Do Stock Returns Really Decrease With Default Risk? New International Evidence☆

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Abstract

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Keywords: Default risk; Bankruptcy; Asset pricing tests; International markets;
JEL classification: G11, G12, G15
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1. Introduction

The cross-sectional relation between default risk and stock returns, the so-called default risk premium, has been a subject of intense debate in the literature. Since the vast majority of defaults occur during recessions (Campbell et al., 2011; Moody's, 2011), that is, when investors' marginal utility is high, standard asset pricing theory predicts that highly distressed stocks should yield higher premia relative to less distressed ones. In stark contrast to this intuition, prior empirical studies of the U.S. market usually report a flat, negative, or even hump-shaped relation between stock returns and several well-established proxies for default risk.[1] Only few recent studies, using either relatively small samples or uncommon proxies for expected stock returns, have reported a significantly positive relation.[2] The puzzling relation between distress risk and stock returns is often called the "distress anomaly".

In a recent insightful study, Gao et al. (2013, hereafter GPS) claim that the "investigation of the distress anomaly among U.S. firms [...] has failed to produce a consensus about even the basic [default risk-stock return relation], let alone its interpretation" (pp. 2-3). As a result, they argue that it is high time to shift the focus to new data for non-U.S. firms. Using interna-

[1] Among the first studies to examine the pricing of default risk is Dichev (1998), who uses Altman's (1968) Z-score and Ohlson's (1980) O-score, two accounting-based proxies, showing that these measures are not positively related to stock returns. Similarly, Griffin and Lemmon (2002) use the O-score to show that, after controlling for the book-to-market ratio, there is no evidence that default risk is priced. More recently, George and Hwang (2010) report a negative relation between stock returns and default risk measured by the O-score after excluding stocks trading at low prices. Departing from the use of accounting models, Vassalou and Xing (2004) extract default risk estimates from the Merton (1974) model and find that a positive return differential exists between stocks with high and low exposures to their default risk measure, but this return differential is significant only for small value firms. Using market-based default probability estimates from the proprietary model of Moody's KMV, Garlappi et al. (2008) and Garlappi and Yan (2011) find a hump-shaped relation between default risk and stock returns, while Anginer and Yildizhan (2013) obtain a flat relation between corporate credit spreads and risk-adjusted returns. Avramov et al. (2009) show that stock returns significantly increase with S&P senior debt credit ratings, implying a negative relationship between returns and default risk. Probably the most comprehensive evidence comes from Campbell et al. (2008), who measure default risk using a dynamic hazard model with both accounting and market variables. They document a strongly negative relation between default risk and stock returns, which becomes even more significant after accounting for size, value, and momentum premia.

[2] Among the few studies finding a significantly positive relation, Chava and Purnanandam (2010) show that expected stock returns implied from accounting valuation models increase with a broad set of default risk measures. Friewald et al. (2014), using a recent but rather small sample of big U.S. firms, find that stock returns increase with firms' credit risk premia estimated from CDS spreads. Finally, Avramov et al. (2012) find that sovereign credit ratings are correlated with future country stock returns, with high credit risk country portfolios outperforming low credit risk ones, giving rise to a world credit risk factor.

tional data over the period 1992-2010, they find a flat relation between stock returns and Moody KMV's Expected Default Frequency (EDF), which becomes significantly negative only among small capitalization stocks. They also fail to find a relation between the default risk premium and creditor protection at the country level, which does not support the empirical evidence of Garlappi et al. (2008), Garlappi and Yan (2011), and Favara et al. (2012). In contrast, country-level individualism, which they claim is a proxy for investor overconfidence, is significantly negatively related to the distress risk premium. Similarly, Eisdorfer et al. (2013, hereafter EGZ) use a distress risk proxy derived from the Merton (1974) model (MDD) to examine the pricing of distress risk in an international sample over the period 1992-2010. They find a significantly negative MDD-stock return relation in their empirical tests, which originates from the developed countries in their dataset.

In the spirit of EGZ and GPS, we also use international data to shed more light on the distress anomaly. However, in contrast to them, we do not use a structural estimate of default risk. Instead, we collect bankruptcy filings for 14 countries, excluding the U.S., over the 1992-2010 period, and we use these data to estimate default probabilities following the reduced-form approach of Campbell et al. (2008, hereafter CHS). While we examine a smaller set of countries than the other two studies, we benefit from the use of a more flexible and better-calibrated default risk proxy.[3,4] In addition, our estimates of the CHS measure should incorporate more efficiently cross-country differences in the bankruptcy filing process, induced

[3] Computing the CHS measure in-sample and imposing exactly the same restrictions as GPS, our dataset features more than 1.6 million firm-month observations from 14 countries (excluding the U.S.) during the period 1992-2010, in comparison to 3.4 million observations from 39 countries (including the U.S.) in their study. Despite the lower number of observations, our dataset includes many countries that exhibit relatively low correlations with the U.S., rendering it suitable for an out-of-sample study (see Foster et al., 1997).

[4] Bharath and Shumway (2008) and Campbell et al. (2008) show that hazard model estimates are superior in forecasting U.S. defaults as compared to structural estimates obtained from the Merton (1974) model (MDD), where the structural estimates are calculated using either the Hillegeist et al. (2004) or Vassalou and Xing (2004) methodology. However, since EDF can be regarded as a more sophisticated version of MDD, it is not immediately clear that reduced-form estimates beat EDF, too. The only available evidence on this issue comes from Bharath and Shumway (2008), who show that MDD and EDF are virtually identical for the small subset of firms for which Moody's KMV made EDF publicly available. We are unaware of any studies testing the forecasting power of these two measures for non-U.S. firms.

by bankruptcy laws and institutional settings.[5] Consistent with this idea, we show that the parameter estimates of our bankruptcy forecasting model vary significantly across countries. For example, the winsorized stock price forecasts bankruptcy with a significantly *positive* coefficient in Japan, but with significantly *negative* ones in Canada and the U.K.

Our asset pricing results are notably different from those in EGZ and GPS. Estimating country-specific LOGIT models to compute out-of-sample (OOS) default probabilities for firms in Australia, Canada, France, Germany, Japan, and the U.K. (hereafter, the C6 countries) over the sample period 2000-2010, we find an economically and statistically significant positive relation between default risk and stock returns. In particular, the spread strategy that is long the highest default risk quintile portfolio and short the lowest one yields an average return of 16.90% p.a. (t-stat: 2.79) in the case of value-weighted portfolios and an average return of 11.52% p.a. (t-stat: 2.12) in the case of equally-weighted portfolios. Next, we estimate bankruptcy regime-specific LOGIT models to compute OOS default probabilities for firms in countries with too few bankruptcies to estimate country-specific LOGIT models (Denmark, Finland, Hong Kong, New Zealand, Portugal, Spain, Sweden, and Taiwan). Using the OOS default probabilities from these eight countries together with the ones from the C6 countries (hereafter, the C14 countries), we obtain very similar conclusions.[6]

Adjusting for market risk does not materially affect these findings. However, adjusting for size and value premia, the magnitude of the default risk premium is reduced, suggesting

[5] As an example, note that cash reserves should, in general, allow a firm to delay or even avoid a bankruptcy filing. However, companies in Germany are legally obliged to file for bankruptcy once their net worth turns negative (Davydenko and Franks, 2008). As a result, one would expect that cash reserves are of lesser importance for the prediction of bankruptcy in Germany. The country-specific LOGIT model results confirm this prediction.

[6] For comparison purposes, we also examine the CHS distress risk-stock return relation in the U.S., over (i) our sample periods, 1992-2010 and 2000-2010, and (ii) imposing our data filters (to be described later). To achieve this goal, we combine the OOS LOGIT model estimates obtained by Campbell et al. (2008) with the LOGIT model's predictor variables constructed from CRSP and COMPUSTAT data following exactly the same procedures as they do. Consistent with their remark that "the outperformance of the portfolio that is long safe stocks and short distressed stocks is concentrated in periods such as the late 1980s" (p. 2928), the 1992-2010 and the 2000-2010 sample periods produce a virtually flat relation between CHS distress risk and stock returns in the U.S., independent of whether we use their data filters or ours. Thus, there is also a distress puzzle in the U.S. in our sample periods. We are grateful to Jens Hilscher for providing their OOS LOGIT model estimates.

that, in line with the conjectures of Chan and Chen (1991) and Fama and French (1996) and the evidence in Vassalou and Xing (2004), the latter factors are related to default risk. Nevertheless, the premium remains significant in the vast majority of cases.

Our results are robust to several modifications to our research design. In particular:

1. Our results continue to hold when we repeat the portfolio formation exercises over the 1992-2010 (at least when the portfolios are equally-weighted) or the 2000-2010 period using in-sample (IS) LOGIT model estimates.[7] Thus, our main results are not driven by potential parameter instability in our OOS default risk estimates. Plotting the cumulative profits of the spread strategy that is long the highest OOS CHS decile and short the lowest one, the lion's share of profits occur after the surge in bankruptcies in 2002. Since the IS estimates are fairly close to the OOS estimates after 2002, this result implies that, if anything, parameter instability may reduce, rather than increase, the magnitude of the default risk premium estimate.
2. Our results remain intact when we set the returns of defaulting stocks to −100%, taking into account the potential effect of missing delisting returns.
3. Our results continue to hold when we impose exactly the same data filters as GPS, thereby contradicting their EDF-based evidence that there is a negative (albeit insignificant) default risk premium during the 1992-2010 period.
4. Our results do not depend on whether or not we allow for a gap between the portfolio formation date and the beginning of the holding period, ruling out that the reported default risk premium is driven by a microstructure bias.
5. We find similar results when we use local currency stock returns to calculate portfolios returns (i.e., when we do not convert returns to U.S. dollar terms), ruling out that the premium is driven by a FOREX effect.

[7] While using the IS estimates induces a look-ahead bias, the majority of studies constructing the CHS measure use the IS estimates reported in Campbell et al. (2008). Examples include Song (2008) and Conrad et al. (2014).

Why do our results differ from those in EGZ and GPS? To address this question, we compare our CHS estimates with the corresponding MDD estimates, calculated using the approach of Vassalou and Xing (2004). It is well-known that, for ranking purposes, MDD is a very close proxy of EDF (Bharath and Shumway, 2008; Correia et al., 2012). In contrast to EDF, MDD is both publicly available and replicable for our international sample. Equipped with CHS and MDD, we repeat the portfolio formation exercises using either of the two as alternative sorting variables only for those firm-month observations for which both measures are available. While CHS still yields a positive default risk premium, MDD yields a U-shaped relation. In particular, for the C6 countries, the spread strategy Q5-Q1 that is long the highest MDD quintile portfolio (Q5) and short the lowest one (Q1) yields a negative but insignificant value-weighted (equally-weighted) premium of -0.71% (-5.47%) per year.

Examining the source of discrepancy between CHS and MDD, we find that the variables mostly disagree on the identification of low default risk firms. On average, only 38% of the stocks in the lowest three MDD deciles are also assigned to the corresponding lowest three CHS deciles. We find some evidence that this rather low overlap is partially driven by unlevered firms. While MDD assigns zero default risk to these firms because it assumes that a default occurs only if the asset value drops below a fraction of the debt value (see Crosbie and Bohn, 2003; Vassalou and Xing, 2004), these firms' CHS values are much higher. A second reason for the small overlap could be that MDD abstracts from default-triggering events other than an economic insolvency. For example, Davydenko (2008) shows that, while most defaulting firms are insolvent *and* illiquid, a fraction of them are only illiquid. Similar to the MDD proxy used by EGZ, the EDF proxy used by GPS also abstracts from bankruptcies triggered by liquidity issues, while the CHS proxy that we use takes them into account.

We also provide evidence on various theories proposed to explain cross-sectional variations in the default risk-stock return relation.[8] To this end, we construct double-sorted portfolios on the CHS measure and a series of firm characteristics. Overall, the default risk premium is found to be relatively higher among big capitalization and growth stocks, stocks that are traded at high prices as well as among firms that are followed by analysts and that are characterized by high asset tangibility and low leverage. Since microstructure biases are most pronounced at low share prices, such biases may thus contribute toward the anomaly. However, given that the book-to-market ratio positively affects the premium, while share volatility does not condition it, mispricing is unlikely to be a valid explanation. Finally, our results support the shareholder advantage hypothesis of Garlappi et al. (2008) and Garlappi and Yan (2011), and is in line with the international evidence of Favara et al. (2012), since the default risk premium is less pronounced among firms with lower asset tangibility.

The rest of our study is organized as follows. In Section 2, we describe the employed dataset. Sections 3 and 4 contain the results from bankruptcy forecasting models and asset pricing tests, respectively, while Section 5 summarizes and concludes.

[8] Garlappi et al. (2008) and Garlappi and Yan (2011) show that, if shareholders possess high bargaining power relative to creditors, then the former can strategically default to extract rents from the latter. As a result, such distressed firms are less risky to hold for shareholders than others, and hence they do not yield a premium. This argument is reinforced by the evidence of Hackbarth et al. (2013), who use the 1978 U.S. Bankruptcy Reform Act as a natural experiment of shifting bargaining power towards shareholders. Along the same lines, Favara et al. (2012) show that equity risk is lower in countries with bankruptcy procedures that favor debt renegotiations and for firms whose shareholders have high bargaining power. George and Hwang (2010) and Johnson et al. (2011) argue that capital structure choice variables can create an endogenous negative relation between default risk and stock returns. However, Johnson et al. (2011) point out that the negative relation derived from the model of George and Hwang (2010) is between default risk and the expected *asset* return, while the relation between default risk and the expected *equity* return remains positive. Aretz (2012) shows that, if default risk arises through the possibility of a catastrophic event manifesting itself as a hump in the left tail of the asset payoff distribution, then a higher default risk can yield a lower expected return. O'Doherty (2012) argues that it is the inability to precisely estimate firm value that causes distressed firms to have low market betas, and hence low expected returns (see also Johnson, 2004). Conrad et al. (2014) attribute the underperformance of highly distressed stocks to investors' preference for stocks with a relatively high probability of jackpot payoffs, a prevalent feature among highly distressed stocks. Given that most distressed stocks trade at very low prices, it is also possible that microstructure effects bias downward the returns of highly distressed stocks (see Blume and Stambaugh, 1983; Boguth et al., 2011). Finally, a negative default risk premium could be the result of equity mispricing that persists due to limits to arbitrage (see Campbell et al., 2008, 2011).

2. Data

2.1 Bankruptcy Data

Table 1 offers an overview of our sources for the bankruptcy filing data, which include commercial data providers, government institutions, stock exchanges, and other researchers.[9] In a number of cases, we have merged data from more than one source to extend the length of the sample period. For most countries, the data extend from January 1996 to December 2009, although for France, Japan, and the U.K. they begin slightly earlier (1992-1993), and they stop slightly earlier for France (2007) and Canada (2008). The data contain, at the very least, the identity of the filing firm and the filing date. The dataset includes filings under any legal procedure, except where noted. Since we often lack information on how long firms spent in reorganization, we drop firms after their initial bankruptcy filing in our sample period.

[Table 1 here]

Table 2 reports the number of bankruptcy filings, the number of firms with complete data, and the proportion of bankruptcy filings per country and year. To save space, filings and descriptive statistics are reported only for the C6 countries.[10] The table shows that our sample composition closely reflects the sizes of the stock markets of the C6 countries.

[Table 2 here]

Table 2 also shows that the frequency of bankruptcy filings varies considerably across countries. Filings are more frequent in countries where the bankruptcy system strongly favors managers or creditors (Germany and the U.K.) relative to countries where employee welfare is more important (France and Japan). In addition, the annual frequencies of bankruptcy filings are strongly correlated across the C6 countries. For the period 2000-2010, the average pairwise correlation is 0.39. However, the correlation is markedly higher for countries that are

[9] The data obtained from government institutions often include filings for both public and private firms, without distinguishing between the two. To extract public filings from these data, we have used a name-matching algorithm comparing the company names featured in the government data with those contained in a Datastream list featuring all public firms.

[10] The complete set of descriptive statistics is available upon request.

geographically close, such as France and Germany (0.74). Moreover, there is at least one bankruptcy filing in each country sample from 1997 onwards. Since we require a sufficient number of bankruptcy filings for the estimation of the LOGIT models and the calculation of default probabilities, we choose an initial recursive window up to December 1999 to run the LOGIT models, implying that we run our OOS asset pricing tests over the period 2000-2010. This choice ensures that there are at least five bankruptcy filings in each country sample before the start of the test period for each country for which we run country-specific LOGIT models (the C6 countries). To ensure that this choice does not drive our conclusions, we perform a battery of robustness tests using alternative sample periods.

2.2 Default Risk Indicators

We use the same default risk indicators as in Campbell et al. (2008) to estimate default probabilities. The first variable is the ratio of net income to a market value-adjusted version of total assets (NIMTA), where the latter is defined as the market value of equity plus the book value of total liabilities. Similar to Campbell et al. (2008), we use the market, instead of the book value of equity in the denominator of NIMTA, because the former captures a firm's prospects more accurately. Leverage is measured using the ratio of total liabilities to the market value-adjusted version of total assets (TLMTA).[11] Since lack of liquidity can also force a firm to file for bankruptcy (Davydenko, 2008), we proxy for internal cash using the ratio of cash holdings plus short-term assets to the market value-adjusted version of total assets (CASHMTA). Moreover, we use the market-to-book ratio (MB) to measure growth opportunities.[12]

[11] We have also experimented with versions of NIMTA and TLMTA scaled by the book value of total assets rather than its market-value adjusted counterpart. Similar to Campbell et al. (2008), we have found that using the book value of total assets decreases the ability of NIMTA and TLMTA to forecast bankruptcy.

[12] To make sure that book values of equity close to zero do not yield extreme values when used in the denominator of MB, we follow Cohen et al. (2003) in adding 10% of the difference between the market and the book value of equity to the latter. In the few cases where this adjustment does not generate a positive book value of equity, we follow Campbell et al. (2008) and set it equal to one unit of the local currency.

We also compute several market-based default risk indicators, including a firm's monthly log return in excess of the index return of the market in which the firm is headquartered (EXRET) and the annualized standard deviation of a firm's daily log returns over the prior three months (SIGMA), estimated by:

$$SIGMA_{i,m-1,m-3} = \left(252 * \frac{1}{N-1} \sum_{k\epsilon\{m-1,m-2,m-3\}} r_{i,k}^2\right)^{\frac{1}{2}},$$

where $r_{i,k}$ is the log return of firm i on day k, and N is the number of days in the 3-month estimation interval.[13] $SIGMA$ is set to missing if there are fewer than five non-zero daily returns. However, to avoid excluding illiquid stocks from our sample, we replace missing values for $SIGMA$ with the corresponding country-month cross-sectional mean. We further use relative market size (RSIZE), defined as the log ratio of a firm's market value to the total market value of firms in the same country-month. Campbell et al. (2008) use log share price (PRICE) as a default risk indicator to capture the inability of distressed firms to engage in reverse stock splits, implying that such firms often trade at low share prices. They winsorize this variable below $15/16 and above $15. Given that the above thresholds correspond vaguely to the 25th and 75th percentiles of the U.S. share price distribution, we also winsorize share prices using the first and the third quartiles of the local share price distributions in each country.

In the remainder, we collectively refer to NIMTA, TLMTA, EXRET, RSIZE, SIGMA, CASHMTA, MB, and PRICE as the default risk indicators. Note that, while NIMTA, TLMTA, RSIZE, and MB are currency-free, EXRET, SIGMA, and PRICE are measured in local currency. Apart from the previously described winsorization of PRICE, we further alleviate the effect of outliers by also winsorizing the rest of the default risk indicators at the 5th and 95th percentiles, computed separately for each country-month combination.

[13] Following Campbell et al. (2008), we assume in our calculation of SIGMA that zero is a more appropriate estimate of the expected daily return relative to a rolling historical average.

As an alternative default risk measure, we use the Merton (1974) Distance-to-Default (MDD). To compute the MDD measure, we require the market value of equity, the default-triggering asset value, and the risk-free rate. Following Crosbie and Bohn (2003) and Vassalou and Xing (2004), we set the default-triggering asset value equal to the book value of short-term debt plus one-and-a-half times the book value of long-term debt. We use the local 3-month interest rate as a proxy for the risk-free rate of return.

Market data are sourced from Thomson Datastream at both daily and monthly frequencies. We consider only shares traded in local currency and exclude non-primary issues. Accounting data are sourced from Worldscope at an annual frequency because quarterly data are unavailable for most non-U.S. firms before 2000. Where necessary, we convert the accounting items into the currency of the issue using the Thomson Datastream conversion factors. As the reporting gap can be substantially longer in international markets than in the U.S. (DeFond et al., 2007), we assume the accounting items are available to investors six months after the fiscal year end. To avoid losing firms shortly before their filing date, we further assume that investors use outdated data for up to twelve months if more recent data are unavailable.

Table 3 reports descriptive statistics for the default risk indicators of active and bankrupt firms over the 1997-2009 period. The default risk indicators of the bankrupt firms are measured in their filing month. The table suggests that firms filing for bankruptcy are in general less profitable (NIMTA), more levered (TLMTA), and more volatile (SIGMA) than non-bankrupt firms. In addition, they tend to have lower stock returns (EXRET), market-to-book ratios (MB), and log stock prices (PRICE) relative to non-filing firms. However, deviating from Campbell et al. (2008), filing firms do not hold less cash (CASHTMA) on average.

[Table 3 here]

A more detailed inspection of Table 3 reveals considerable differences between filing and non-filing firms across countries. For example, firms filing for bankruptcy in France or Japan are only slightly less profitable in the filing month relative to non-bankrupt firms. In particular, the difference in their average NIMTA is only -0.07 in France and -0.04 in Japan, while it is much greater in the other countries. Similarly, German firms do not use up their internal slack to delay bankruptcy filings and thus enter bankruptcy with substantially more cash holdings (mean=0.19) than other firms, with the exception of Canadian ones. An explanation for these results could be that both France and Germany have “stop-early” bankruptcy regimes. In particular, in France managers are obliged to file for bankruptcy within 45 days once the value of their liquid assets drops below that of their short-term liabilities. In Germany, managers are obliged to file within three weeks if net worth drops below a specific threshold. Failure to do so can render managers personally liable to creditors and subject them to a prison sentence in both countries (Wood, 2007). While there are no similar obligations in Japan, possibly Japanese banks are able to use their great power to force managers to file early, when the bank’s claims are still relatively secure (Pinkowitz and Williamson, 2001).

Table 3 also documents that the excess returns (EXRET) of bankrupt firms in France and the U.K. are less negative during their filing month than those of the firms in the remaining countries. A possible explanation is that stock payoffs in bankruptcy are likely to be very low in these two countries, implying that equity prices probably crashed a long time before the filing date. In France, it is the court that decides whether a bankrupt firm should be restructured, and its main objectives are to keep the firm alive, to preserve employment, and to satisfy creditors (Kaiser, 1996). In the U.K., it is usually secured creditors that take the reorganization decision (Davydenko and Franks, 2008). In both countries, most bankrupt firms are liquidated, and residual firm value is distributed adhering to strict priority rules, leaving little for stockholders (Kaiser, 1996; Franks and Sussman, 2005; Altman and Hotchkiss, 2011).

Overall, the univariate analysis in Table 3 highlights important cross-country variations in the ability of the default risk indicators to distinguish between bankrupt and non-bankrupt firms. These variations can often be linked to differences in bankruptcy codes or institutional features across countries. Our evidence above motivates the estimation of country-specific LOGIT models to calculate default probabilities, as described in Section 3.

2.3 *Market, Size, Value, and Momentum Factors*

Our asset pricing tests adjust portfolio returns for combinations of the market, size, value, and momentum factor exposures, using the CAPM, the Fama-French (FF) 3-factor model, and the Fama-French-Carhart (FFC) 4-factor model. To this end, we use the Global Fama-French market, size, value, and momentum factors, which are available from Kenneth French's online data library.[14] Given that our distress risk portfolios intentionally exclude U.S. stocks, a disadvantage of using the Global Fama-French factors is that they are constructed from data including U.S. stocks. To study how this issue affects our conclusions, we also repeat our asset pricing results using benchmark factors calculated from the corresponding "MSCI World ex US" indices, sourced from Thomson Datastream. In particular, the market portfolio is proxied for by the "MSCI World ex US Index." The size factor return is equal to the spread return between the "MSCI World ex US Small Cap Index" and the "MSCI World ex US Large Cap Index." The value factor return is equal to the spread return between the "MSCI World ex US Value Index" and the "MSCI World ex US Growth Index." Due to the lack of corresponding MSCI indices, we are unable to create a momentum factor and thus have to rely on the FF model in these robustness tests. Results are reported in the Appendix.

3. Forecasting Bankruptcies Around the World

3.1 *The Bankruptcy Forecasting Model*

Following Campbell et al. (2008, 2011), we use a reduced-form hazard model to construct our default risk measure (see also Shumway, 2001; Chava and Jarrow, 2004; Hillegeist et al., 2004). This hazard model specifies the conditional probability of bankruptcy as:

[14] This library is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

$$Prob_{m-12}(Y_{i,m} = 1) = \frac{1}{1 + \exp(-\alpha - \boldsymbol{\beta}'\boldsymbol{X}_{i,m-12})}, \tag{1}$$

where $Y_{i,m}$ is a dummy variable that equals one if firm i files for bankruptcy in month m and zero otherwise and $\boldsymbol{X_{i,m-12}}$ is a vector containing the publicly available values (i.e., allowing for a reporting gap for the accounting items) of the default risk indicators for firm i in month $m-12$.[15] We call the default probability estimated from the above model CHS.

We firstly estimate the LOGIT model in (1) for each of the C6 countries using the full sample period. Combining these full sample coefficient estimates with the default risk indicators for each firm i in December of year $t-1$, we calculate the corresponding in-sample (IS) default probability that we assign to every month in year t. For the remaining eight countries, which all feature too few (i.e., less than 40) bankruptcy filings to be analyzed separately, we compute for each firm IS default probabilities by pooling our data by bankruptcy law regime, estimating the corresponding full sample regime-specific LOGIT model, and then repeating the remaining steps of the above procedure. Following Wood (2007), we assume that Australia, Canada, Hong Kong, New Zealand, and the U.K. belong to the common law regime, France, Spain, and Portugal to the Napoleonic regime, Denmark, Finland, Germany, and Sweden to the Roman-Germanic regime, and Taiwan and Japan to the mixed regime.

While IS default probability estimates are informative, they are obviously not available to investors in real time, and they thus induce a look-ahead bias in our asset pricing tests. To address this issue, we also compute out-of-sample (OOS) default probabilities that are based on recursive estimations of model (1). When choosing the initial estimation window, we face the dilemma that, on the one hand, OOS default probabilities should be estimated over sufficiently long estimation windows to ensure that the distress risk proxy is precisely estimated. On the other hand, asset pricing tests should also be run over sufficiently long time periods to ensure that the average return is close to the expected return. We opt for an initial estimation

[15] Note that the probability shown in (1) is the probability of defaulting twelve months ahead, conditional on surviving the interim eleven months.

window using data up to December 1999. This choice ensures that each window includes at least five bankruptcy filings for each country, while still allowing us to perform the asset pricing tests using eleven years of monthly returns. To ensure that this choice does not drive our main empirical conclusions, we run several robustness checks varying the split between the initial estimation window and the testing period.

Having estimated each LOGIT model using data until December of year $t-1$, we combine the estimated coefficients with the corresponding publicly available values for the default risk indicators in December of year $t-1$ to compute OOS default probabilities for each firm and each month in the following year t, as in Campbell et al. (2008).

We compare CHS with a popular distress risk proxy extracted from the structural model of Merton (1974), MDD, given by:

$$MDD_{i,t} = -\frac{\ln\left(\frac{V_{i,t}}{X_{i,t}}\right) + \left(\mu_{i,t} - .5\sigma_{i,t}^2\right)}{\sigma_{i,t}} \tag{2}$$

where $V_{i,t}$ is the implied asset value, $\sigma_{i,t}$ is the estimated asset volatility, $\mu_{i,t}$ is the mean return of the implied asset value series, and $X_{i,t}$ is the default-triggering asset value.

We follow Vassalou and Xing (2004) in calculating MDD. In particular, we use as initial guess of the firm's asset volatility its stock return volatility, calculated from daily data over the prior twelve months. Using this initial guess together with the market value of equity, the default-triggering asset value, and the risk-free rate, we derive the firm's asset value from the Black and Scholes (1973) call option formula on each trading day over the prior twelve months. The time-series of asset values allow us to derive a new estimate of the firm's asset volatility. We iterate this process until the asset volatility estimate converges. Plugging the asset volatility estimate and the other variables into (2), we obtain MDD. By construction, MDD is available OOS, and we thus compare it only to the OOS version of CHS. As with CHS, MDD also captures default risk twelve months ahead.

3.2 Estimates of the In-Sample LOGIT Models

Table 4 reports the full sample estimates of the LOGIT model in (1) for each of the C6 countries. For the sake of brevity, we do not show the results for the bankruptcy law regimes, but they are available upon request. In general, the reported results confirm the initial findings from the descriptive statistics in Table 3. In particular, the default probability tends to increase with total liabilities (TLMTA) and stock return volatility (SIGMA), while it tends to decrease with profitability (NIMTA), excess returns (EXRET), relative size (RSIZE), and cash holdings (CASHTMA). Based on their significance levels, TLMTA, RSIZE, and SIGMA are the most important default risk indicators. The log stock price (PRICE) is related to the default probability with an ambiguous sign, while MB is found to be insignificant in most cases.

Using the same variables in a LOGIT model forecasting U.S. failures (defaults, bankruptcies, or performance-related delistings), Campbell et al. (2008) report a pseudo-R^2 of 11.4% for a 12-month forecasting horizon (see their Table 4). Keeping in mind that we do not have data on defaults or performance-related delistings, the pseudo-R^2s in our Table 4 suggest that the default risk indicators attract a higher forecasting power in Japan (12.5%), a similar one in Canada (10.6%) and the U.K. (8.4%), and a lower one in Australia (4.4%), France (5.3%), and Germany (6.9%). It is noteworthy that the second and third-lowest pseudo-R^2s occur in France and Germany, the only two 'stop-early' bankruptcy law countries among the C6 countries (see the discussion above). Our evidence thus supports the notion that it is difficult to distinguish between future solvent and bankrupt firms in 'stop-early' bankruptcy regimes, because there are not as striking differences across these two groups of firms in such bankruptcy regimes as in other ones.

The results reported in Table 4 also suggest that there are strong variations in the estimated coefficients of the default risk indicators across countries. These variations are often, albeit not always, consistent with the patterns revealed by the descriptive statistics in Table 3. For example, NIMTA is never significant in distinguishing between bankrupt and non-bankrupt firms in countries with either a duty to petition for bankruptcy once a firm hits hard times (France and Germany) or in countries with powerful banks (Japan). Moreover, CASHMTA is the least significant in Germany. To test whether cross-country variations in the estimated coefficient of one default risk indicator are statistically significant, we pool all countries' data and estimate a single LOGIT model with a complete set of country interaction terms (unrestricted model). We then take turns in dropping the country interaction terms associated with each default risk indicator (restricted model), re-estimate the model, and compute the corresponding likelihood ratio (LR) test. Under the null hypothesis of no cross-country variations, this statistic is distributed as a chi-square variable with five degrees of freedom. The final column of Table 4 shows that the resulting statistics imply the rejection of the null hypothesis of no cross-country variations for all default risk indicators, except for EXRET and MB.

[Table 4 here]

Next, we compare bankruptcy forecasting power across the LOGIT model advocated by Campbell et al. (2008) and MDD. To this end, Table 5 presents the results from country-specific LOGIT models including either only MDD (Panel A), MDD together with the CHS default risk indicators (Panel B), or only the CHS default risk indicators (Panel C). These models are estimated using only firm-month observations for which both MDD and the CHS default risk indicators are available. Panel A suggests that, on its own, MDD is a significant predictor of bankruptcy, and its coefficient carries the correct sign. However, the results reported in Panel B show that adding the CHS default risk indicators substantially decreases the magnitude of the MDD coefficient in all countries, and the coefficient becomes insignificant in Australia, France, and the U.K. Comparing pseudo-R^2s, we find that adding the CHS default risk indicators more than doubles bankruptcy forecasting power, with the exception of Germany.[16] Moreover, when we drop MDD and use only the CHS default risk indicators as

[16] It is perhaps not surprising that MDD performs almost as well as the CHS default risk indicators in Germany. A major shortcoming of MDD is that it ignores cash reserves in forecasting bankruptcies. However,

bankruptcy predictors (Panel C), pseudo-R^2s remain high and very close to the ones reported in Panel B, indicating that for each of these countries the CHS default risk indicators subsume the bankruptcy-relevant information contained in MDD.

[Table 5 here]

4. The Global Default Risk Premium

4.1 Default Risk and Stock Returns in the C6 and C14 Countries

In this section, we study the relation between CHS and post-ranking portfolio returns. Our benchmark tests use monthly portfolio returns calculated from the perspective of a U.S. investor, that is, they are expressed in U.S. dollar terms. We sort stocks in ascending order on the basis of CHS in December of each year $t-1$ and then assign them to quantile portfolios. In our main tests, we follow Da and Gao (2010) and calculate portfolio returns from February of year t to January of year $t+1$, that is, we allow for a one month gap between portfolio formation and the start of the 12-month holding period.[17]

Since non-U.S. stock return data can be of lower quality than U.S. return data, we impose several data filters. In particular, our main results exclude a stock in year t if its market capitalization or its price in December of year $t-1$ is lower than the 5th percentile of the corresponding distribution calculated from all stocks in the same market. These filters are useful to alleviate the effect of market microstructure biases, such as the bid-ask bounce. We calculate both value-weighted (vw) and equally-weighted (ew) portfolio returns. We report average excess portfolio returns as well as portfolio alphas adjusted for market risk (CAPM alphas) or,

given that bankruptcy laws in Germany force a firm to file for bankruptcy once its net worth drops below a certain threshold, regardless of its cash reserves, this limitation may not be too important for German firms.

[17] As Da and Gao (2010) show, the negative returns of distressed stocks exhibit short-term reversals due to a market microstructure-induced liquidity shock. This feature may bias upward the returns of distressed stocks. Since CHS depends on a firm's stock return in December of year $t-1$, allowing for a gap between the portfolio formation month and the start of the holding period is advisable when CHS is used as sorting variable.

alternatively, for market, size (SMB), value (HML), and momentum (MOM) factor exposures according to the FFC model (FFC alphas). Reported returns and alphas are annualized.

In Table 6, we report the risk premia estimates of portfolios sorted on the basis of OOS CHS estimates for the C6 (Panel A) and C14 countries (Panel B) over the 2000-2010 sample period. We construct portfolios using the same quantiles of the CHS distribution as Campbell et al. (2008). To measure the default risk premium, we calculate the return of a spread strategy that is long the quintile portfolio with the highest default risk stocks (Q5) and short the quintile portfolio with the lowest default risk stocks (Q1). Finally, we also calculate the corresponding return of a spread strategy that is long the decile portfolio with the highest default risk stocks (P10) and short the decile portfolio with the lowest default risk stocks (P1).

[Table 6 here]

The results in Table 6 show that average excess returns and CAPM alphas increase almost monotonically across the default risk portfolios in both the C6 and the C14 countries. In the case of the value-weighted portfolios, the spread return between the highest and the lowest default risk quintiles (Q5-Q1) is equal to 16.90% p.a. in the C6 countries and 15.07% p.a. in the C14 countries, indicating the existence of an economically significant default risk premium in both cases. This premium is also highly statistically significant in both cases (C6 country t-stat: 2.79, C14 country t-stat: 2.75).[18] The corresponding default risk premia are of similar magnitude when we use equally-weighted portfolio returns: 11.52% p.a. (t-stat: 2.12) in the C6 countries and 11.02% p.a. (t-stat: 2.35) in the C14 countries. Adjusting for market risk, the magnitude and the significance of the default risk premia are not affected. This occurs because the market premium over the examined sample period is very low.

On the other hand, when we adjust portfolio returns for their size, value, and momentum factor loadings, the default risk premium is considerably reduced. Figure 1 shows why adjusting for these additional factors reduces the alphas of the spread strategies. The figure shows

[18] Newey-West (1987) standard errors are used for the calculation of t-statistics.

that the portfolios containing the most distressed stocks attract much higher SMB and HML betas relative to the portfolios containing the least distressed stocks. Therefore, the FFC model explains a large fraction of their high mean returns. Despite the fact that the FFC adjustment almost halves the magnitude of the distress risk premium, the premium remains statistically significant, at least when equally-weighted portfolios are considered.

[Figure 1 here]

While our results are certainly not driven by under-diversification (see the high number of stocks per portfolio), a potential concern is that they are attributable to estimation error in the initial LOGIT estimations, since these are often based on few bankruptcy filings. The evidence shown in the upper Panel of Figure 2 addresses this concern. Figure 2 plots the cumulative profits of a trading strategy that is long the decile portfolio with the highest OOS CHS stocks (P10) and short the decile portfolio with the lowest OOS CHS stocks (P1). The figure shows that the spread strategy's profits are not attributable to the early sample period, and that they can hence not be driven by estimation error in the OOS CHS proxy. Another interesting result of Figure 2 is that distressed stocks outperformed other stocks in the 2003-2007 bull market period. However, as expected, they were more negatively affected during the 2007-2009 global financial crisis, supporting the idea that they are 'marginal stocks'.[19]

[Figure 2 here]

To further rule out that estimation error drives our conclusions, we repeat the portfolio formation exercises using the IS version of CHS. Notwithstanding the look-ahead bias that the IS-CHS estimates induce, they have the advantages that (i) they should be more accurately estimated relative to the OOS ones, and that (ii) they allow us to consider a longer asset pricing test period that is close to identical to the ones analyzed in EGZ and GPS.

Table 7 presents the results from repeating the asset pricing tests in Table 6 using the IS-CHS estimates over the 1992 to 2010 period. The reported results suggest a positive relation

[19] Shaded areas in Figure 2 indicate recession periods in the examined markets.

between default risk and excess portfolio returns, which is almost monotonic. The magnitude of the average spread return between the highest and the lowest default risk deciles or quintiles is somewhat lower relative to the corresponding OOS results in Table 6, but it is statistically significant in the case of equally-weighted portfolios. Adjusting for market risk does not substantially affect the magnitude of the default risk premium. However, adjusting additionally for size, value, and momentum risk reduces the distress risk premium derived from the value-weighted portfolios further, while it does not seem to materially change the magnitude or significance of the premium derived from the equally-weighted portfolios.

[Table 7 here]

Panel B of Figure 2 helps us understand why the default risk premium is slightly lower using the IS-CHS relative to the OOS-CHS estimates. The figure reveals that the cumulative profits of the spread strategy that is long the highest default risk decile and short the lowest one (P10-P1) are low until the year 2000, but thereafter resemble the cumulative profits of the corresponding strategy based on the OOS-CHS estimates. There are two possible explanations for this finding. The first explanation is that the C6 or C14 country distress risk premium was substantially lower in the 1990s than in the 2000s. However, the more likely explanation is that the distress risk proxy estimated over the 1996-2009 period does not accurately reflect distress risk during the 1990s, highlighting that a timely and accurately estimated distress risk proxy is necessary to capture the distress risk premium.

Table 8 reports the results from a series of robustness checks further analyzing the default risk-stock return relation in the C6 (Panel A) and the C14 countries (Panel B). To save space, we only show the average excess returns of the extreme CHS-sorted quintile portfolios Q1 and Q5 as well as their spread return (Q5-Q1). Results for the rest portfolios are available upon request. Our first robustness test examines the relation between the IS-CHS measure and portfolio returns over the 2000-2010 period (i.e., the period used in our benchmark results). This test is conducted to further examine the effect of parameter instability in the OOS estimates on the default risk premium. In the second robustness test, we set the returns of filing firms in the filing month to −100% to study whether missing delisting returns could have led to an overestimation of the magnitude of the default risk premium in our main tests. In the third robustness test, we impose exactly the same data filters as GPS do, in order to ensure that the different conclusions we derive regarding the sign and the magnitude of the default risk premium are not driven by different data filters.[20] In the fourth robustness test, we do not impose any gap between the portfolio formation date (December of year $t - 1$) and the beginning of the holding period, which now becomes January of year t.[21] Finally, we also examine whether FOREX effects influence the magnitude of the default risk premium estimate. In particular, in this robustness test, we use local currency stock returns to calculate portfolio returns.[22]

[Table 8 here]

The results of the robustness tests show that the positive relation between default risk and stock returns remains remarkably stable. The mean return of the spread strategy Q5-Q1 shows that there is a highly economically and statistically significant default risk premium in all cases considered. The corresponding CAPM and FFC portfolio alphas are similar to the main results in Table 6. Adjusting for market risk does not affect the magnitude of the default risk premium. However, adjusting for the exposures of the portfolios to size and value factors captures some fraction of the default risk premium, because the returns of the high default risk

[20] In particular, GPS additionally omit stocks with a zero ex-dividend return or less than 12 months of complete historical data on their main analysis variables.

[21] We have also repeated the original portfolio formation exercises using a longer gap of two or three months between the portfolio formation month and the start of the holding period. Interestingly, we find that a longer gap renders the default risk premium larger and more significant, suggesting that the market microstructure effects discussed in Da and Gao (2010) may actually underestimate the magnitude of the default risk premium.

[22] Moreover, to ensure that the reported default risk premium is not driven by a country effect, we have also examined the country composition of our default risk portfolios. We can confirm that these portfolios are well diversified with respect to the various markets examined. This is particularly true for the highest default risk portfolios that give rise to the magnitude of the reported default risk premium.

portfolios covary positively with the SMB and HML factor returns. Nevertheless, the distress risk premium remains significant in most cases (results available upon request).

As an additional robustness check, we have re-estimated portfolio alphas using a different set of factor returns. In particular, the results reported in Table A.1 of the Appendix repeat the asset pricing tests in Table 6 using market, size, and value factor returns calculated from MSCI World ex US indices. The magnitude and the significance of the default risk premium is confirmed using this alternative set of risk factors.

4.3 Comparison of the CHS and the MDD measure

Our main results indicate a robust positive default risk-stock return relation, which is markedly different from the evidence in EGZ and GPS, who use MDD or EDF to proxy for default risk, respectively. In this subsection, we examine the source of this difference. To this end, we repeat the portfolio formation exercise using as sorting criterion MDD. MDD should be a close proxy for the proprietary EDF proxy, which is neither publicly available nor replicable for our international sample. For comparison purposes, we also report the corresponding results using our OOS-CHS estimates. However, the OOS-CHS portfolios are now constructed using only firms for which both OOS-CHS and MDD are available, in order to ensure that the same sample is examined. Equally- and value-weighted excess portfolio returns during the period 2000-2010 are reported in Table 9 for both default risk measures.

[Table 9 here]

The reported results confirm the almost monotonically positive relation between the OOS CHS measure and portfolio returns for this subsample of firms. In sharp contrast, when MDD is used as sorting variable, a U-shaped relation between default risk and portfolio returns emerges. For example, decile portfolio P1 containing the C6 country-firms with the lowest MDD values yields an average excess value-weighted return of 5.76% p.a., portfolios P5 and P6 yield an average excess return of 2.01% p.a., and portfolio P10 containing the firms with the highest MDD values yields an average excess return of 3.95% p.a. As a result, the average spread portfolio return Q5-Q1 (P10-P1) is negative and equal to −0.71% (−1.82%) p.a., but it is insignificant. These findings are qualitatively consistent with the main empirical results reported in both EGZ and GPS.

The difference in the default risk premium estimate obtained from the two sets of portfolios is caused by the fact that OOS-CHS and MDD disagree on the identity of the least distressed firms. Although on average 55% of the firms in the highest three MDD decile portfolios are also present in the highest three CHS decile portfolios, only 38% of the firms in the lowest three MDD deciles are also present in the lowest three CHS deciles. This discrepancy can be also seen from the average CHS default risk estimates of the MDD-sorted portfolios, calculated as the time-series average of the cross-sectional average taken over all firms in one MDD portfolio. While the firms in the highest MDD portfolios also exhibit the highest average CHS default risk, the lowest MDD decile portfolio (P1) contains firms with higher than average CHS default risk estimates. Consistent with our previous findings, this portfolio yields a relatively high mean excess return because it contains moderately distressed firms according to the OOS-CHS measure.

A reason why these two distress risk proxies disagree on the identify of low default risk stocks is that the Merton (1974) model assumes that a default occurs once the asset value drops below a fraction of the book value of debt, implying that the model must assign a zero default risk to stocks with no debt. Consistent with this idea, unreported results show that once we drop zero debt firms from our sample, the U-shaped relation between MDD and portfolio returns becomes less pronounced. Another reason could be that the Merton (1974) model fails to take into account all the events that can trigger a bankruptcy filing in practice. For example, Davydenko (2008) finds that, although most bankrupt firms are insolvent *and* illiquid, a fraction of them are only illiquid. Given that structural models, including the one used by Moody KMV, usually abstract from liquidity reserves, it is possible that they classify firms with liquidity problems as low default risk. Furthermore, Bharath and Shumway (2008) show that MDD does not produce a sufficient statistic for the probability of default.

4.4 Double-sorted Portfolios

In this subsection, we use double-sorted portfolios to examine whether the default risk premium is contingent upon a series of firm characteristics. In this way, we test the validity of theories suggested to explain cross-sectional variations in the default risk premium, and we corroborate prior U.S.-based evidence on these theories using our international sample. For example, Garlappi et al. (2008) and Garlappi and Yan (2011) hypothesize that the distress risk premium becomes hump-shaped if shareholders have high bargaining power allowing them to strategically default on their debt obligations and to extract rents from creditors. George and Hwang (2010) and Johnson et al. (2011) show that the default risk-stock return relation can be negative if high deadweight costs of distress or asset volatility decrease optimal leverage, but raise systematic risk. Campbell et al. (2008) argue that mispricing arising from limits to arbitrage and market microstructure biases are behind the distress risk anomaly. GPS find a significant negative relation between default risk and stock returns only among small capitalization stocks in their international sample. On the other hand, Vassalou and Xing (2004) find a significant default risk premium only for small and value U.S. stocks.

As Garlappi et al. (2008) and Favara et al. (2012) argue, shareholders' bargaining power decreases with firm size (SIZE) and asset tangibility (TANGIBILITY). We proxy for size using the market value of equity and for asset tangibility using the ratio of gross property, plant and equipment to total assets. We also use stock return volatility (SIGMA) to proxy for cash flow uncertainty. Following George and Hwang (2010), we also examine the importance of leverage, defined as the ratio of total liabilities to total assets (TLTA). To capture limits to arbitrage, we employ SIZE and SIGMA (see Wurgler and Zhuravskaya, 2002; Ali et al., 2003), because small capitalization stocks with a high volatility are difficult to sell short. To measure the degree of information asymmetry, we use analyst coverage, defined as the number of analysts issuing at least one earnings forecast over the prior twelve months in the I/B/E/S database (ANALYST). The latter proxy as well as BM allow us also to capture the ease with which a firm can be valued. Finally, since microstructure biases, such as the bid-ask bounce and infrequent trading, are more severe for firms traded at low stock prices, we use PRICE to capture such biases (see Blume and Stambaugh, 1983; Lo and MacKinlay, 2001).

To construct double-sorted portfolios, we sort stocks in ascending order according to their OOS-CHS values in December of year $t-1$ and then allocate them into tercile portfolios (T1 to T3). We also independently sort stocks in ascending order according to each of the firm characteristics, measured in December of year $t-1$ and expressed in U.S. dollars to ensure comparability, and then allocate them into tercile portfolios (Low, Medium, High).[23] The intersection of these two classifications yields the double-sorted portfolios. Portfolios are held from February of year t to January of year $t+1$, allowing for a one month gap between formation and the beginning of the holding period.

In Table 10, we report the average excess returns of the extreme double-sorted portfolios as well as the spread strategy (T3-T1) that is long the tercile portfolio with the highest default risk stocks (T3) and short the tercile portfolio with the lowest default risk stocks (T1) and only contains stocks from the highest or lowest firm characteristic portfolio. For comparison, we also report in the second column (ALL) the mean tercile portfolio returns from univariate sorts on OOS-CHS estimates. Panels A and B show results based on the value- and equally-weighted portfolios constructed from the C6 countries, respectively, and Panels C and D show results based on the same portfolios formed from the C14 countries.

[Table 10 here]

[23] The only exception is analyst coverage, where we assign firms to two portfolios depending on whether there is at least one analyst following the firm or none.

Table 10 suggests that the default risk premium is relatively higher among big capitalization and growth stocks, stocks that are traded at high prices as well as among firms that are followed by analysts and are characterized by a high asset tangibility and low leverage. Therefore, the default risk premium documented in this study cannot be attributed to microstructure biases and it is not driven by small capitalization or value firms. Moreover, in line with GPS, we find a flat or even a negative default risk-stock return relation among smaller stocks. The same is true for stocks traded at low prices in the C6 countries and firms that are not followed by analysts in the case of the equally-weighted portfolios. This is in line with the arguments of Campbell et al. (2008) that market microstructure effects, information asymmetry, and limits to arbitrage may explain the absence of a default risk premium. Finally, our results support the shareholder advantage hypothesis of Garlappi et al. (2008) and Garlappi and Yan (2011), and are also in line with the evidence of Favara et al. (2012), since the default risk premium is less pronounced among firms with low tangibility. The latter results hold for both the C6 and the C14 countries.

5. Conclusions

Our study is the first in the literature to use bankruptcy filing data for a large sample of non-U.S. firms to shed new light on the relation between default risk and stock returns. Such an analysis is warranted because, inconsistent with intuition, several studies for the U.S. market have found this relation to be flat, negative, or hump-shaped. Using the approach of Campbell et al. (2008, 2011) to estimate default risk probabilities, we offer robust evidence supporting the existence of an economically and statistically significant positive default risk premium in international markets. In our empirical work, we estimate IS and OOS default risk probabilities from country- and bankruptcy law regime-specific LOGIT models using a set of intuitive market and accounting variables for firms in 14 developed markets. We show that portfolios containing the highest default risk firms significantly outperform portfolios containing the ones with the lowest default risk. This finding is robust to different portfolio weighting schemes, data filters, sample periods, and holding period definitions.

Our conclusions are markedly different from those reported in the recent studies of EGZ and GPS, who also examine the default risk-stock return relation using a large sample of non-U.S. firms over a similar period. In contrast to our approach, these studies use either the Merton (1974) Distance-to-Default (MDD) or Moody KMV's Expected Default Frequency (EDF) to capture distress risk. Since EDF is neither publicly available nor replicable, we compare our CHS proxy with MDD, which should be a close proxy of EDF. This comparison reveals that CHS often disagrees with MDD on the identity of low default risk firms. A reason for this disagreement is that, unlike CHS, which is more flexible, MDD assumes that a default occurs once the asset value drops below a fraction of the book value of debt. Another reason that might explain why our results differ from the ones in the two other studies is that structural models focus exclusively on economic insolvency risk, abstracting from corporate liquidity issues. However, as Davydenko (2008) shows, even solvent firms are sometimes driven into bankruptcy due to a lack of internal cash reserves. Therefore, structural models, including the Merton (1974) model and the one of Moody's KMV, may classify firms with liquidity problems as low default risk firms. In addition, Bharath and Shumway (2008) question the ability of MDD to produce a sufficient statistic for the probability of default.

Finally, our rich international dataset allows us to examine whether the magnitude of the default risk premium is contingent upon a series of firm characteristics. We find that the default risk premium is relatively higher among big capitalization and growth stocks, stocks that are traded at high prices as well as among firms that are followed by analysts and that are characterized by high asset tangibility and low leverage. Therefore, the default risk premium that we document cannot be attributed to microstructure biases and it is not driven by small or value firms. Finally, our results support the shareholder advantage hypothesis of Garlappi et al. (2008) and Garlappi and Yan (2011), since the default risk premium is less pronounced among firms with low tangibility, which is a proxy for high shareholder bargaining power.

Echoing the concerns of Chava and Purnanandam (2010), our results raise the possibility that the distress anomaly documented in the U.S. market could be sample-specific. Therefore, as the quality of international bankruptcy filing data is bound to improve in the future, there is scope for expanding the cross-section of firms by additionally considering less developed markets as well as extending the time period under examination to study the behavior of the default risk premium across different economic and market conditions. Another important research direction is to delve into the drivers of the outperformance of distressed stocks outside the U.S. market. Of particular interest is the question whether proposed explanations for the anomalous returns of U.S. distressed stocks (i.e. investors' inability to value distressed stocks correctly (Eisdorfer et al., 2011); differences in corporate liquidity (Medhat, 2014); lottery-like payoffs of distressed stocks (Conrad et al., 2014)) can also help us understand the behavior of distressed stocks in non-U.S. markets.

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Table 1
Bankruptcy Filing Data Sources

This table provides detailed information on the sources we used to collect the international bankruptcy filing data. For each of the 14 countries included in our analysis, we report the sample period over which we have collected these data and the source that we have used, including information on our contact person, their employer, and the employer's details. The superscript "1" next to the name of a person indicates that we were asked to keep their contact information confidential and, as a result, we only report institutional contact details. The last column provides further useful information about the bankruptcy filing data.

		Source			
Country	*Period*	*Contact Person*	*Institution*	*Contact Information*	*Bankruptcy Source Information*
Australia	1996-2007	S. Jones	Department of Accounting, University of Sydney, Australia	tel.: +61 2 9351 7755 e-mail: s.jones@econ.usyd.edu.au	
	2004-2009	T. McLeen	Delisted.com.au	e-mail: admin@delisted.com.au	Hand-collected data obtained from website
Canada	1996-2002	D. Kennedy	School of Accountancy, University of Waterloo, Canada	tel.: +1 519 888 4752 e-mail: dkennedy@uwaterloo.ca	Hand-collected data obtained from media and press releases
	1996-2008	S. Cavanagh[1]	Office of the Superintendent of Bankruptcy, Canada	tel.: +1 613 941 1000 (Headquarters) web: www.ic.gc.ca	Bankruptcy data contain both private and public firms; data lack re-organizations under the new CCAA procedure
Denmark	2000-2009	None	NASDAQ OMX	web: www.nordic. nasdaqomxtrader.com	Hand-collected data obtained from website; features only bankruptcy filings leading to a delisting
France	1993-2007	A. Holmes	Duns & Bradstreet (D&B)	tel.: +44 0 1628 492677 e-mail: holmesa@dnb.com	Hand-collected data obtained from French bankruptcy courts purchased from D&B
Finland	1996-2009	H. Hämäläinen[1]	Office of the Bankruptcy Ombudsman, Finland	tel.: +35 810 3665111 web: www.konkurssiasiamies.fi	
Germany	1995-2009	None	Hoppenstedt Database	web: www.hoppenstedt.de	
Hong Kong	1996-2009	M. Chow[1]	Registrar of Companies, Hong Kong	tel.: +852 2234 9933 (Enquiries) web: www.cr.gov.hk	Bankruptcy data contain both private and public firms
Japan	1993-2009	C.Y. Shirata	Department of Accounting, University of Tsukuba Tokyo, Japan	e-mail: shirata@mbaib. gsbs.tsukuba.ac.jp	Bankruptcy data obtained from Teikoku Database
New Zealand	1996-2009	P. Davey[1]	Ministry of Economic Development	tel.: +64 4 472 0030 web: www.med.govt.nz	Bankruptcy data contain both private and public firms with substantial shareholdings; filing date identified using website
Portugal	1996-2009	C. Albuquerque Correia	Comissão do Mercado de Valores Mobiliários (CMVM)	e-mail cmvm@cmvm.pt	
Spain	1996-2009	None	Comisión Nacional del Mercado de Valores (CNMV)	web: www.cnmv.es	Hand-collected data obtained from website
Sweden	1998-2009	B. Ståhl	Kronofogden (Swedish Enforcement Authority)	email: kronofogdemy ndigheten@kronofogden.se	
Taiwan	1996-2009	C. Shao-Wei	Taiwanse Economic Journal (TEJ)	e-mail: tina@tej.com.tw web: www.tej.com.tw	
United Kingdom	1992-2007	M. Staunton	London Business School	e-mail: m.staunton@london.edu	Bankruptcy data obtained from London Business School Share Price Database
	2007-2009	None	London Stock Exchange	web: www.londonstockexchange.com	

Table 2
Number and Proportion of Bankruptcies per Country and Year

This table reports the total number of bankruptcies (#B), the total number of active firms with complete data (#ALL) and the proportion of active firms with complete data that went bankrupt (%) each year in our sample period, over the full sample period (1992-2009), and over the initial estimation window (1992-1999). In the latter two cases (periods 1999-2009 and 1992-1999) #ALL refers to the total number of firm/months rather than the total number of firms. This information is reported for each country with more than 40 bankruptcies in our sample period, namely Australia, Canada, France, Germany, Japan and the UK (the C6 countries). In the last column, we provide the corresponding information for the pooled sample of all C6 countries.

	Australia			**Canada**			**France**			**Germany**			**Japan**			**United Kingdom**			**All countries**		
Year	*#B*	*#ALL*	*%*	*#B*	*#ALL*	*%*	*#B*	*#ALL*	*%*	*#B*	*#ALL*	*%*	*#B*	*#ALL*	*%*	*#B*	*#ALL*	*%*	*#B*	*#ALL*	*%*
1992																14	1,176	1.19	14	1,176	1.19
1993							2	464	0.43				2	1,775	0.11	5	1,170	0.43	9	3,409	0.26
1994							0	470	0.00				0	1,866	0.00	3	1,177	0.25	3	3,513	0.09
1995							1	483	0.21	1	342	0.29	1	1,991	0.05	4	1,198	0.33	7	4,014	0.17
1996	1	250	0.40	0	359	0.00	4	482	0.83	2	350	0.57	1	2,063	0.05	8	1,213	0.66	16	4,717	0.34
1997	1	306	0.33	2	410	0.49	1	477	0.21	1	372	0.27	8	2,132	0.38	6	1,296	0.46	19	4,993	0.38
1998	2	331	0.60	0	430	0.00	2	613	0.33	1	463	0.22	7	2,167	0.32	11	1,487	0.74	23	5,491	0.42
1999	1	365	0.27	4	494	0.81	1	737	0.14	4	514	0.78	3	2,787	0.11	16	1,506	1.06	29	6,403	0.45
2000	3	487	0.62	4	676	0.59	1	821	0.12	3	594	0.51	11	2,972	0.37	7	1,425	0.49	29	6,975	0.42
2001	9	700	1.29	4	863	0.46	3	889	0.34	16	708	2.26	11	3,032	0.36	22	1,369	1.61	65	7,561	0.86
2002	6	1,214	0.49	3	898	0.33	10	884	1.13	30	789	3.80	29	3,173	0.91	24	1,364	1.76	102	8,322	1.23
2003	6	1,255	0.48	1	1,005	0.10	10	857	1.17	16	775	2.06	18	3,254	0.55	16	1,330	1.20	67	8,476	0.79
2004	5	1,276	0.39	4	1,164	0.34	4	796	0.50	9	728	1.24	11	3,298	0.33	10	1,277	0.78	43	8,539	0.50
2005	6	1,346	0.45	1	1,273	0.08	3	760	0.39	4	700	0.57	8	3,405	0.23	9	1,318	0.68	31	8,802	0.35
2006	7	1,490	0.47	6	1,614	0.37	2	737	0.27	7	699	1.00	2	3,507	0.06	7	1,457	0.48	31	9,504	0.33
2007	7	1,619	0.43	5	2,290	0.22	3	777	0.38	13	739	1.76	6	3,644	0.16	5	1,604	0.31	39	10,673	0.37
2008	22	1,785	1.23	7	2,440	0.29				10	829	1.21	32	3,729	0.86	33	1,681	1.96	104	10,464	0.99
2009	12	1,841	0.65							11	856	1.29	18	3,673	0.49	21	1,650	1.27	62	8,020	0.77
1992-2009	88	14,265	0.58	41	13,916	0.31	47	8,830	0.48	128	9,116	1.25	168	42,836	0.37	221	19,977	0.96	693	108,940	0.59
1992-1999	5	1,252	0.40	6	1,693	0.32	11	3,726	0.31	9	2,041	0.43	22	14,781	0.15	67	10,223	0.64	120	33,716	0.41

Table 3
Summary Statistics

This table presents summary statistics (means, medians and standard deviations) for each of the following variables: NIMTA (net income scaled by the sum of market value of equity and total liabilities), TLMTA (total liabilities scaled by the sum of market value of equity and total liabilities), EXRET (monthly log stock return of a firm minus that of the index of the market in which the firm is headquartered), RSIZE (log ratio of a firm's market value to the sum of market values for all firms in the same market and month), SIGMA (annualized standard deviation of a firm's daily log stock return in the prior three months, as defined in section 2.2), CASHMTA (ratio of cash and short-term assets to the sum of market value of equity and total liabilities), MB (market-to-book value ratio) and PRICE (log stock price). In each Panel, the statistics are reported for active (act) and for bankrupt firms (bank) in their filing month, respectively. The statistics are reported for each country with more than 40 bankruptcies over the period 1992-2009, namely Australia, Canada, France, Germany, Japan and the UK (the C6 countries). In Panel G, we also provide the corresponding statistics for the pooled sample of firms in all C6 countries.

	NIMTA		TLMTA		EXRET		RSIZE		SIGMA		CASHMTA		MB		PRICE	
	act	bank	act	bank	act	bank	act	bank	act	bank	act	bank	act	bank	act	bank
Panel A: Australia																
Mean	-0.08	-0.23	0.25	0.60	0.00	-0.09	-9.93	-11.24	0.70	1.14	0.16	0.17	2.22	1.20	-0.62	-1.35
Median	0.00	-0.12	0.18	0.69	-0.01	-0.09	-10.22	-11.38	0.64	1.13	0.06	0.07	1.59	0.59	-0.54	-1.70
St.Dev	0.24	0.31	0.24	0.25	0.15	0.19	2.03	1.45	0.40	0.44	0.25	0.23	1.80	1.81	1.12	1.08
All firm/months (N=157,651); Bankruptcy Group (N=87)																
Panel B: Canada																
Mean	-0.06	-0.32	0.27	0.60	0.00	-0.12	-9.93	-11.82	0.84	1.57	0.12	0.20	2.46	3.03	0.58	-0.54
Median	-0.01	-0.29	0.19	0.70	-0.01	-0.22	-9.89	-12.56	0.72	1.41	0.04	0.03	1.78	1.55	0.79	-0.80
St.Dev	0.16	0.35	0.26	0.27	0.18	0.25	2.12	2.32	0.58	0.85	0.21	0.41	1.95	2.74	1.31	1.25
All firm/months (N=188,579); Bankruptcy Group (N=41)																
Panel C: France																
Mean	0.01	-0.06	0.44	0.67	0.00	-0.04	-9.64	-11.93	0.47	0.73	0.10	0.10	2.34	2.55	2.96	2.25
Median	0.02	-0.05	0.44	0.76	-0.01	-0.03	-9.89	-12.45	0.41	0.68	0.06	0.04	1.79	0.89	3.02	1.97
St.Dev	0.06	0.11	0.25	0.29	0.11	0.15	2.08	1.43	0.24	0.40	0.10	0.14	1.71	2.52	0.81	0.86
All firm/months (N=101,330); Bankruptcy Group (N=40)																
Panel D: Germany																
Mean	-0.02	-0.18	0.44	0.78	0.00	-0.15	-9.28	-11.96	0.51	1.19	0.12	0.19	2.29	1.13	2.41	1.34
Median	0.02	-0.07	0.43	0.88	-0.01	-0.18	-9.48	-12.30	0.45	1.29	0.06	0.08	1.75	0.48	2.47	1.11
St.Dev	0.15	0.31	0.28	0.23	0.12	0.14	1.88	1.14	0.30	0.41	0.18	0.24	1.75	1.72	0.99	0.79
All firms/months (N=102,484); Bankruptcy Group (N=125)																
Panel E: Japan																
Mean	0.01	-0.03	0.55	0.91	0.00	-0.14	-10.03	-12.19	0.45	0.88	0.16	0.11	1.31	0.91	6.35	5.67
Median	0.02	-0.02	0.57	0.94	-0.01	-0.15	-10.21	-12.30	0.41	0.90	0.12	0.08	0.99	0.34	6.27	5.43
St.Dev	0.03	0.05	0.24	0.08	0.10	0.10	1.51	0.70	0.20	0.19	0.12	0.09	1.00	1.18	0.71	0.56
All firms/months (N=471,800); Bankruptcy Group (N=164)																
Panel F: United Kingdom																
Mean	-0.03	-0.18	0.36	0.71	0.00	-0.07	-9.82	-12.32	0.42	0.73	0.11	0.12	2.42	1.88	4.45	3.23
Median	0.02	-0.13	0.34	0.78	-0.01	-0.05	-9.95	-12.40	0.37	0.72	0.05	0.03	1.70	0.59	4.60	3.33
St.Dev	0.15	0.23	0.24	0.19	0.12	0.17	1.90	1.00	0.24	0.31	0.15	0.20	1.97	2.47	0.93	0.70
All firms/months (N=215,524); Bankruptcy Group (N=187)																
Panel G: All Countries																
Mean	-0.02	-0.15	0.42	0.75	0.00	-0.11	-9.87	-12.01	0.54	0.96	0.13	0.14	1.96	1.52	3.65	2.57
Median	0.01	-0.07	0.41	0.83	-0.01	-0.14	-10.04	-12.28	0.44	0.90	0.08	0.06	1.36	0.52	4.10	2.85
St.Dev	0.14	0.25	0.27	0.23	0.13	0.16	1.84	1.24	0.36	0.46	0.17	0.21	1.68	2.09	2.78	2.49
All firms/months (N=1,237,368); Bankruptcy Group (N=644)																

Table 4
Logit Regressions of Bankruptcy Indicator on 12-month Lagged Predictor Variables

This table reports results from country-specific LOGIT regressions of a bankruptcy indicator on predictors that are lagged by 12 months. NIMTA is net income scaled by the sum of the market value of equity and total liabilities. TLMTA is total liabilities scaled by the sum of the market value of equity and total liabilities. EXRET is the monthly log stock return of a firm minus that of the index of the market in which the firm is headquartered. RSIZE is the log ratio of a firm's market value to the sum of market values for all firms in the same market and month. SIGMA is the annualized standard deviation of a firm's daily log stock returns in the prior three months, as defined in section 2.2. CASHMTA is ratio of cash and short-term assets to the sum of the market value of equity and total liabilities. MB is the market-to-book value ratio, while PRICE is the log stock price. Estimated coefficients are in bold, while *z*-statistics, which are constructed using heteroscedasticity-robust standard errors, are reported in square brackets. The column titled 'LR test' reports the results from a likelihood ratio test on whether the coefficients of each predictor differ significantly across the six countries. The bold number in the last column is twice the difference between the log-likelihood of a pooled LOGIT model including country-specific interaction terms on all predictors (including constants) except for the variable in the row in which the statistic is reported (restricted model), and that from a pooled LOGIT model including all country interactions terms (unrestricted model). The *p*-value associated with the LR test statistic is shown below in parenthesis. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Predictors 12-month lag	AUSTRALIA	CANADA	FRANCE	GERMANY	JAPAN	UNITED KINGDOM	LR TEST
NIMTA	**-0.182**	**-3.301** ***	**-3.199**	**0.117**	**-1.586**	**-0.397**	**15.97** **
	[-0.53]	[-6.05]	[-1.57]	[0.31]	[-0.63]	[-1.07]	(0.01)
TLMTA	**1.929** ***	**2.008** ***	**0.494**	**1.142** ***	**6.553** ***	**1.735** ***	**73.85** ***
	[3.95]	[3.55]	[0.67]	[2.99]	[8.05]	[5.89]	(0.00)
EXRET	**-2.563** ***	**-1.902**	**-0.304**	**-0.556**	**-1.280** *	**-1.312** **	**4.85**
	[-3.14]	[-1.42]	[-0.22]	[-0.74]	[-1.92]	[-2.12]	(0.56)
RSIZE	**0.091**	**0.445** ***	**-0.369** ***	**-0.257** ***	**-0.265** ***	**-0.183** ***	**36.80** ***
	[0.90]	[3.13]	[-3.00]	[-3.73]	[-4.31]	[-3.62]	(0.00)
SIGMA	**1.438** ***	**0.014**	**0.881**	**1.725** ***	**2.506** ***	**1.830** ***	**26.23** ***
	[3.96]	[0.04]	[1.27]	[6.14]	[6.42]	[5.53]	(0.00)
CASHMTA	**-0.536**	**-0.481**	**-1.119**	**-0.056**	**-3.839** ***	**-2.488** ***	**16.27** **
	[-0.77]	[-0.50]	[-0.57]	[-0.13]	[-3.46]	[-3.39]	(0.01)
MB	**-0.053**	**-0.020**	**-0.059**	**-0.003**	**0.141** **	**-0.004**	**4.83**
	[-0.80]	[-0.27]	[-0.70]	[-0.05]	[2.14]	[-0.12]	(0.57)
PRICE	**0.193**	**-1.045** ***	**0.084**	**-0.069**	**0.745** ***	**-0.525** ***	**70.84** ***
	[1.19]	[-3.84]	[0.33]	[-0.61]	[5.40]	[-5.12]	(0.00)
CONSTANT	**-8.003** ***	**-4.394** ***	**-12.380** ***	**-10.660** ***	**-20.770** ***	**-8.064** ***	
	[-9.48]	[-3.16]	[-7.31]	[-13.40]	[-15.21]	[-9.33]	
Observations	135,245	157,058	92,191	93,367	447,151	196,104	
Failures	77	40	40	115	162	177	
Pseudo-R^2	0.044	0.106	0.053	0.069	0.125	0.084	

Table 5
Logit Regressions including Merton's (1974) Distance-to-Default

This table reports selected results from country-specific LOGIT regressions of a bankruptcy indicator on sets of predictors that are lagged by 12 months. As exogenous variables, the models use either *(i)* only Merton's (1974) Distance-to-Default (MDD) in Panel A, or *(ii)* MDD together with the Campbell et al. (2008, CHS) default risk indicators, namely NIMTA, TLMTA, EXRET, RSIZE, SIGMA, CASHMTA, MB and PRICE (see the caption of Table 4 for a description of these variables) in Panel B or *(iii)* only the CHS default risk indicators in Panel C. The LOGIT models are estimated using only the firm-month observations for which both MDD and the CHS default risk indicators are available. Reported results refer to the slope coefficient of MDD (in bold) and the associated z-statistic, computed using heteroscedasticity-robust standard errors (in square brackets) where applicable, as well as the pseudo R^2 of each model. *** and ** denote statistical significance at 1% and 5% levels, respectively.

Predictors 12-month lag	AUSTRALIA	CANADA	FRANCE	GERMANY	JAPAN	UNITED KINGDOM
***Panel A**: Merton (1974) Distance-to-Default*						
MDD	**1.942** ***	**2.585** ***	**2.658** ***	**2.843** ***	**3.679** ***	**2.951** ***
	[4.40]	[4.41]	[4.78]	[12.01]	[20.16]	[13.21]
Pseudo-R^2	0.013	0.034	0.034	0.059	0.064	0.043
***Panel B**: Merton (1974) Distance-to-Default + CHS Default Risk Indicators*						
MDD	**-0.282**	**2.521** ***	**1.935**	**1.367** ***	**0.887** **	**0.246**
	[-0.36]	[3.67]	[1.86]	[3.35]	[2.89]	[0.65]
Pseudo-R^2	0.057	0.103	0.067	0.085	0.130	0.106
***Panel C**: CHS Default Risk Indicators*						
Pseudo-R^2	0.057	0.091	0.057	0.078	0.127	0.106
Observations	108,001	114,776	76,767	83,360	412,260	160,656
Failures	48	22	24	104	159	115

Table 6
Out-of-Sample Global Default Risk Portfolios

This table reports average excess returns, CAPM alphas, and four-factor alphas from the Fama-French-Carhart asset pricing model (FFC alphas) for portfolios constructed on the basis of out-of-sample (OOS) estimates of the Campbell et al. (2008, CHS) default risk measure. We construct these portfolios for stocks in the C6 countries (Australia, Canada, France, Germany, Japan and the United Kingdom; Panel A) and the C14 countries (the C6 countries plus Denmark, Finland, Hong Kong, New Zealand, Portugal, Spain, Sweden and Taiwan; Panel B). To estimate OOS CHS measures, a LOGIT model is recursively run for each of the C6 countries; see Section 3. For the rest countries that feature too few bankruptcies, we run recursively a LOGIT model for each bankruptcy law regime. We consider four bankruptcy law regimes: *Common Law* (Australia, Canada, Hong Kong, New Zealand and the U.K.), *Napoleonic* (France, Spain and Portugal), *Roman-Germanic* (Denmark, Finland, Germany and Sweden) and *Mixed* (Japan and Taiwan). The recursive LOGIT estimations start with an initial window including data up to December 1999. At the end of December of year *t-1*, we sort stocks in ascending order on the basis of their OOS CHS default risk estimates and allocate them into decile and quintile portfolios. We form the spread strategy Q5-Q1 that is long the quintile portfolio with the highest default risk stocks (Q5) and short the quintile portfolio with the lowest default risk stocks (Q1). We also form the spread strategy P10-P1 that is long the decile portfolio with the highest default risk stocks (P10) and short the decile portfolio with the lowest default risk stocks (P1). We exclude stocks whose price or market capitalization is below the 5th percentile of the corresponding country-month distribution at the portfolio formation date. Portfolios are held from February of year *t* to January of year *t+1*, at which point they are rebalanced, allowing for a one month gap between the portfolio formation date and the beginning of the holding period. Returns are calculated in U.S. dollar terms and they are reported for value-weighted (vw) and equally-weighted (ew) portfolios. Average excess portfolio returns and alphas are annualized and bolded; their associated t-statistics are reported in square brackets. The lower part of each panel reports the average number of firms per portfolio, stocks' average standard deviation of returns (SIGMA), their average log relative size (RSIZE) and their average OOS CHS default probability estimate. The examined period is 2000-2010. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

		Deciles								
		1	2	3-4	5-6	7-8	9	10	Q5-Q1	P10-P1
Panel A: C6 Countries										
Excess return	vw	**-3.45**	**-4.22**	**2.04**	**6.34**	**10.48**	**11.52**	**14.19**	**16.90** ***	**17.63** **
		[-0.50]	[-0.52]	[0.28]	[0.81]	[1.23]	[1.15]	[1.20]	[2.79]	[2.15]
	ew	**6.29**	**6.50**	**9.70**	**12.11**	**14.50**	**13.44**	**22.39** **	**11.52** **	**16.10** **
		[0.78]	[0.73]	[1.09]	[1.25]	[1.45]	[1.33]	[2.00]	[2.12]	[2.41]
CAPM alpha	vw	**-4.82**	**-5.84**	**0.16**	**4.26** ***	**8.34** ***	**9.02** ***	**11.77** *	**15.93** ***	**16.59** **
		[-1.35]	[-1.45]	[0.11]	[3.02]	[3.44]	[2.72]	[1.83]	[3.02]	[2.31]
	ew	**5.12**	**5.02**	**7.79** **	**9.97** ***	**12.35** ***	**11.29** ***	**20.24** ***	**10.70** **	**15.12** ***
		[0.89]	[0.86]	[2.11]	[3.13]	[3.36]	[2.75]	[3.16]	[2.33]	[2.63]
FFC alpha	vw	**-4.69** **	**-6.47** **	**-0.66**	**1.94**	**1.98**	**0.64**	**3.62**	**7.64** **	**8.31**
		[-2.22]	[-2.07]	[-0.55]	[1.22]	[0.73]	[0.27]	[0.66]	[2.03]	[1.38]
	ew	**1.42**	**0.28**	**2.53**	**4.45**	**6.86** **	**6.02** *	**15.18** ***	**9.76** **	**13.76** ***
		[0.34]	[0.06]	[0.83]	[1.37]	[1.97]	[1.77]	[3.20]	[2.17]	[2.57]
average # of firms		806	807	1613	1613	1613	806	807		
average sigma		0.42	0.47	0.49	0.52	0.55	0.59	0.69		
average RSIZE		-9.49	-9.71	-9.43	-9.44	-9.88	-10.46	-11.09		
average CHS		0.00%	0.01%	0.02%	0.04%	0.09%	0.15%	0.56%		

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Table 6 (continued)
Out-of-Sample Global Default Risk Portfolios

		Deciles								
		1	2	3-4	5-6	7-8	9	10	Q5-Q1	P10-P1
Panel B: C14 Countries										
Mean excess return	vw	**-2.71**	**-2.98**	**3.48**	**6.17**	**9.00**	**10.49**	**14.30**	**15.07** ***	**17.01** **
		[-0.38]	[-0.36]	[0.45]	[0.77]	[1.05]	[1.04]	[1.23]	[2.75]	[2.29]
	ew	**7.44**	**6.29**	**9.95**	**12.30**	**14.16**	**14.26**	**21.51** *	**11.02** **	**14.07** **
		[0.94]	[0.78]	[1.15]	[1.27]	[1.43]	[1.41]	[1.94]	[2.35]	[2.49]
CAPM alpha	vw	**-4.21**	**-4.82**	**1.49**	**4.11** ***	**6.87** ***	**8.05** **	**11.89** **	**14.27** ***	**16.10** **
		[-1.22]	[-1.45]	[0.97]	[2.73]	[2.95]	[2.55]	[1.98]	[2.98]	[2.49]
	ew	**6.07**	**4.72**	**8.01** **	**10.14** ***	**12.01** ***	**12.08** ***	**19.37** ***	**10.33** ***	**13.30** ***
		[1.20]	[1.02]	[2.50]	[3.20]	[3.46]	[3.17]	[3.31]	[2.84]	[2.85]
FFC alpha	vw	**-4.05** **	**-3.85** *	**1.48**	**2.18**	**1.12**	**-0.36**	**3.06**	**5.04**	**7.11**
		[-2.00]	[-1.81]	[0.96]	[1.26]	[0.43]	[-0.15]	[0.59]	[1.59]	[1.40]
	ew	**2.54**	**0.25**	**3.65**	**5.18**	**6.55** *	**6.70** *	**14.09** ***	**9.00** **	**11.55** ***
		[0.63]	[0.07]	[1.25]	[1.51]	[1.87]	[1.96]	[3.30]	[2.39]	[2.60]
average # of firms		998	999	1998	1998	1998	999	999		
average sigma		0.42	0.45	0.47	0.51	0.54	0.59	0.70		
average RSIZE		-9.22	-9.17	-8.85	-9.08	-9.63	-10.27	-10.91		
average CHS		0.00%	0.01%	0.02%	0.04%	0.08%	0.17%	0.59%		

Table 7
In-Sample Global Default Risk Portfolios

This table reports average excess returns, CAPM alphas, and four-factor alphas from the Fama-French-Carhart asset pricing model (FFC alphas) for portfolios constructed on the basis of in-sample (IS) estimates of the Campbell et al. (2008, CHS) default risk measure. We construct these portfolios for stocks in the C6 countries (Australia, Canada, France, Germany, Japan and the United Kingdom; Panel A) and the C14 countries (the C6 countries plus Denmark, Finland, Hong Kong, New Zealand, Portugal, Spain, Sweden and Taiwan; Panel B). To estimate IS CHS measures, a full sample LOGIT model is run for each of the C6 countries; see Section 3. For the rest countries that feature too few bankruptcies, we run a full sample LOGIT model for each bankruptcy law regime. We consider four bankruptcy law regimes: *Common Law* (Australia, Canada, Hong Kong, New Zealand and the U.K.), *Napoleonic* (France, Spain and Portugal), *Roman-Germanic* (Denmark, Finland, Germany and Sweden) and *Mixed* (Japan and Taiwan). At the end of December of year *t-1*, we sort stocks in ascending order on the basis of their IS CHS default risk estimates and allocate them into decile and quintile portfolios. We form the spread strategy Q5-Q1 that is long the quintile portfolio with the highest default risk stocks (Q5) and short the quintile portfolio with the lowest default risk stocks (Q1). We also form the spread strategy P10-P1 that is long the decile portfolio with the highest default risk stocks (P10) and short the decile portfolio with the lowest default risk stocks (P1). We exclude stocks whose price or market capitalization is below the 5th percentile of the corresponding country-month distribution at the portfolio formation date. Portfolios are held from February of year *t* to January of year *t+1*, at which point they are rebalanced, allowing for a one month gap between the portfolio formation date and the beginning of the holding period. Returns are calculated in U.S. dollar terms and they are reported for both value-weighted (vw) and equally-weighted (ew) portfolios. Average excess portfolio returns and alphas are annualized and bolded; their associated t-statistics are reported in square brackets. The lower part of each panel reports the average number of firms per portfolio, stocks' average standard deviation of returns (SIGMA), their average log relative size (RSIZE) and their average IS CHS default probability estimate. The examined period is 1992-2010. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

		Deciles								
		1	2	3-4	5-6	7-8	9	10	Q5-Q1	P10-P1
Panel A: C6 Countries										
Mean excess return	vw	**0.42**	**3.68**	**3.98**	**5.13**	**6.68**	**6.03**	**8.32**	**5.45**	**7.90**
		[0.07]	[0.72]	[0.86]	[1.14]	[1.26]	[0.94]	[0.98]	[1.47]	[1.51]
	ew	**2.59**	**3.42**	**7.58**	**10.39** *	**9.74**	**11.33** *	**12.29**	**8.80** **	**9.70** **
		[0.42]	[0.54]	[1.28]	[1.78]	[1.60]	[1.89]	[1.55]	[2.40]	[2.00]
CAPM alpha	vw	**-3.79**	**-1.72**	**-0.60**	**0.51**	**1.55**	**0.33**	**2.11**	**4.45**	**5.91**
		[-0.94]	[-0.78]	[-0.38]	[0.31]	[0.59]	[0.10]	[0.42]	[1.33]	[1.34]
	ew	**-0.99**	**-1.21**	**2.87**	**5.56** *	**5.01**	**6.73** *	**7.28**	**8.10** **	**8.26** *
		[-0.20]	[-0.27]	[0.78]	[1.75]	[1.53]	[1.72]	[1.47]	[2.33]	[1.93]
FFC alpha	vw	**-3.82**	**-2.87**	**-1.52**	**-1.57**	**-0.92**	**-1.60**	**1.18**	**3.62**	**5.00**
		[-1.22]	[-1.38]	[-1.13]	[-1.02]	[-0.43]	[-0.60]	[0.29]	[1.38]	[1.48]
	ew	**-2.80**	**-2.85**	**0.59**	**2.84**	**2.76**	**4.24**	**7.21** *	**8.55** **	**10.01** **
		[-0.73]	[-0.84]	[0.22]	[1.14]	[1.11]	[1.45]	[1.79]	[2.32]	[2.23]
average # of firms		649	649	1299	1299	1299	649	650		
average sigma		0.38	0.43	0.43	0.44	0.47	0.51	0.59		
average RSIZE		-9.02	-8.98	-8.83	-9.06	-9.50	-9.95	-10.65		
average CHS		0.00%	0.00%	0.01%	0.02%	0.04%	0.07%	0.15%		

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Table 7 (continued)
In-Sample Global Default Risk Portfolios

		Deciles								
		1	2	3-4	5-6	7-8	9	10	Q5-Q1	P10-P1
Panel B: C14 Countries										
Mean excess return	vw	**1.20**	**5.35**	**5.71**	**5.61**	**5.92**	**7.19**	**7.19**	**4.46**	**5.99**
		[0.20]	[1.09]	[1.12]	[1.23]	[1.17]	[1.08]	[0.87]	[1.26]	[1.24]
	ew	**3.62**	**4.47**	**8.25**	**10.67** *	**10.82** *	**12.06** *	**12.95**	**8.47** ***	**9.34** **
		[0.66]	[0.74]	[1.46]	[1.85]	[1.78]	[1.99]	[1.64]	[2.66]	[2.25]
CAPM alpha	vw	**-3.38**	**0.18**	**0.60**	**1.03**	**0.91**	**1.21**	**1.05**	**3.36**	**4.44**
		[-0.88]	[0.10]	[0.37]	[0.60]	[0.39]	[0.35]	[0.22]	[1.05]	[1.06]
	ew	**-0.43**	**-0.15**	**3.51**	**5.80** *	**6.04** *	**7.37** **	**7.90**	**7.93** ***	**8.33** **
		[-0.11]	[-0.04]	[1.08]	[1.90]	[1.87]	[1.97]	[1.64]	[2.61]	[2.24]
FFC alpha	vw	**-3.18**	**-0.81**	**0.44**	**-0.84**	**-1.62**	**-0.80**	**0.10**	**2.25**	**3.28**
		[-1.05]	[-0.46]	[0.32]	[-0.57]	[-0.82]	[-0.28]	[0.03]	[0.92]	[1.04]
	ew	**-2.00**	**-1.47**	**1.30**	**3.13**	**3.44**	**4.68** *	**7.62** **	**7.88** **	**9.62** ***
		[-0.63]	[-0.46]	[0.55]	[1.32]	[1.39]	[1.70]	[1.97]	[2.48]	[2.59]
average # of firms		790	790	1,580	1,580	1,580	790	791		
average sigma		0.38	0.42	0.42	0.44	0.47	0.51	0.59		
average RSIZE		-8.47	-8.60	-8.31	-8.73	-9.31	-9.79	-10.53		
average CHS		0.00%	0.00%	0.01%	0.02%	0.04%	0.07%	0.14%		

Table 8
Robustness Tests

This table reports the results of various robustness tests regarding the sample period and method of estimation of Campbell et al.'s (2008, CHS) default risk measure as well as regarding data filters, the beginning of the portfolio holding period and the currency of portfolio returns. The table reports results only for the extreme quintile CHS-sorted stock portfolios (Q1 and Q5) and the spread strategy Q5-Q1 that is long the quintile portfolio with the highest default risk stocks (Q5) and short the quintile portfolio with the lowest default risk stocks (Q1). The average excess portfolio returns are annualized and bolded; their associated t-statistics are in square brackets. We construct these portfolios for stocks in the C6 countries (Australia, Canada, France, Germany, Japan and the United Kingdom; Panel A) and for stocks in the C14 countries (the C6 countries plus Denmark, Finland, Hong Kong, New Zealand, Portugal, Spain, Sweden and Taiwan; Panel B). Returns are calculated in U.S. dollar terms, with the exception of the last line in each panel where local currency stock returns are used, and they are reported for both value-weighted (vw) and equally-weighted (ew) portfolios. The column titled "Est" indicates whether the portfolios are constructed using out-of-sample (OOS) estimates of the CHS default risk measure, as described in Table 6, or in-sample (IS) estimates, as described in Table 7. The first robustness test ("Sample period 2000-2010") replicates the results in Table 7 for the period 2000-2010 using IS estimates. The second robustness test ("Return of Defaulting Stocks=−100%") replicates the results in Table 6 setting the returns of filing firms to −100% in the filing month. The third robustness test ("Same Restrictions as Gao et al. (2013)") replicates the results in Table 6 excluding stocks with a zero price change from month *m-1* to *m* and stocks with incomplete data on the market and accounting variables used in the LOGIT model in the prior 12 months. The fourth robustness test ("No Gap Between Formation & Holding Period") replicates the results in Table 6 leaving no gap between the portfolio formation month (i.e., December of year *t-1*) and the beginning of the holding period, which now becomes January of year *t*. The final robustness test ("Local Currency Returns") replicates the results in Table 6 calculating portfolio returns using local currency returns for each stock instead of U.S. dollar returns. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

		Value-weighted Portfolios			Equally-weighted Portfolios		
Modifications	Est	Q1	Q5	Q5-Q1	Q1	Q5	Q5-Q1
Panel A: C6 Countries							
Sample period 2000-2010	IS	**-2.88**	**9.63**	**12.51** ***	**5.68**	**15.73**	**10.05** **
		[-0.40]	[0.90]	[2.64]	[0.72]	[1.49]	[2.19]
Return of Defaulting Stocks = -100%	OOS	**-3.79**	**12.99**	**16.79** ***	**6.38**	**16.80**	**10.42** *
		[-0.52]	[1.25]	[2.77]	[0.76]	[1.59]	[1.89]
Same Restrictions as Gao et al. (2012)	OOS	**0.57**	**15.10**	**14.54** **	**9.47**	**22.71** *	**13.24** **
		[0.09]	[1.32]	[2.33]	[1.09]	[1.88]	[1.99]
No Gap Between Formation & Holding Period	OOS	**-4.88**	**14.18**	**19.06** ***	**6.54**	**18.28** *	**11.75** **
		[-0.65]	[1.38]	[2.93]	[0.77]	[1.77]	[2.10]
Local Currency Returns	OOS	**-6.77**	**9.86**	**16.63** ***	**2.90**	**15.14** *	**12.24** ***
		[-0.94]	[1.09]	[3.26]	[0.36]	[1.66]	[2.72]
Panel B: C14 Countries							
Sample period 2000-2010	IS	**-1.49**	**9.50**	**10.99** **	**6.76**	**15.91**	**9.15** **
		[-0.20]	[0.89]	[2.48]	[0.90]	[1.51]	[2.28]
Return of Defaulting Stocks = -100%	OOS	**-2.88**	**12.07**	**14.95** ***	**6.84**	**16.84**	**10.00** **
		[-0.38]	[1.16]	[2.73]	[0.86]	[1.60]	[2.11]
Same Restrictions as Gao et al. (2012)	OOS	**1.22**	**15.07**	**13.85** **	**10.30**	**23.09** *	**12.79** **
		[0.18]	[1.35]	[2.54]	[1.26]	[1.95]	[2.22]
No Gap Between Formation & Holding Period	OOS	**-3.60**	**13.59**	**17.19** ***	**7.08**	**18.52** *	**11.44** **
		[-0.47]	[1.32]	[2.85]	[0.89]	[1.81]	[2.45]
Local Currency Returns	OOS	**-5.38**	**9.27**	**14.65** ***	**3.89**	**15.19** *	**11.30** ***
		[-0.75]	[1.03]	[3.29]	[0.52]	[1.69]	[3.38]

Table 9
Out-of-Sample Comparison of CHS and MDD-Sorted Portfolios

This table reports average excess returns for portfolios sorted on the basis of out-of-sample (OOS) estimates of the Campbell et al. (2008, CHS) default risk measure or, alternatively, estimates of Merton's (1974) Distance-to-Default measure (MDD). We construct these portfolios for stocks in the C6 countries (Australia, Canada, France, Germany, Japan and the U.K.; Panel A) and the C14 countries (the C6 countries plus Denmark, Finland, Hong Kong, New Zealand, Portugal, Spain, Sweden and Taiwan; Panel B). The OOS CHS measures are recursively estimated as described in Section 3 and the caption of Table 6. Moreover, we follow the methodology of Vassalou and Xing (2004) to estimate MDD for each firm in our sample. At the end of December of year *t-1*, we sort stocks in ascending order on the basis of their OOS CHS or, alternatively, on the basis of their OOS MDD estimates and allocate them into decile and quintile portfolios. We form the spread strategy Q5-Q1 that is long the quintile portfolio with the highest default risk stocks (Q5) and short the quintile portfolio with the lowest default risk stocks (Q1). We also form the spread strategy P10-P1 that is long the decile portfolio with the highest default risk stocks (P10) and short the decile portfolio with the lowest default risk stocks (P1). We only consider stocks for which both default risk proxies are available. We exclude stocks whose price or market capitalization is below the 5th percentile of the corresponding country-month distribution at the portfolio formation date. Portfolios are held from February of year *t* to January of year *t+1*, at which point they are rebalanced, allowing for a one month gap between the portfolio formation date and the beginning of the holding period. Returns are calculated in U.S. dollar terms and they are reported for both value-weighted (vw) and equally-weighted (ew) portfolios. Average excess portfolio returns are annualized and bolded; their associated t-statistics are reported in square brackets. The lower part of each panel reports the average number of firms per portfolio. For the MDD-sorted portfolios, it also reports stocks' average standard deviation of returns (SIGMA), their average log relative size (RSIZE) and their average OOS CHS default risk estimate. The examined period is 2000-2010. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

		Deciles								
		1	2	3-4	5-6	7-8	9	10	Q5-Q1	P10-P1
Panel A: C6 Countries										
CHS	vw	**-3.32**	**-3.77**	**2.05**	**6.47**	**10.52**	**12.00**	**14.49**	**17.12** ***	**17.81** **
		[-0.49]	[-0.47]	[0.28]	[0.84]	[1.24]	[1.21]	[1.24]	[2.88]	[2.19]
	ew	**6.48**	**6.55**	**9.12**	**11.95**	**14.37**	**14.06**	**22.84** **	**11.92** **	**16.36** **
		[0.84]	[0.79]	[1.06]	[1.28]	[1.47]	[1.42]	[2.05]	[2.14]	[2.34]
MDD	vw	**5.76**	**6.14**	**1.91**	**2.01**	**2.68**	**5.13**	**3.95**	**-0.71**	**-1.82**
		[0.69]	[0.83]	[0.27]	[0.27]	[0.33]	[0.47]	[0.35]	[-0.12]	[-0.33]
	ew	**24.02** **	**17.29**	**8.33**	**7.05**	**9.05**	**11.14**	**19.22**	**-5.47**	**-4.80**
		[2.19]	[1.60]	[1.10]	[0.90]	[1.06]	[1.09]	[1.56]	[-1.12]	[-0.73]
average # of firms		740	738	1457	1453	1470	732	717		
average sigma		0.64	0.55	0.40	0.42	0.49	0.58	0.73		
average RSIZE		-10.26	-9.78	-8.93	-9.20	-9.92	-10.45	-10.85		
average CHS		0.11%	0.05%	0.04%	0.05%	0.09%	0.18%	0.35%		
Panel B: C14 Countries										
CHS	vw	**-2.55**	**-2.69**	**3.51**	**6.29**	**8.97**	**11.06**	**14.30**	**15.33** ***	**16.85** **
		[-0.36]	[-0.33]	[0.46]	[0.79]	[1.05]	[1.11]	[1.23]	[2.82]	[2.26]
	ew	**7.86**	**6.72**	**9.70**	**12.55**	**14.12**	**15.07**	**21.88** **	**11.13** **	**14.03** **
		[1.03]	[0.86]	[1.16]	[1.33]	[1.45]	[1.52]	[1.97]	[2.32]	[2.34]
MDD	vw	**9.33**	**2.96**	**2.51**	**2.49**	**3.61**	**4.66**	**3.67**	**-1.21**	**-5.66**
		[1.17]	[0.40]	[0.34]	[0.32]	[0.43]	[0.41]	[0.33]	[-0.23]	[-1.22]
	ew	**23.92** **	**15.36**	**8.28**	**8.01**	**9.90**	**12.75**	**19.76** *	**-3.43**	**-4.16**
		[2.27]	[1.52]	[1.11]	[1.01]	[1.13]	[1.24]	[1.65]	[-0.80]	[-0.72]
average # of firms		917	913	1805	1807	1817	903	890		
average sigma		0.62	0.52	0.39	0.42	0.49	0.57	0.72		
average RSIZE		-10.04	-9.42	-8.51	-8.85	-9.55	-10.12	-10.55		
average CHS		0.13%	0.04%	0.03%	0.05%	0.10%	0.18%	0.33%		

Table 10
Double-Sorted Default Risk Portfolios

This table reports average excess returns for double-sorted portfolios on the basis of out-of-sample (OOS) estimates of the Campbell et al. (2008, CHS) default risk measure and each of the following firm characteristics: *(i)* SIZE (dollar market capitalization), *(ii)* BM (book-to-market value ratio), *(iii)* PRICE (log stock price expressed in U.S. dollars), *(iv)* TANGIBILITY (ratio of property, plant and equipment to total assets), *(v)* TLTA (ratio of total liabilities to total assets), *(vi)* ANALYST (dummy variable indicating whether a company is followed by at least one analyst or none) and *(vii)* SIGMA (the annualized standard deviation of a firm's daily log stock returns in the prior three months). Panels A and B report the results for the C6 countries, while Panels C and D report the corresponding results for the C14 countries. The OOS CHS default risk measures are recursively estimated as described in Section 3 and the caption of Table 6. We sort stocks into ascending order according to their OOS CHS default risk estimates in December of year $t-1$ and allocate them into tercile portfolios (T1 to T3), while we also independently sort stocks into ascending order according to the value of each firm characteristic in December of year $t-1$ and allocate them into tercile portfolios (Low, Medium, High). The only exception is analyst coverage, where we assign firms to two portfolios depending on whether there is at least one analyst following the firm or none. The intersection of these two classifications yields the double-sorted portfolios. Portfolios are held from February of year t to January of year $t+1$, at which point they are rebalanced, allowing for a one month gap between the portfolio formation date and the beginning of the holding period. Results are reported only for the highest and the lowest default risk tercile portfolios (T3 and T1, respectively) within the High or the Low classification for each firm characteristic, respectively. Moreover, we report the average excess return for the spread strategy T3-T1 within the High or Low classification. For comparison, column ALL reports the returns for the tercile portfolios T3 and T1 from univariate sorts according to OOS CHS default risk estimates. Returns are calculated in U.S. dollar terms and they are reported for both value-weighted (vw) and equally-weighted (ew) portfolios. Average excess portfolio returns are annualized and bolded; their associated t-statistics are reported in square brackets. The examined period is 2000-2010. ***, ** and * in the column "Diff" indicate that the difference between the High and Low classification returns in each case is statistically significant at 1%, 5% and 10% levels, respectively.

		SIZE			BM			PRICE			TANGIBILITY			TLTA			ANALYST			SIGMA		
CHS	ALL	High	Low	Diff	High	Low	Diff	High	Low	Diff	High	Low	Diff	High	Low	Diff	0	>0	Diff	High	Low	Diff
Panel A: Value-weighted Global Portfolios Based on C6 Countries																						
T3	**11.63**	**11.94**	**12.94**		**14.80**	**10.94**		**8.79**	**19.19**	**	**15.94**	**3.87**	***	**10.02**	**12.12**		**-0.93**	**12.42**	**	**5.40**	**12.27**	
	[1.23]	[1.26]	[1.29]		[1.45]	[1.15]		[0.95]	[1.68]		[1.72]	[0.36]		[1.08]	[0.88]		[-0.43]	[1.34]		[0.41]	[1.52]	
T1	**-3.33**	**-3.57**	**19.62**	***	**8.42**	**-8.18**	***	**-4.67**	**27.21**	***	**-6.54**	**-5.30**		**-1.59**	**-4.34**		**-7.28**	**3.03**		**-5.88**	**0.21**	
	[-0.45]	[-0.48]	[1.82]		[1.19]	[-1.02]		[-0.62]	[2.43]		[-0.89]	[-0.56]		[-0.22]	[-0.56]		[-2.01]	[0.39]		[-0.39]	[0.03]	
Spread (T3-T1)	**14.96**	**15.51**	**-6.68**	***	**6.38**	**19.12**	***	**13.46**	**-8.02**	***	**22.48**	**9.16**	***	**11.61**	**16.47**		**6.36**	**9.39**	**	**11.28**	**12.06**	
	[3.24]	[3.25]	[-1.40]		[1.32]	[4.15]		[3.15]	[-1.45]		[3.73]	[2.01]		[3.53]	[1.91]		[1.98]	[2.37]		[1.46]	[2.98]	
Panel B: Equally-weighted Global Portfolios Based on C6 Countries																						
T3	**16.66**	**12.72**	**25.98**	***	**23.38**	**10.52**	**	**5.14**	**26.83**	***	**25.32**	**8.89**	***	**13.24**	**24.92**	*	**-11.60**	**21.08**	***	**25.57**	**10.03**	**
	[1.62]	[1.20]	[2.44]		[2.20]	[0.98]		[0.60]	[2.18]		[2.45]	[0.76]		[1.41]	[1.89]		[-3.23]	[2.00]		[2.02]	[1.26]	
T1	**7.35**	**0.86**	**29.60**	***	**13.95**	**0.20**	***	**-0.94**	**36.01**	***	**10.81**	**6.43**		**6.28**	**9.95**		**-9.86**	**13.16**	**	**14.64**	**6.78**	
	[0.87]	[0.12]	[2.49]		[1.78]	[0.02]		[-0.11]	[2.69]		[1.35]	[0.57]		[0.77]	[0.97]		[-2.37]	[1.33]		[0.96]	[1.21]	
Spread (T3-T1)	**9.31**	**11.87**	**-3.62**	***	**9.43**	**10.32**		**6.07**	**-9.19**	***	**14.51**	**2.46**	**	**6.96**	**14.98**		**-1.74**	**7.92**	**	**10.93**	**3.25**	
	[2.08]	[2.13]	[-0.83]		[1.72]	[2.04]		[1.18]	[-2.32]		[2.77]	[0.49]		[1.72]	[2.42]		[-0.53]	[2.22]		[1.69]	[0.73]	

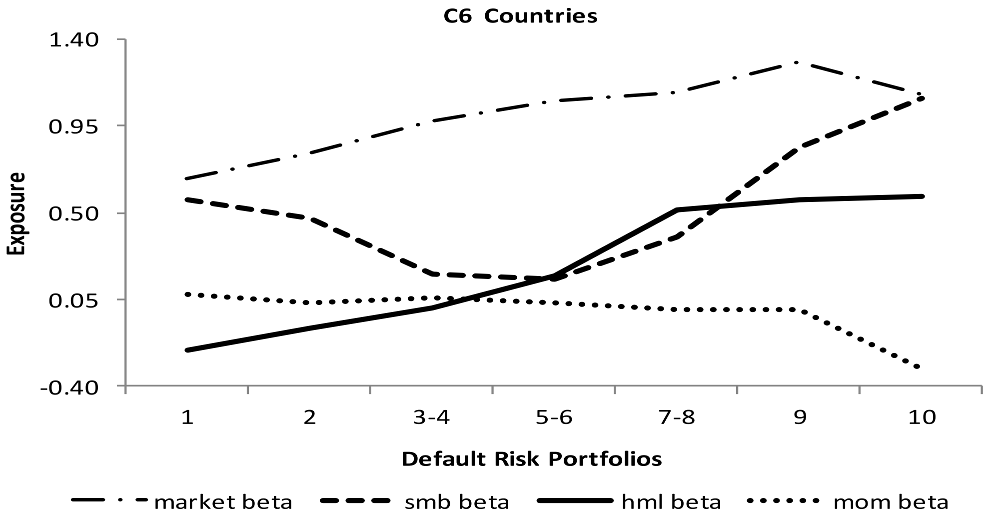
(continued on next page)

Table 10 (continued)
Double-Sorted Sorted Default Risk Portfolios

		SIZE			BM			PRICE			TANGIBILITY			TLTA			ANALYST			SIGMA		
CHS	ALL	High	Low	Diff	High	Low	Diff	High	Low	Diff	High	Low	Diff	High	Low	Diff	0	> 0	Diff	High	Low	Diff
Panel C: Value-weighted Global Portfolios Based on C14 Countries																						
T3	**10.60**	**10.73**	**11.11**		**15.14**	**9.63**		**8.36**	**18.28**	*	**14.44**	**2.47**	***	**8.70**	**11.21**		**-1.52**	**11.82**	**	**5.53**	**12.00**	**
	[1.12]	[1.14]	[1.06]		[1.46]	[0.99]		[0.90]	[1.45]		[1.58]	[0.23]		[0.93]	[0.83]		[-0.66]	[1.29]		[0.44]	[1.51]	
T1	**-1.24**	**-1.44**	**17.95**	***	**8.94**	**-3.85**	**	**-3.20**	**7.04**	*	**-2.31**	**-3.06**		**1.78**	**-2.47**		**-8.42**	**6.03**		**-6.70**	**3.79**	**
	[-0.16]	[-0.19]	[1.73]		[1.25]	[-0.46]		[-0.42]	[0.66]		[-0.29]	[-0.33]		[0.25]	[-0.30]		[-2.59]	[0.77]		[-0.45]	[0.65]	
Spread (T3-T1)	**11.84**	**12.17**	**-6.84**	***	**6.20**	**13.48**		**11.56**	**11.24**		**16.74**	**5.53**	***	**6.91**	**13.69**		**6.91**	**5.79**	*	**12.23**	**8.21**	**
	[2.89]	[2.86]	[-1.38]		[1.21]	[3.10]		[2.71]	[1.94]		[3.12]	[1.12]		[2.44]	[1.92]		[2.59]	[1.84]		[1.71]	[2.42]	
Panel D: Equally-weighted Global Portfolios Based on C14 Countries																						
T3	**16.77**	**12.10**	**24.74**	***	**23.87**	**9.76**	***	**4.87**	**28.27**	***	**24.13**	**9.52**	***	**13.43**	**24.03**	*	**-11.19**	**20.80**	***	**23.91**	**10.56**	**
	[1.63]	[1.20]	[2.35]		[2.26]	[0.91]		[0.56]	[2.25]		[2.37]	[0.82]		[1.44]	[1.86]		[-3.35]	[1.97]		[1.91]	[1.34]	
T1	**7.75**	**2.10**	**25.94**	***	**15.30**	**-0.07**	***	**0.06**	**24.63**	***	**10.73**	**6.05**		**8.27**	**8.96**		**-8.33**	**12.53**	**	**12.32**	**8.85**	
	[0.96]	[0.29]	[2.35]		[1.95]	[-0.01]		[0.01]	[2.37]		[1.42]	[0.57]		[1.03]	[0.95]		[-2.27]	[1.38]		[0.85]	[1.62]	
Spread (T3-T1)	**9.02**	**10.00**	**-1.20**	**	**8.57**	**9.83**		**4.81**	**3.64**		**13.40**	**3.47**	**	**5.16**	**15.07**	*	**-2.86**	**8.28**	***	**11.59**	**1.71**	
	[2.35]	[2.25]	[-0.29]		[1.74]	[2.34]		[0.99]	[0.92]		[3.20]	[0.76]		[1.39]	[2.70]		[-1.15]	[2.88]		[1.90]	[0.41]	

Figure 1
Default Risk Portfolio Factor Loadings

This figure presents the market, size (SMB), value (HML) and momentum (MOM) factor loadings (betas) of decile portfolios sorted on the basis of the out-of-sample (OOS) Campbell et al. (2008, CHS) default risk estimates. These betas are estimated from full-sample regressions of each excess portfolio return on the excess market return and the SMB, HML and MOM factor returns according to the four-factor Fama-French-Carhart (FFC) asset pricing model. The sample period is 2000-2010. Factor loadings are presented for portfolios of stocks from the C6 countries (Australia, Canada, France, Germany, Japan and the U.K.) and the C14 countries (the C6 countries plus Denmark, Finland, Hong Kong, New Zealand, Portugal, Spain, Sweden and Taiwan). To estimate OOS CHS default risk estimates, a LOGIT model is recursively run for each of the C6 countries; see section 3 and the caption of Table 6. For the rest countries that feature too few bankruptcies, we run recursively a LOGIT model for each bankruptcy law regime, see caption of Table 6 for details.



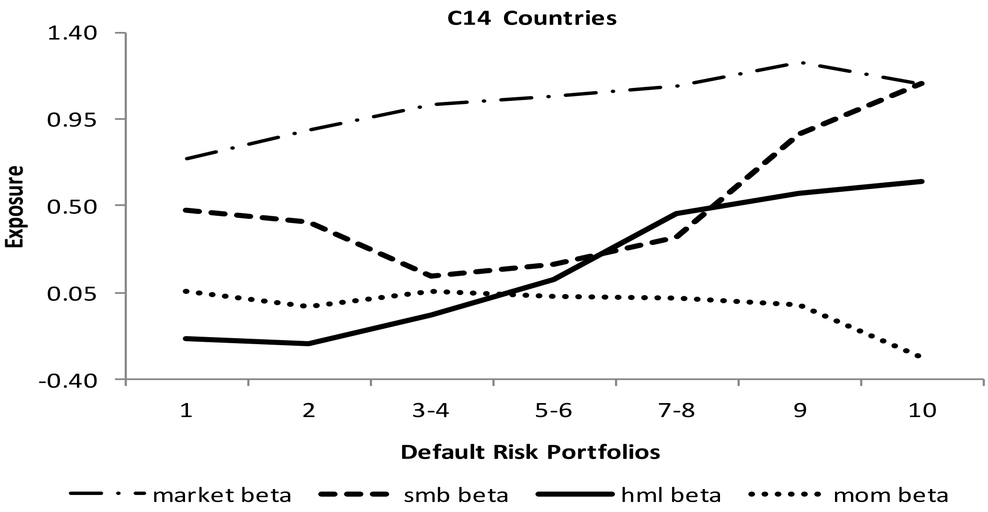
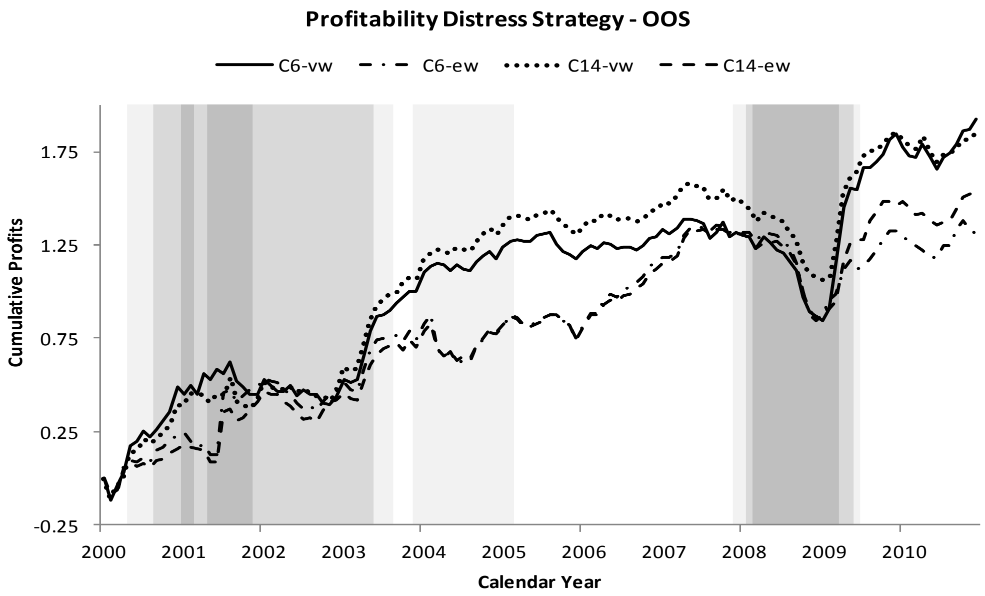
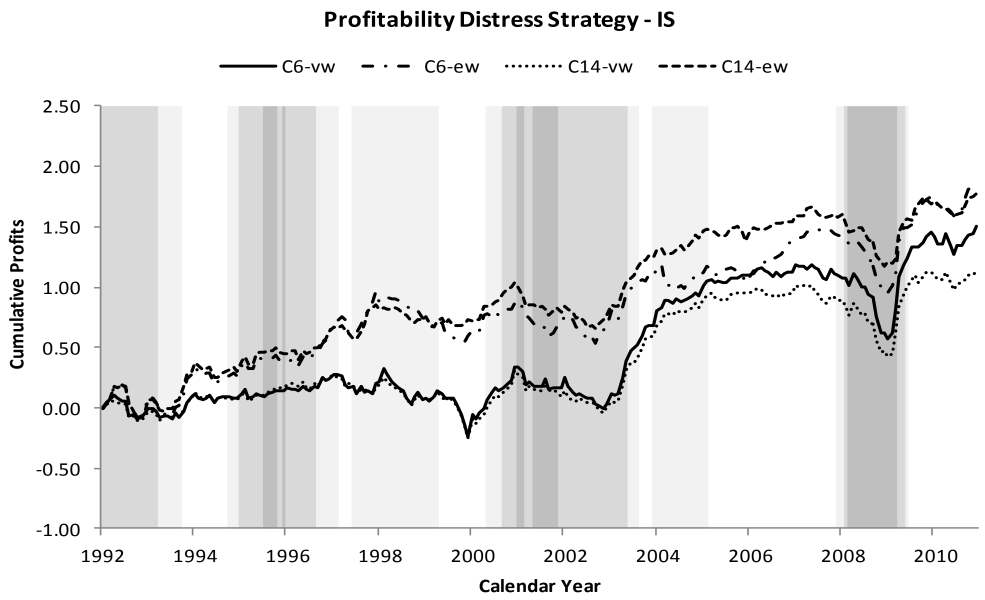


Figure 2
Profitability of Distress Risk Spread Strategies

This figure shows the profitability of distress risk spread strategies that are long the decile portfolio with the highest default risk stocks (P10) and short the decile portfolio with the lowest default risk stocks (P1), as classified on the basis of the Campbell et al. (2008, CHS) default risk estimates. The upper panel uses as a portfolio sorting variable out-of-sample (OOS) CHS default risk values, estimated recursively using LOGIT models, as described in the caption of Table 6, and the examined period is 2000-2010. The lower panel uses as a portfolio sorting variable in-sample (IS) CHS values, estimated from full sample LOGIT models, as described in the caption of Table 7, and the examined period is January 1992-December 2010. Portfolios P10 and P1 are formed at the end of each December of year *t-1* and they are held from February of year *t* to January of year *t+1*, at which point they are rebalanced. Returns are calculated in U.S. dollar terms and they are reported for both value-weighted (vw) and equally-weighted (ew) portfolios. Results are reported for the C6 countries (Australia, Canada, France, Germany, Japan and the U.K.) and the C14 countries (the C6 countries plus Denmark, Finland, Hong Kong, New Zealand, Portugal, Spain, Sweden and Taiwan). The shaded areas in the graphs indicate OECD-defined recession periods, where the light grey indicates that 4-8 of our sample countries are in a recession, the moderately dark grey that 8-12 are in a recession, and the dark grey that more than 12 are in a recession.





Appendix

Table A.1
Out-of-Sample Global Default Risk Portfolios- MSCI Factors

This table reports average excess returns, CAPM alphas and three-factor alphas from the Fama-French asset pricing model (FF alphas) for portfolios constructed on the basis of out-of-sample (OOS) estimates of the Campbell et al. (2008, CHS) default risk measure. The construction of the portfolios is described in the notes of Table 6. We construct these portfolios for stocks in the C6 countries (Australia, Canada, France, Germany, Japan and the United Kingdom; Panel A) and the C14 countries (the C6 countries plus Denmark, Finland, Hong Kong, New Zealand, Portugal, Spain, Sweden and Taiwan; Panel B). We form the spread strategy Q5-Q1 that is long the quintile portfolio with the highest default risk stocks (Q5) and short the quintile portfolio with the lowest default risk stocks (Q1). We also form the spread strategy (P10-P1) that is long the decile portfolio with the highest default risk stocks (P10) and is short the decile portfolio with the lowest default risk stocks (P1). We exclude stocks whose price or market capitalization is below the 5^{th} percentile of the corresponding country-month distribution at the portfolio formation date. Returns are calculated in U.S. dollar terms and they are reported for value-weighted (vw) and equally-weighted (ew) portfolios. Average excess portfolio returns and alphas are annualized and bolded; their associated t-statistics are reported in square brackets. To compute CAPM and FF alphas we utilize MSCI World ex US indices to construct factor returns. In particular, the market return is set equal to the MSCI World ex US index return. SMB return is given by the spread return between the MSCI World ex US Small Cap index and the MSCI World ex US Large Cap index. HML return is given by the spread return between the MSCI World ex US Value index and the MSCI World ex US Growth index. The lower part of each panel reports the average number of firms per portfolio, stocks' average standard deviation of returns (SIGMA), their average log relative size (RSIZE) and their average OOS CHS estimate. The examined period is 2000-2010. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

		Deciles								
		1	2	3-4	5-6	7-8	9	10	Q5-Q1	P10-P1
Panel A: C6 Countries										
Excess return	vw	**-3.45**	**-4.22**	**2.04**	**6.34**	**10.49**	**11.52**	**14.19**	**16.90** ***	**17.63** **
		[-0.50]	[-0.52]	[0.28]	[0.81]	[1.23]	[1.15]	[1.20]	[2.79]	[2.15]
	ew	**6.29**	**6.50**	**9.70**	**12.11**	**14.50**	**13.44**	**22.39** **	**11.52** **	**16.10** **
		[0.78]	[0.73]	[1.09]	[1.26]	[1.45]	[1.33]	[2.00]	[2.12]	[2.41]
CAPM alpha	vw	**-3.33**	**-4.08**	**2.21**	**6.52** ***	**10.68** ***	**11.74** ***	**14.40** **	**16.99** ***	**17.73** **
		[-0.96]	[-1.06]	[1.64]	[5.87]	[4.98]	[3.52]	[2.10]	[3.20]	[2.40]
	ew	**6.39**	**6.64**	**9.87** ***	**12.30** ***	**14.69** ***	**13.63** ***	**22.58** ***	**11.59** **	**16.19** ***
		[1.10]	[1.11]	[2.63]	[3.96]	[3.98]	[3.18]	[3.36]	[2.50]	[2.76]
FF alpha	vw	**-2.70**	**-4.23**	**2.81** ***	**6.49** ***	**8.64** ***	**8.20** ***	**9.48**	**12.56** ***	**12.18** **
		[-1.06]	[-1.22]	[2.73]	[6.17]	[4.27]	[2.88]	[1.51]	[3.59]	[2.21]
	ew	**4.57**	**4.31**	**8.24** **	**10.63** ***	**12.67** ***	**11.12** ***	**19.33** ***	**10.79** ***	**14.76** ***
		[0.82]	[0.72]	[2.11]	[3.29]	[3.37]	[2.60]	[3.18]	[2.58]	[2.93]
average # of firms		806	807	1613	1613	1613	806	807		
average sigma		0.42	0.47	0.49	0.52	0.55	0.59	0.69		
average RSIZE		-9.49	-9.71	-9.43	-9.44	-9.88	-10.46	-11.09		
average CHS		0.00%	0.01%	0.02%	0.04%	0.09%	0.15%	0.56%		

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Table A.1
Out-of-Sample Global Default Risk Portfolios- MSCI Factors (continued)

		Deciles								
		1	2	3-4	5-6	7-8	9	10	Q5-Q1	P10-P1
Panel B: C14 Countries										
Mean excess return	vw	**-2.71**	**-2.98**	**3.48**	**6.18**	**9.01**	**10.49**	**14.30**	**15.07** ***	**17.01** **
		[-0.38]	[-0.36]	[0.45]	[0.77]	[1.05]	[1.04]	[1.23]	[2.75]	[2.29]
	ew	**7.44**	**6.29**	**9.95**	**12.30**	**14.17**	**14.26**	**21.51** *	**11.02** **	**14.07** **
		[0.94]	[0.77]	[1.15]	[1.27]	[1.43]	[1.41]	[1.94]	[2.35]	[2.49]
CAPM alpha	vw	**-2.58**	**-2.82**	**3.66** ***	**6.36** ***	**9.20** ***	**10.71** ***	**14.51** **	**15.14** ***	**17.09** ***
		[-0.75]	[-0.88]	[2.89]	[5.95]	[4.71]	[3.43]	[2.29]	[3.21]	[2.61]
	ew	**7.56**	**6.43**	**10.12** ***	**12.49** ***	**14.36** ***	**14.45** ***	**21.70** ***	**11.08** ***	**14.14** ***
		[1.46]	[1.35]	[3.12]	[4.04]	[4.17]	[3.72]	[3.55]	[3.06]	[3.04]
FF alpha	vw	**-1.70**	**-2.36**	**4.68** ***	**6.45** ***	**7.78** ***	**7.16** ***	**9.88** *	**10.43** ***	**11.57** ***
		[-0.66]	[-0.84]	[5.60]	[7.46]	[4.17]	[2.73]	[1.73]	[3.73]	[2.56]
	ew	**6.36**	**5.06**	**9.09** **	**11.21** ***	**12.59** ***	**12.10** ***	**18.76** ***	**9.72** ***	**12.40** ***
		[1.18]	[0.98]	[2.55]	[3.41]	[3.57]	[3.14]	[3.42]	[2.80]	[2.99]
average # of firms		998	999	1998	1998	1998	999	999		
average sigma		0.42	0.45	0.47	0.51	0.54	0.59	0.70		
average RSIZE		-9.22	-9.17	-8.85	-9.08	-9.63	-10.27	-10.91		
average CHS		0.00%	0.01%	0.02%	0.04%	0.08%	0.17%	0.59%		