves (a measure of model predictive accuracy). All variables are further defined in the Appendix. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively, based on standard errors clustered by firm. For brevity, we do not report the estimated intercept or standard errors.

Variables:	***N***	***LERET***	***LSIGMA***	***LRSIZE***	***ROA***	***LTA***	***DTD***	***RFRATE1YR***	**Pseudo-R^2**	***ROCArea***
Pred. Sign		–	+	–	–	+	–	**?**		
Australia	17,145	-0.806***	1.877**	0.153***	-0.352	1.543***	-0.610***	0.458***	0.170	0.860
Canada	10,384	-0.833*	1.816*	0.049	-1.082**	2.066***	-0.510***	-0.008	0.200	0.863
China	13,688	-0.620**	-2.511	-0.201***	-7.918***	2.247***	-0.011	0.114*	0.074	0.754
Denmark	2,214	1.177**	4.873	-0.209	-5.870***	4.443**	-0.572***	0.156	0.377	0.955
France	9,835	0.097	2.108	-0.202**	-5.626**	3.713***	-0.225*	0.053	0.209	0.890
Germany	10,835	-0.367	2.088**	-0.059	-3.589***	0.052	-0.437***	0.435***	0.195	0.863
Hong Kong	12,621	-0.320	0.234	0.096	-1.880**	2.345***	-0.216	0.104*	0.100	0.760
India	18,494	0.168	0.817	0.423***	-5.382*	1.438	-0.519***	-0.126	0.133	0.755
Indonesia	2,965	-0.924**	1.479	0.400***	-1.517	0.931	-0.329*	0.018	0.125	0.820
Italy	3,276	-1.117***	1.948	0.044	-5.695	7.791***	-1.428***	-0.021	0.400	0.942
Japan	50,551	-0.441	2.270**	-0.118**	-7.205***	6.380***	-0.648***	-0.350	0.271	0.919
Malaysia	11,922	-0.295	1.172	-0.048	-6.458***	2.406***	-0.330***	-0.050	0.188	0.874
Netherlands	2,508	0.146	5.279	-0.085	-3.257	1.171	-0.533**	0.176**	0.210	0.870
Norway	2,256	-0.963	1.372	0.269	-4.257**	1.283	-1.479***	0.091	0.383	0.926
Philippines	1,870	-0.455	-0.019	0.104	-3.405**	0.351	-0.385***	-0.086*	0.092	0.776
Singapore	7,086	-1.201*	2.901	-0.001	1.434	4.359***	-0.555**	-0.095	0.183	0.883
S Korea	17,006	-0.287	0.428	-0.082	-0.528	5.101***	-0.092	0.224***	0.199	0.880
Sweden	4,803	-0.015	2.190	-0.118	-0.609	0.944	-0.590**	-0.002	0.149	0.867
Taiwan	12,601	-0.632	0.444	-0.112	-11.877***	4.255***	-0.108	0.411***	0.210	0.855
Thailand	5,295	-0.071	-0.884	0.063	-3.219**	6.260***	-0.619***	-0.016	0.304	0.916
UK	24,151	-0.827***	1.981**	-0.077*	-0.706**	1.355***	-0.207***	0.008	0.101	0.795
US	83,606	-0.742***	2.436***	-0.075***	-1.051***	2.143***	-0.489***	0.008	0.228	0.875
% Correct Sign		81.8%	86.4%	59.1%	95.5%	100.0%	100.0%			
%Sig. Incorrect Sign		4.5%	0.0%	13.6%	0.0%	0.0%	0.0%			

Table 5
Predictive accuracy and country-level short selling constraints

Table 5 presents results of the maximum likelihood estimation of the multiperiod logit model in Eq. (1) estimated separately for *ShortPract* partitions. *DEFAULT* is an indicator variable that equals one if a firm-year observation is a default-year observation, and equals zero otherwise. *LERET*, *LSIGMA*, and *LRSIZE* are market-based measures of firms' cumulative annual excess return, return volatility, and relative market capitalization, respectively. *ROA* and *LTA* are accounting-based measures of return-on-assets and leverage, respectively. *DTD* is distance to default calculated via the Merton model. *RFRATE1YR* is the country-specific one-year risk-free rate. *ROCArea* is the area under receiver operating characteristic curves (a measure of model predictive accuracy). *ShortPract* is an indicator variable that equals one if short-selling is practiced in country *c* and equals zero otherwise. All variables are further defined in the Appendix. Robust standard errors clustered by firm are reported in parentheses. *, **, and *** indicate significance (two-sided) at the 10%, 5% and 1% levels, respectively. #, ##, and ### indicate differences that are significant at the 10%, 5% and 1% levels, respectively, based on Monte-Carlo randomization tests.

	ShortPract		
	No	**Yes**	
Dep. Var.:	***DEFAULT***	***DEFAULT***	**Diff (Y-N)**
Column:	**(1)**	**(2)**	**(3)**
Intercept	-6.005***	-6.947***	
	(0.307)	(0.174)	
LERET	-0.428***	-0.772***	-0.344###
	(0.092)	(0.068)	
LSIGMA	-0.104	2.324***	2.428###
	(0.371)	(0.161)	
LRSIZE	0.020	-0.056***	-0.076###
	(0.021)	(0.012)	
ROA	-2.353***	-0.947***	1.406###
	(0.282)	(0.087)	
LTA	2.200***	2.174***	-0.026
	(0.169)	(0.104)	
DTD	-0.135***	-0.484***	-0.349###
	(0.034)	(0.028)	
RFRATE1YR	0.007	0.057***	0.050###
	(0.010)	(0.011)	
N	87,395	247,836	
Pseudo-R^2	0.078	0.195	
ROCArea	0.775	0.871	0.096
p-value			(0.00)

Table 6
Alternative measures of short selling constraints

Panel A of Table 6 presents model predictive accuracy results using areas under receiver operating characteristic curves (*ROCArea*) from maximum likelihood estimation of the default prediction model in Eq. (1) across sample partitions based on country-level *SBRatio*. Panel B (Panel C) of Table 6 presents model predictive accuracy results using areas under receiver operating characteristic curves from maximum likelihood estimation of the default prediction model in Eq. (1) across sample partitions based on country-level (firm-year residual) *InstOwn*. All variables are further defined in the Appendix.

Panel A: Country-level scaled borrowing ratio

SBRatio	***N***	**Mean *SBRatio***	***ROCArea***
Low	147,013	0.171	0.8003
Medium	45,945	1.877	0.8299
High	142,273	3.282	0.8711
Diff (M-L)			0.0296
p-value			(0.11)
Diff (H-M)			0.0412
p-value			(0.02)

Panel B: Country-level institutional ownership

InstOwn	***N***	**Mean *InstOwn***	***ROCArea***
Low	66,069	N/A	0.7811
Medium	138,037	13.09	0.8430
High	131,125	31.08	0.8761
Diff (M-L)			0.0619
p-value			(0.00)
Diff (H-M)			0.0331
p-value			(0.00)

Panel C: Firm-year-level institutional ownership

InstOwnResid	***N***	**Mean *InstOwnResid***	***ROCArea***
Low	79,724	-0.035	0.8081
Medium	80,016	0.000	0.8479
High	79,970	0.089	0.8950
Diff (M-L)			0.0398
p-value			(0.00)
Diff (H-M)			0.0471
p-value			(0.00)

Table 7
Additional analyses

Table 7 presents model predictive accuracy results using areas under receiver operating characteristic curves (*ROCArea*) from the maximum likelihood estimation of a default prediction model of alternative specifications of the multiperiod logit default prediction model in Eq. (1) across *ShortPract* partitions. In Panel A, we estimate Eq. (1) as in Table 5 with the addition of industry fixed effects. In Panel B, we estimate Eq. (1) as in Table 5 with the addition of country fixed effects. In Panel C, we estimate Eq. (1) as in Table 5, after excluding observations from the United States. *ShortPract* is an indicator variable that equals one if short-selling is practiced in country *c* and equals zero otherwise.

Panel A: Industry fixed effects

	ShortPract			
	No	**Yes**	**Diff (Y-N)**	**P-value (Diff)**
ROCArea	0.7772	0.8746	0.0974	0.00
N	87,395	247,836		

Panel B: Country fixed effects

	ShortPract			
	No	**Yes**	**Diff (Y-N)**	**P-value (Diff)**
ROCArea	0.8416	0.8767	0.0351	0.00
N	87,395	247,836		

Panel C: Excluding the United States

	ShortPract			
	No	**Yes**	**Diff (Y-N)**	**P-value (Diff)**
ROCArea	0.7747	0.8573	0.0826	0.00
N	87,395	164,230		

Table 8

Time-series variation in country-level pessimistic trading constraints

Table 8 presents model predictive accuracy results using areas under receiver operating characteristic curves (*ROCArea*) from maximum likelihood estimation of the multiperiod logit default prediction model in Eq. (1) across various time-related partitions that capture variation in the extent of pessimistic trading constraints within a few sample countries. Panel A exploits time series variation in the extent to which short selling was practiced in Malaysia during our sample period. Panel B exploits variation in pessimistic trading constraints attributable to changes in put options trading during our sample period in Malaysia and South Korea. *PostPut* is an indicator variable that equals zero (equals one) for the time period during which put options were traded in Malaysia and South Korea. *PseudoPostPut* is an indicator variable that applies to countries that did not change their put option regime during the sample period, which delineates the sample at the same general time as *PostPut* (June 2001). *ShortPract* is an indicator variable that equals one if short-selling is allowed/practiced in country *c* and equals zero otherwise.

Panel A: Within-country changes in short selling practice (Malaysia)

	Sample Size		
	N_{default}	$N_{\text{non-default}}$	***ROCArea***
(i) Pre-1998 (short selling practiced)	5	1,856	0.937
(ii) 1998-2006 (short selling not practiced)	34	5,833	0.867
(iii) Post-2006 (short selling practiced)	27	4,167	0.921
Diff (ii-i)			-0.070
p-value			(0.023)
Diff (iii-ii)			0.054
p-value			(0.098)

Panel B: Put option introduction where *ShortPract*=*No* (Malaysia, South Korea)

	***PostPut* =**			
ROCArea	**0**	**1**	**Diff (1-0)**	**P-value (Diff)**
ShortPract = *No*; Puts began trading during sample pd. (Malaysia, South Korea)	0.8103	0.8656	0.0553	0.06
	***PseudoPostPut* =**			
	0	**1**	**Diff (1-0)**	**P-value (Diff)**
ShortPract = *No*; Puts never traded during sample pd. (China, Philippines, Taiwan, Thailand)	0.7886	0.8047	0.0161	0.53
ShortPract = *Yes*; Puts trade throughout sample pd. (refer to Table 1 for list of countries)	0.8680	0.8746	0.0066	0.48

Panel C: Within-country changes in short selling practice and put option trading (Malaysia)

	Sample Size		
	N_{default}	$N_{\text{non-default}}$	***ROCArea***
(i) Pre-1998 (short selling practiced; *PostPut* = 0)	5	1,856	0.937
(ii) 1998-2000 (short selling not practiced; *PostPut* = 0)	18	1,676	0.853
(iii) 2000-2006 (short selling not practiced; *PostPut* = 1)	16	4,157	0.890
(iv) Post-2006 (short selling practiced; *PostPut* = 1)	27	4,167	0.921
Diff (ii-i)			-0.084
p-value			(0.092)
Diff (iii-ii)			0.037
p-value			(0.503)
Diff (iv-iii)			0.031
p-value			(0.385)
Diff (iv-i)			-0.016
p-value			(0.542)

Table 9
The role of accounting information

Table 9 presents model predictive accuracy results using areas under receiver operating characteristic curves (*ROCArea*) from maximum likelihood estimation of the multiperiod logit default prediction model in Eq. (1). In Panel A, we estimate Eq. (1) separately across *ShortPract* partitions. In Panel B, we estimate Eq. (1) separately across *FRTransp* partitions in countries where *ShortPract* equals zero. In Panel C, we estimate Eq. (1) separately across *FRTransp* partitions in countries where *ShortPract* equals one. *ShortPract* is an indicator variable that equals one if short-selling is practiced in country *c* and equals zero otherwise. All variables are further defined in the Appendix.

Panel A: Full sample

	ShortPract			
ROCArea	**No**	**Yes**	**Diff (Y-N)**	**P-value (Diff)**
Market variables only	0.6573	0.8058	0.1485	0.00
Full default model specification	0.7747	0.8707	0.0960	0.00
Diff (Accounting increment)	0.1174	0.0649	-0.0525	0.00
N	87,395	247,936		

Panel B: *ShortPract = No*

	FRTransp			
ROCArea	**Low**	**High**	**Diff (H-L)**	**P-value (Diff)**
Market variables only	0.6721	0.7084	0.0363	0.10
Full default model specification	0.7575	0.8394	0.0819	0.00
Diff (Accounting increment)	0.0854	0.1310	0.0456	0.01
N	25,550	61,845		

Panel C: *ShortPract = Yes*

	FRTransp			
ROCArea	**Low**	**High**	**Diff (H-L)**	**P-value (Diff)**
Market variables only	0.8159	0.8060	-0.0099	0.50
Full default model specification	0.8698	0.8721	0.0023	0.85
Diff (Accounting increment)	0.0539	0.0661	0.0122	0.19
N	34,727	213,109		

Table 10
Macroeconomic uncertainty analysis
Table 10 presents model sensitivity (the percentage of correctly classified default observations) and specificity (the percentage of correctly classified non-default observations) for various sample partitions using a classification threshold default probability of 0.74% (the 70th percentile of estimated default probabilities in the pooled sample from Table 3 column (3)). *ShortPract* is an indicator variable that equals one if short-selling is practiced in country *c* and equals zero otherwise. *MacroUncert* is the standard deviation of country-level index returns, where the bottom (upper) sample tercile reflects low (high) macroeconomic uncertainty. All variables are further defined in the Appendix.

Panel A: Baseline model specs at the 30th percentile of predicted default probability (0.74%)

		Sensitivity	Specificity
ShortPract = No	(i)	57.8	80.1
ShortPract = Yes	(ii)	81.0	78.9
	(i)-(ii)	-23.2***	1.2

Panel B: Interactive effects - pessimistic trading constraints and macroeconomic uncertainty

		MacroUncert		
		Low	***High***	***Low-High***
Sensitivity				
ShortPract = No	(i)	51.5	63.7	-12.2***
ShortPract = Yes	(ii)	66.8	85.7	-18.9***
	(i)-(ii)	-15.3***	-22.0***	6.7*
Specificity				
ShortPract = No	(iii)	80.5	78.4	2.1
ShortPract = Yes	(iv)	88.1	74.1	14.0***
	(iii)-(iv)	-7.6***	4.3**	-11.9***