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

Kevin Aretz[*], Chris Florackis[†], and Alexandros Kostakis[‡]

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Abstract

This study constructs a novel dataset of bankruptcy filings for a large sample of non-US firms in 14 developed markets and sheds new light on the cross-sectional relation between default risk and stock returns. Using the reduced-form approach of Campbell et al. (2008) to estimate default probabilities, we offer conclusive evidence supporting the existence of a significant positive default risk premium in international markets. This finding is robust to different portfolio weighting schemes, data filters, risk-adjusting approaches and holding period definitions. Decomposing the default risk measure into its systematic and idiosyncratic components, we find that the former drives this positive relation. We also show that the default risk premium is more pronounced in countries where creditor protection is stronger and shareholder bargaining power is lower.

Keywords: Default risk; Bankruptcy; Stock returns; International financial markets; Creditor protection.
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[*] Accounting and Finance Division, Manchester Business School, University of Manchester, Booth Street, Manchester, M15 6PB, UK, tel.: +44 (0) 161 275 6368, e-mail: kevin.aretz@manchester.ac.uk.

[†] Department of Economics, Finance, and Accounting, University of Liverpool Management School, Chatham Street, Liverpool, L69 7ZH, UK, tel.: +44 (0) 151 795 53807, e-mail: c.florackis@liverpool.ac.uk.

[‡] Corresponding author. Accounting and Finance Division, Manchester Business School, University of Manchester, Booth Street, Manchester M15 6PB, UK, tel.: +44 (0) 161 275 0434, e-mail: alexandros.kostakis@manchester.ac.uk.

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. However, most of the prior empirical studies for the US market 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 default risk and stock returns is often called the "distress anomaly".

In a recent insightful study, Gao et al. (2015, hereafter GPS) claim that the literature on the distress anomaly in the US market "[...] is currently characterized by disagreement, both about the basic finding and its interpretation" (p. 1). As a result, GPS argue that it is high time to shift the focus to new data for non-US firms. Using international data over the period 1992-2013,

[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, 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. Moreover, Da and Gao (2010) show that the premium reported in Vassalou and Xing (2004) is mainly driven by a short-term return reversal effect, and disappears when allowing for a one-month gap between portfolio formation and the beginning of the holding period. 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, whereas Anginer and Yildizhan (2014) 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 relation between returns and default risk. The most comprehensive evidence comes from Campbell et al. (2008), who measure default risk using a dynamic hazard model. 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] 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 US firms, find that stock returns increase with firms' credit risk premia estimated from CDS spreads.

they find a negative relation between stock returns and Moody's KMV Expected Default Frequency (EDF), which becomes more pronounced among small capitalization stocks. GPS fail to find a relation between the default risk premium and creditor protection at the country level, which contradicts the empirical evidence of Garlappi et al. (2008), Garlappi and Yan (2011), and Favara et al. (2012). In contrast, they claim that country-level individualism, which serves as a proxy for investor overconfidence, is significantly negatively related to the default risk premium. Similarly, Eisdorfer et al. (2013, hereafter EGZ) use a default risk proxy derived from the Merton (1974) model (hereafter MDD) to examine the pricing of default risk in an international sample over the period 1992-2010. They find a significant negative MDD-stock return relation, 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, we do not use a structural model estimate of default risk. Instead, we collect firm bankruptcy filings for 14 developed countries, excluding the US, over the period 1992-2013, and we estimate default probabilities following the reduced-form approach of Campbell et al. (2008, hereafter CHS). Whereas 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] In particular, our CHS measure incorporates more efficiently cross-country variations with respect to average default rates and the importance of the various default risk indicators; these variations arise from differences in the bankruptcy filing process and are induced by the local bankruptcy laws and institutional settings. Consistent with this conjecture, we show that the parameter estimates of our bankruptcy forecasting model vary significantly across countries.

[3] Our dataset features 2.03 million firm-month observations from 14 countries (excluding the US) during the period 1992-2013, in comparison to 4.3 million observations from 38 countries (including the US) in GPS. Despite the lower number of observations, our dataset includes many countries that exhibit relatively low correlations with the US, rendering it suitable for an out-of-sample study (see Foster et al., 1997).

Importantly, in-sample and out-of-sample tests show that the reduced-form approach that we follow in this study exhibits a clearly superior bankruptcy forecasting ability relative to MDD. Adding the CHS default risk indicators to MDD almost doubles the explanatory power of the bankruptcy forecasting LOGIT model in most cases. On the other hand, adding MDD to the CHS default risk indicators typically has a negligible contribution to the model's explanatory power. The CHS measure is also more successful than MDD in classifying as high default risk the firms that subsequently file for bankruptcy. Interestingly, 40% of all firms that filed for bankruptcy in our sample were ex ante classified into the 5th highest default risk percentile according to CHS, whereas the corresponding portion of bankruptcies classified into the 5th highest percentile according to MDD is only 30.8%. These results confirm, for the first time in an international setup, the superiority of the reduced-form approach reported for US firms by Campbell et al. (2008), and echo the conclusion of Bharath and Shumway (2008) that MDD is not a sufficient statistic for bankruptcy forecasting.[4]

Our asset pricing results are notably different from those in EGZ and GPS. We estimate country-specific LOGIT models to compute out-of-sample (OOS) default probabilities for firms in Australia, Canada, France, Germany, Japan, and the UK (hereafter, the C6 countries) over the sample period 2000-2014. Taking the perspective of an international investor, we use the entire cross-section of these estimated default probabilities to sort stocks into international portfolios and to compute their post-ranking returns. 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 13.86% p.a. (t-stat: 2.71) in the case of value-weighted portfolios and 10.24%

[4] Bharath and Shumway (2008) and Campbell et al. (2008) show that hazard model estimates are superior in forecasting US firm defaults as compared to structural estimates obtained from the Merton (1974) model (MDD) and calculated using either the Hillegeist et al. (2004) or the Vassalou and Xing (2004) methodology. We are unaware of any prior study testing the forecasting ability of CHS and MDD for non-US firms.

p.a. (t-stat: 2.43) 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.[5]

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 in the case of value-weighted portfolio returns, suggesting 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 default risk premium remains significant. Moreover, in line with the arguments of Kapadia (2011), the returns of the market, size, and value factors are negatively correlated with contemporaneous innovations in aggregate default risk, whereas the market and size factor returns also contain predictive ability with respect to future changes in firms' failure rates.

Why do our results differ from those in EGZ and GPS?[6] To address this question, we compare our CHS estimates with the corresponding MDD estimates. MDD is thought to be a close

[5] For comparison, we also examine the CHS default risk-stock return relation in the US market during our sample period. To this end, 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), and the evidence provided in O'Doherty (2012), the asset pricing tests presented in the Supplementary Appendix show that the default risk-stock return relation has become insignificant post-2000. Nevertheless, we still fail to find the theoretically expected positive relation. Thus, the different conclusions that we derive from our international sample relative to the puzzling evidence documented in the literature for US firms are not solely driven by the fact that we consider a more recent sample period. We are grateful to Jens Hilscher for providing their OOS LOGIT model estimates.

[6] In particular, GPS find that, outside the US market, an equally-weighted spread strategy, which is long low default risk stocks and short high default risk stocks, yields an abnormal performance of around 30 basis points per month. This abnormal performance becomes stronger among small capitalization firms. Moreover, EGZ find that, in developed markets, value-weighted portfolios of stocks in the most distressed quintile underperform the corresponding portfolios of stocks in the least distressed quintile by an average of 17 to 63 basis points per month.

proxy for EDF (Bharath and Shumway, 2008; Correia et al., 2012). Also, in contrast to EDF, which is proprietary, MDD is replicable for our international sample. Equipped with CHS and MDD, we repeat the portfolio formation exercises using each of the two measures as alternative sorting criteria only for those firm-month observations for which both measures are available. Whereas CHS still yields a positive default risk premium, MDD yields a U-shape 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 an insignificant value-weighted (equally-weighted) premium of 1.21% (-0.86%) p.a..

Examining the source of discrepancy between CHS and MDD, we find that these two measures considerably disagree on the identification of low default risk firms. In particular, out-of-sample bankruptcy forecasting tests show that CHS is also superior to MDD in identifying low default risk firms. Computing the frequency of actual bankruptcies across portfolios constructed on the basis of each of these two measures, we find that the proportion of filings by firms classified into the lowest MDD default risk quintile is twice as high as the corresponding proportion of firms classified into the lowest CHS quintile.

This disagreement is driven by unlevered firms as well as default-triggering events ignored by MDD, but not by CHS. Whereas MDD assigns zero default risk to unlevered firms because it assumes that default occurs only if the asset value drops below a fraction of the debt value (see Crosbie and Bohn, 2003; Vassalou and Xing, 2004), CHS assigns a higher default risk to such firms. Moreover, Davydenko (2008) shows that whereas 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, whereas the CHS proxy takes them into account.

In further analysis, we examine what drives the documented positive default risk premium. To this end, we construct double-sorted portfolios on CHS and a series of country-level characteristics. Overall, the premium is found to be relatively higher in countries where creditor

protection is higher and shareholder bargaining power is lower, in line with the arguments of Favara et al. (2012). Moreover, consistent with the shareholder advantage hypothesis of Garlappi et al. (2008) and Garlappi and Yan (2011), we find that the default risk premium is more pronounced among firms with high asset tangibility.[7] To the contrary, we do not find any evidence that the default risk premium is driven by investor overconfidence, stock market liquidity conditions or the quality of accounting standards at the country level.

Finally, following Anginer and Yildizhan (2014), we decompose the CHS default risk measure into its systematic and idiosyncratic components. Consistent with the arguments of Anginer and Yildizhan (2014), Friewald et al. (2014), and Hilscher and Wilson (2015), we find that it is the systematic component of firm default risk that drives the positive relation between default risk and stock premia. On the other hand, the idiosyncratic component of default risk yields an insignificant relation.

2. Data

2.1 Bankruptcy Data

Our sources for the bankruptcy filing data are provided in the Supplementary Appendix. These sources include commercial data providers, government institutions, stock exchanges, and other researchers. 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 cover the period from January 1996 to December 2013, although for France, Japan, and the UK they begin slightly earlier (1992-1993). 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

[7] 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. Distressed firms in which shareholder bargaining power is high are less risky for shareholders, and hence they do not yield a premium. This argument is reinforced by the evidence of Hackbarth et al. (2015), who use the 1978 US 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 with low creditor recovery rate.

lack information on how long firms spent in re-organization, we drop firms after their initial bankruptcy filing in our sample period.

Table 1 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. This is the most comprehensive bankruptcy dataset for non-US firms that has been examined in the literature, containing 944 bankruptcies across 14 developed markets. Table 1 shows that the frequency of bankruptcy filings considerably varies across countries. Filings are more frequent in countries where the bankruptcy system strongly favors managers or creditors (Germany and the UK) relative to countries where employee welfare is more important (France and Japan). In addition, bankruptcy filings are strongly correlated through time, reaching a peak in the aftermath of the 2007-2008 global financial crisis.

[Table 1 here]

Since we require a sufficient number of filings for model estimation and calculation of default probabilities, we recursively estimate our LOGIT models starting from December 1999; hence we perform our OOS asset pricing tests for the period 2000-2014. This choice ensures that there are at least five bankruptcy filings for each country for which we separately run LOGIT models (i.e., the C6 countries) before the start of the test period.

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 firms' prospects more accurately. Leverage is measured using the ratio of total liabilities to the market value-

adjusted version of total assets (TLMTA).[8] Since lack of liquidity can also force a firm to file for bankruptcy (Davydenko, 2008), we proxy internal cash by 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.[9]

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

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

where $r_{i,k}$ is the log stock return of firm i on day k, and N is the number of trading days in the 3-month estimation interval $SIGMA$ 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 the firm's market value to the total market value of firms in the same country-month. Finally, following Campbell et al. (2008), we also 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.

In the remainder, we collectively refer to NIMTA, TLMTA, EXRET, RSIZE, SIGMA, CASHMTA, MB, and PRICE as the CHS default risk indicators. Whereas NIMTA, TLMTA, RSIZE, and MB are currency-free, EXRET, SIGMA, and PRICE are measured in local currency. To alleviate the effect of outliers, we winsorize the default risk indicators at the 5th and

[8] 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.

[9] To make sure that book values of equity that are 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.

95th percentiles, computed for each country-month distribution separately. The only exception is PRICE, which is winsorized at the 25th and 75th percentiles.

Market data are sourced from Thomson Datastream at 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-US 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 US (DeFond et al., 2007), we assume that the accounting items are available to investors six months after the fiscal year end. To avoid dropping 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 2 reports descriptive statistics for the default risk indicators of active and bankrupt firms. The default risk indicators of the bankrupt firms are measured in the month prior to their filing (*t-1*). 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. They also 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 considerably less cash (CASHMTA) on average.

[Table 2 here]

A more detailed inspection of Table 2 reveals notable differences between filing and non-filing firms across countries. For example, firms filing for bankruptcy in Japan are only slightly less profitable relative to non-bankrupt firms. In particular, the difference in their average NIMTA is only -0.03, whereas it is much larger in the other countries, with the exception of France where the difference is also relatively small (-0.08). Moreover, German firms do not use up their internal slack to delay bankruptcy filings, and hence they typically enter bankruptcy with more cash holdings (mean=0.16) than filing firms in the other countries of our sample.

An explanation for these features could be that both France and Germany have "stop-early" bankruptcy regimes. 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 fact, it is the French court that ultimately 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 Germany, managers are also obliged to file within three weeks if firm net worth drops below a specific threshold. Failure to do so can render managers personally liable to creditors (Wood, 2007).

Whereas there are no similar obligations in Japan, it is possible that Japanese banks are able to use their dominant position to force managers to file early, while the bank's claims are still relatively secure (Pinkowitz and Williamson, 2001). This feature may also explain why the stock returns of Japanese firms prior to filing are, on average, the least negative relative to filing firms in the other countries.

Overall, the univariate analysis in Table 2 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. This evidence motivates the estimation of country-specific LOGIT models to compute default probabilities, as described in Section 3.

2.3 Market, Size, Value, and Momentum Factors

Our asset pricing tests adjust portfolio returns for their 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, respectively. To this end, we use the Developed Markets Global *ex US* Fama-French market, size, value, and momentum factors, which are available

from Kenneth French's online data library; [10] see Fama and French (2012, p. 459-460), for their construction details. Interestingly, the set of developed markets that are used to construct the above factors has a very large degree of overlap with the C14 countries that we use in our study, rendering these factors appropriate for risk-adjusting our portfolio returns.[11]

We have additionally used two alternative sets of factors to risk-adjust portfolio returns. First, we have computed our own market, size, value, and momentum factor returns using the same universe of stocks as the one used to construct portfolios for the C6 and C14 countries, respectively. Second, we have computed market, size, and value factor returns using the returns on the relevant MSCI World *ex US* Indices. The Supplementary Appendix discusses the construction of these factors and reports the corresponding asset pricing results. In sum, the magnitude and significance of the international default risk premium that we report in the benchmark results remain robust to the use of the alternative sets of factors.

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; O'Doherty, 2012). This hazard model specifies the probability of bankruptcy 12 months ahead conditional on survival in the interim 11 months as:

$$Prob_{m-12}\left(Y_{i,m} = 1 |\, Y_{i,m-1} = 0\right) = \frac{1}{1 + \exp(-\alpha - \boldsymbol{\beta}' \boldsymbol{X}_{i,m-12})}, \tag{2}$$

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

[10] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Developed.
[11] For the list of countries used to construct the Developed Markets Global ex US Fama-French factors, see: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/details_globalexus.html.

$m-12$. We term the default probability estimated from the above hazard model as the CHS default risk measure. The standard LOGIT specification in (2) implies that this default risk measure is a non-linear transformation of the firm characteristics that are used to compute it.

We firstly estimate the LOGIT model in (2) for each of the C6 countries. For the remaining eight countries that feature too few (less than 40) bankruptcies to be analyzed separately, we pool the data by bankruptcy law regime and estimate the corresponding regime-specific LOGIT model. Following Wood (2007), we assign Australia, Canada, Hong Kong, New Zealand, and the UK 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.

The estimation of country- and bankruptcy regime-specific LOGIT models provides an important source of flexibility relative to estimating a single (global) LOGIT model. In particular, this approach allows us to capture cross-country variations with respect to average default rates (through the constant term) as well as the contribution of the various default risk indicators (through the coefficients in $\boldsymbol{\beta}$). This is an important feature since we subsequently use these estimated default probabilities to sort the entire cross-section of stocks into international portfolios.

Whereas in-sample default probability estimates are informative, they are obviously not available to investors in real time, and hence they would induce a look-ahead bias in our asset pricing tests. Therefore, our asset pricing tests make use of out-of-sample (OOS) default probabilities that are based on recursive estimations of model (2). Determining the initial estimation window, we face the following dilemma. On the one hand, OOS default probabilities should be estimated using sufficiently long windows to ensure that the default risk proxy is precisely estimated. On the other hand, asset pricing tests should be conducted over sufficiently long time periods to derive meaningful results. We opt for an initial estimation window using data up to

December 1999. This choice ensures that each window includes at least five bankruptcy filings for each country, and allows us to perform asset pricing tests using 15 years of monthly returns.

Having estimated each LOGIT model using data until December of year $t-1$, we combine the recursively 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 default risk proxy, Merton's (1974) Distance-to-Default (MDD). This is given by:

$$MDD_{i,t} = \frac{\ln\left(\frac{V_{i,t}}{X_{i,t}}\right) + \left(\mu_{i,t} - .5\sigma_{i,t}^2\right)}{\sigma_{i,t}}, \tag{3}$$

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. To compute MDD, 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-half of 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.

We follow Vassalou and Xing (2004) in computing 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 (3), we obtain MDD. By construction, MDD is available OOS. As with CHS, MDD also captures default risk twelve months ahead.

Computing MDD from (3), the corresponding implied default probability is given by:

$$\pi_{MDD,i,t} = \mathcal{N}\left(-MDD_{i,t}\right), \tag{4}$$

where $\mathcal{N}(\cdot)$ is the normal cumulative density function. Throughout the remainder, we term the MDD-implied default probability as the MDD default risk proxy.[12]

3.2 Estimates of the In-Sample LOGIT Models

Table 3 reports the full sample estimates of the LOGIT model in (2) for each of the C6 countries. For the sake of brevity, we do not report the results for the bankruptcy law regimes, but these are available upon request. In general, the reported results confirm the univariate analysis from the descriptive statistics in Table 2. In particular, the default probability tends to increase with total liabilities (TLMTA) and stock return volatility (SIGMA), whereas it tends to decrease with profitability (NIMTA), excess returns (EXRET), relative size (RSIZE), and cash holdings (CASHMTA). 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, whereas MB is insignificant in most cases.

[Table 3 here]

Using the same LOGIT model to forecast US failures, Campbell et al. (2008) report a pseudo-R^2 of 11.4% for a 12-month forecasting horizon. Noting that we do not consider performance-related delistings, and that our sample period is shorter, the pseudo-R^2s in Table 3 suggest that this LOGIT model also exhibits good forecasting power for the countries we examine, which is particularly high in France (9.4%), Canada (9.2%) and Japan (8.3%).

The results reported in Table 3 also suggest that there are notable variations in the estimated coefficients of the default risk indicators across countries. These variations are often, albeit not

[12] In the Supplementary Appendix, we alternatively compute MDD using two other proxies for the expected return of firms' assets, and we re-examine the performance of the MDD-sorted portfolios. Using either of these two alternative proxies, the corresponding MDD-based asset pricing results are very similar to the ones derived using the benchmark approach that is presented here.

always, consistent with the patterns revealed by the descriptive statistics in Table 2. For example, CASHMTA is insignificant in Germany and NIMTA is insignificant in Japan. To test whether cross-country variations in the estimated coefficient of a 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. The last column in Table 3 reports these LR statistics, suggesting the rejection of the null hypothesis of no cross-country variations for all default risk indicators, except for EXRET.

3.3 Bankruptcy Forecasting Ability Comparison between CHS and MDD

Advocating the use of CHS as a default risk proxy for our international sample, we compare its bankruptcy forecasting ability with the one of MDD. To this end, we perform both in-sample and out-of-sample tests, similar to the ones performed by Campbell et al. (2008) and Bharath and Shumway (2008) for the US market.

With respect to in-sample tests, Table 4 presents the results from country-specific LOGIT models that include either only MDD (Panel A), or 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 to the model substantially decreases the magnitude of the MDD coefficient, which now becomes insignificant in 3 out of 6 countries. Equally importantly, comparing pseudo-R^2s between Panels A and B, we find that adding the CHS default risk indicators to MDD doubles the bankruptcy forecasting power of the LOGIT

models across all countries, with the exception of Germany where the increase is still notable but not that high.

[Table 4 here]

Another way to confirm the in-sample superiority of the CHS default risk indicators is to compare how the LOGIT models' pseudo-R^2s change when we add MDD on top of these indicators. Comparing the pseudo-R^2s in Panel C with the ones in Panel B, it becomes apparent that MDD has a negligible contribution to the models' explanatory power, again with the exception of Germany. In sum, the CHS default risk indicators subsume the bankruptcy-relevant information contained in MDD. These results closely resemble the ones reported in Campbell et al. (2008) for the US market, confirming the in-sample superiority of these default risk indicators relative to MDD in our international setup. Moreover, these results echo the conclusion of Bharath and Shumway (2008) that MDD is not a sufficient statistic for default risk.

To assess the out-of-sample bankruptcy forecasting ability of these two default risk measures, we compute their corresponding accuracy ratios following the approach of Vassalou and Xing (2004, p. 842-843). In particular, for each of these two measures we rank firms in descending order according to their default probabilities estimated in December of year $t-1$ and then compute the corresponding areas under curve using the actual defaults that occurred in year t. The area under curve reflects the portion of firms that actually defaulted within a given percentage of firms with the highest default risk. The accuracy ratio is given by the ratio of each measure's area under curve divided by the area under curve of the "perfect foresight measure", which could ex ante assign the highest rank exactly to those firms that subsequently defaulted. The accuracy ratio of the perfect default risk measure would be equal to 1, whereas the accuracy ratio of a zero-information measure would be equal to 0.

We compute the accuracy ratios for each of the two default risk measures in each year of our sample. For the C6 (C14) countries, CHS yields an average accuracy ratio of 0.667 (0.668), whereas the corresponding figure for MDD is 0.595 (0.591). Interestingly, CHS also

yields a higher average accuracy ratio for each of the C6 countries (see Panel D of Table 4). These results confirm the ability of CHS to predict out-of-sample corporate defaults in our international sample, both in absolute and in relative terms.

To further assess the out-of-sample bankruptcy forecasting ability of these two default risk measures, we have also performed a portfolio-based analysis, which is presented in the Supplementary Appendix. In sum, we find that CHS exhibits a superior ability to ex ante classify as extremely high default risk a notably higher portion of firms that subsequently filed for bankruptcy.

4. The International Default Risk Premium

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

In this section, we examine the performance of international default risk-sorted portfolios. In our benchmark tests, we use monthly portfolio returns that are calculated from the perspective of an international investor and are expressed in US dollar (USD) terms. Similarly, excess portfolio returns are computed in excess of the USD risk-free rate. In particular, we sort the entire cross-section of stocks in ascending order on the basis of their CHS estimates in December of each year $t-1$ and assign them to international quantile portfolios. For our benchmark analysis, we follow the practice of 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 beginning of the 12-month holding period to alleviate concerns that portfolio performance is driven by a short-term return reversal effect.

Since non-US stock return data can be of lower quality, 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 5^{th} percentile of the corresponding country-month distribution. Using these filters, we alleviate concerns that the performance of high default risk portfolios is driven by microcap stocks or microstructure biases. 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, 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 5, we report the premia of several quantile portfolios constructed on the basis of OOS CHS estimates for the C6 (Panel A) and C14 countries (Panel B) during the period 2000-2014. 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 5 here]

The results in Table 5 show that average premia and CAPM alphas increase almost monotonically as we move from low to high default risk portfolios across both the C6 and the C14 countries. In the case of value-weighted portfolios, the average return of the spread strategy Q5-Q1 is equal to 13.86% p.a. in the C6 and 13.42% p.a. in the C14 countries, indicating the existence of an economically significant default risk premium. The premium is also highly statistically significant (C6 countries t-stat: 2.71, C14 countries t-stat: 3.03).[13] Moreover, the premium is of similar magnitude when we use equally-weighted portfolio returns: 10.24% p.a. (t-stat: 2.43) in the C6 and 9.99% p.a. (t-stat: 2.66) in the C14 countries.

Adjusting for market risk, the magnitude and the significance of the premium are not affected. This result originates from the fact that the average excess market return over the examined sample period has been quite low (3.83% p.a.), so potentially different market exposures cannot explain the default risk premium. In particular, in the C14 countries, the spread strategy

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

Q5-Q1 yields a CAPM alpha of 12.26% p.a. (t-stat: 2.83) in the case of value-weighted portfolios and 8.86% p.a. (t-stat: 2.88) in the case of equally-weighted portfolios.

It should be noted that in the case of equally-weighted returns, the default risk premium is predominantly driven by the significantly high excess returns and alphas that the high default risk stocks yield. In the case of value-weighted returns, the portfolios containing the lowest default risk stocks exhibit negative (but insignificant) excess returns and significantly negative CAPM alphas. Therefore, in this case, the documented premium appears to be driven both by the outperformance of the highest default risk stocks and the underperformance of the lowest default risk stocks. As discussed in the Supplementary Appendix, a potential explanation for this underperformance is that the lowest default risk quintile portfolio can provide a hedge against increases in aggregate default risk.[14]

Furthermore, when we adjust portfolio returns for their size, value, and momentum factor loadings, the default risk premium is reduced by a third in the case of value-weighted portfolios. In particular, the FFC alpha of the spread strategy Q5-Q1 is 8.13% p.a. (t-stat: 2.16) in the C6 and 7.86% p.a. (t-stat: 2.80) in the C14 countries. Figure 1 illustrates why adjusting for these additional factors reduces the alphas of the spread strategies in the case of value-weighted portfolio returns. In particular, the portfolios containing the highest default risk stocks exhibit much higher SMB and HML betas relative to the portfolios containing the lowest default risk stocks, with the lowest default risk portfolios exhibiting negative HML betas. Since the SMB and HML factors carry positive premia in our sample period, adjusting for value and size factor exposures reduces the magnitude of the default risk premium relative to the CAPM. At the same time, however, the highest default risk stocks are typically past year losers, so their portfolios exhibit negative MOM betas (see Figure 1). Therefore, the resulting default risk premium is higher

[14] In particular, following the approach of Kapadia (2011), we find that the returns of the lowest (highest) default risk quintile portfolio are positively (negatively) associated with contemporaneous changes in aggregate default risk, as measured by the median CHS default probability across firms in a given month. As a result, in line with intertemporal asset pricing theory, a risk averse investor may be willing to hold low default risk stocks, despite their underperformance, so as to hedge against adverse shocks in aggregate default risk.

when we adjust returns using the FFC model as compared to the FF model (results from the FF model are available upon request). Finally, we should note that in the case of equally-weighted portfolios, the magnitude and the statistical significance of the default risk premium remain intact regardless of the model we use to perform the risk-adjustment.[15]

[Figure 1 here]

Whereas our results are certainly not driven by under-diversification (see the high number of stocks per portfolio), a potential concern is that they may be attributable to estimation error in the initial estimation windows, since these are often based on few bankruptcy filings. Figure 2 addresses this concern by plotting 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). This figure shows that the profits of this strategy are not attributable solely to the initial years of the test period, and hence the reported magnitude of the default risk premium cannot be driven by estimation error in the initial windows. Another interesting conclusion derived from Figure 2 is that high default risk stocks outperformed during the 2003-2006 and 2009-2010 bull market periods, whereas, as expected, they were severely hit during the 2007-2008 global financial crisis. These patterns confirm that, in line with standard asset pricing theory, the highest default risk stocks perform poorly during "bad times", rendering them very risky, but earn a high premium during "good times" to compensate risk averse investors for holding them.

[Figure 2 here]

[15] Equally-weighted portfolio returns and CAPM alphas are higher than the corresponding value-weighted portfolio returns and alphas across all default risk quantiles. This pattern is consistent with the existence of a significant size effect in our sample of international developed markets. The significance of this size effect is also confirmed in Fama-MacBeth regressions (see Table 7). Once we adjust portfolio returns for their SMB factor loadings via the FFC model, the wedge between equally- and value-weighted FFC alphas reported in Table 5 is reduced for the low and medium default risk portfolios, whereas it remains large for the highest default risk portfolio. This finding is consistent with the conjecture that there is a particular size effect *within* the highest default risk stocks, beyond the systematic size effect that is captured by the SMB factor. This finding may also be related to the very high idiosyncratic volatility that the highest default risk stocks exhibit.

4.2 Robustness Checks

Table 6 reports the results from a series of robustness checks with respect to the magnitude of the default risk premium in the C6 (Panel A) and the C14 countries (Panel B). To save space, we only report the average excess returns of the extreme CHS-sorted quintile portfolios Q1 and Q5 as well as of the spread strategy Q5-Q1. Results for all other portfolios and risk-adjusted returns are available upon request.

[Table 6 here]

In the first robustness test, we set the returns of filing firms to −100% during their filing month, examining whether missing delisting returns could have led to an overestimation of the default risk premium reported in our benchmark results. In the second robustness test, we impose additional data filters.[16] In the third robustness test, we do not impose a one-month 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.[17]

The corresponding results reported in Table 6 show that the premium derived from the spread strategy Q5-Q1 remains economically and statistically significant, and is very similar to the benchmark results reported in Table 5. The unreported CAPM and FFC portfolio alphas are also similar to the corresponding alphas reported in Table 5. More specifically, adjusting for market risk does not affect the magnitude of the default risk premium. However, adjusting for size and value premia captures part of the default risk premium, because the returns of the high default risk portfolios are positively associated with the SMB and HML factor returns. Nevertheless, the default risk premium remains significant in most cases.

[16] In particular, we additionally omit stocks with a zero ex-dividend monthly return and stocks with incomplete market and accounting data in the year up to portfolio formation.
[17] We have also repeated this analysis using alternatively a longer gap of two or three months. Interestingly, we find that a longer gap renders the default risk premium larger and more significant.

In addition, we have alternatively computed the international default risk premium as a value-weighted average of country-level premia. In particular, we firstly sort stocks into quantile portfolios for each country, and then average across countries. In this way, we can examine whether the reported default risk premium in our benchmark results is driven by within-country or across-country variation in default probabilities. Unreported results, which are available upon request, show that the international default risk premium remains significant, especially when country-level portfolios are formed using equal weights. However, it is reduced relative to our benchmark approach. These results show that both within-country and across-country variation in default probabilities plays a role in the formation of the international default risk premium, but the latter yields a stronger effect.[18]

Finally, we have also examined whether FOREX effects could influence the magnitude of the reported default risk premium. In particular, in the unlikely case that the highest (lowest) default risk stocks in a given month are predominantly domiciled in countries whose currencies simultaneously appreciate (depreciate) relative to the USD, then the reported default risk premium could have been driven by exchange rate movements rather than a genuine outperformance of the highest default risk stocks. To address this potential concern, we have examined the country composition of the default risk portfolios. We confirm that none of these portfolios is dominated by firms domiciled in a single country. This is particularly true for the highest and the lowest default risk portfolios that give rise to the reported premium.[19]

4.3 Fama-MacBeth Regressions

In this section, we further examine how robust is the positive relation between the CHS default risk measure and subsequent stock returns using Fama-MacBeth regressions. In particular, for

[18] We would like to thank an anonymous referee for suggesting this robustness test.

[19] Moreover, in unreported results, we have alternatively computed portfolio returns using local currency stock returns, i.e., without converting them to USD returns. In this case, we find that the default risk premium remains positive and significant, and hence we exclude the possibility that exchange rate movements may be driving the reported default risk premium.

each month of our sample we run cross-sectional regressions of excess stock returns on lagged CHS estimates and a series of lagged firm characteristics. Table 7 reports the average slope coefficients estimated from these monthly regressions as well as their t-statistics computed using Newey-West standard errors. We have normalized each regressor by its standard deviation, and hence the corresponding Fama-MacBeth estimate can be interpreted as the effect of a one standard deviation increase in this firm characteristic on stock premia.

[Table 7 here]

Model 1 in Table 7 includes only CHS as regressor, documenting a strongly significant positive relation between default risk and stock premia (t-stat: 7.23). The magnitude of the CHS coefficient accurately reflects the magnitude of the default risk premium derived from the univariate portfolio sorts in Table 5. In particular, a one standard deviation increase in default probability would increase the stock premium by 86 basis points per month. Model 2 controls for firms' beta, size and book-to-market value ratio. The results show that CHS is significantly priced in the presence of these commonly used firm characteristics, and hence it does not simply capture a size effect, even though the magnitude of the CHS coefficient is almost halved, as expected.

Another potential concern is that the positive relation between default risk and stock premia may be driven by a short-term return reversal effect (see Lehman, 1990, and Da and Gao, 2010) or by microstructure biases, such as the bid-ask bounce or infrequent trading, which are more pronounced for firms traded at low prices (see Blume and Stambaugh, 1983; Lo and MacKinlay, 2001). To address this concern, Model 3 additionally controls for momentum, reversal and price effects. Whereas we find that the reversal and price effects are significant indeed, the magnitude and the significance of the examined relation remain intact in the presence of these additional control variables. Finally, Model 4 also includes the default risk indicators that are used to estimate the CHS measure but are not already accounted for in the previous model specifications. In particular, we additionally control for stock return volatility (SIGMA),

profitability (NIMTA), leverage (TLMTA) and cash holdings (CASHMTA). In this way, we address the potential concern that CHS may simply capture the explanatory power of these firm characteristics with respect to stock premia. We find that the magnitude and significance of the CHS coefficient remain remarkably robust to the inclusion of these variables; CHS is priced in the cross-section of our international sample of stocks over and above its constituent variables. This is because CHS is a country-specific, non-linear transformation of these firm characteristics, and hence their inclusion in the regression model in a linear fashion cannot absorb the explanatory ability of CHS.

Fama-MacBeth regressions also allow us to address the potential concern that the positive relation between default risk and stock returns may be driven by a particular country effect. To this end, we include a set of country dummies and re-estimate the previous model specifications. In particular, Model 5 includes only CHS apart from the country dummies, whereas Model 6 also contains the full set of firm characteristics that we used in Model 4. The results reported in Table 7 convincingly show that the benchmark results reported for Models 1 and 4 remain unaffected by the addition of the country dummies. Based on this evidence, we conclude that the positive cross-sectional relation between default risk and stock returns is genuine and it is not driven by a particular country effect.

4.4 MDD-sorted Portfolios

The previous results indicate a robust positive default risk-stock return relation, which is markedly different from the findings of EGZ and GPS, who use MDD and EDF, respectively, to proxy for default risk. In this section, we examine the source of these different findings. To this end, we repeat the portfolio formation exercise using MDD as an alternative portfolio sorting criterion. 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 CHS estimates. However, the CHS portfolios are now constructed using only firms for which both CHS and MDD are available, to ensure that the same sample is examined. Table 8 reports equally- and value-weighted excess portfolio returns during the period 2000-2014 for both default risk measures.

[Table 8 here]

The results confirm the almost monotonic relation between CHS and portfolio premia for this subsample of firms. In sharp contrast, when MDD is used as sorting variable, a U-shape relation between default risk and portfolio returns emerges. As a result, the corresponding spread strategies using either quintile or decile portfolios yield premia that are very close to zero and insignificant. This finding is consistent for both value-weighted and equally-weighted portfolio returns in the C6 and C14 countries. Hence, we confirm that using MDD as a default risk proxy, one would conclude that there is no default risk premium in our international sample, corroborating the puzzling evidence for the US market.

Even though we confirm the findings of GPS and EGZ regarding the lack of a default risk premium on the basis of MDD, we have shown that MDD is an inferior default risk proxy relative to CHS, both in-sample and out-of-sample (see Section 3.3). In fact, the difference in the default risk premium estimates obtained from the two sets of portfolios is caused by the fact that CHS and MDD disagree on identifying both the lowest and the highest default risk firms. This discrepancy is exacerbated among the lowest default risk stocks and it becomes evident by examining the average CHS values across the MDD-sorted portfolios in the C14 countries. Though the firms in the highest MDD portfolios also exhibit the highest average CHS values, the lowest MDD decile portfolio (P1) contains firms with higher than average CHS estimates. Consistent with our previous findings, this portfolio yields a relatively higher mean excess return, exactly because it contains moderately distressed firms according to the CHS measure.

A reason why these two proxies disagree on the classification of low default risk stocks is that Merton's model assumes that default occurs once the asset value drops below a fraction of

the book value of debt, implying that a zero default risk is assigned to stocks with no debt. Consistent with this idea, unreported results show that once we drop zero leverage firms from our sample, the U-shape relation between MDD and portfolio returns becomes less pronounced. Moreover, Merton's model fails to take into account bankruptcy-triggering reasons other than insolvency. 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's KMV, usually abstract from liquidity reserves, these models possibly classify firms with liquidity problems as low default risk.[20]

5. What Drives the International Default Risk Premium?

This section examines what drives the significant international default risk premium documented on the basis of the CHS measure in Section 4. In particular, we examine whether a series of country-level characteristics affect the magnitude and the significance of this premium.

Motivated by the evidence of Favara et al. (2012), we ask whether cross-country variations with respect to creditor protection rights and shareholders' ability to renege outstanding debt affect the default risk premium. As Djankov et al. (2008) highlight, insolvency procedures considerably vary across countries; in countries where the legal framework and judicial practices favor debt renegotiation and increase shareholders' bargaining power relative to creditors', we expect default risk to be less significantly priced. This is because shareholders' expected payoffs in default may be higher, motivating them to default for strategic rather than solvency reasons. On the other hand, in countries where creditors have strict priority and can recover the

[20] In the Supplementary Appendix, we also consider hybrid MDD default risk measures and examine their asset pricing implications. In sum, we find that adding only one of the CHS indicators to MDD is not sufficient to yield a positive relation between the corresponding hybrid default risk measure and future stock returns. However, the hybrid MDD measure computed by using the full set of CHS indicators together with MDD yields a significant positive default risk premium.

proceeds of the insolvency procedure quickly and without incurring considerable costs, shareholders' ability to extract rents from creditors is low, and hence the former should require a significant premium to invest in high default risk firms.

To test these conjectures, we construct double-sorted portfolios on the basis of CHS and two alternative proxies for creditor rights at the country level. In particular, we use the *Renegotiation Failure Index* and the *Creditors' Recovery Rate* from the survey of Djankov et al. (2008).[21] The *Renegotiation Failure Index* summarizes a number of characteristics of debt enforcement procedures that protect creditors from shareholders' strategic default (see Djankov et al., 2008, and Favara et al., 2012, for details). The higher the index score, the more difficult it is for shareholders to attempt to renege the outstanding debt. *Creditors' Recovery Rate* is an inverse measure of the shareholders' benefits to engage in strategic default. This index takes into account not only the order in which secured creditors are paid, but also the overall estimated costs of the insolvency procedure as well as its duration. The higher the creditors' recovery rate, the lower the shareholders' bargaining power.

The results from these double-sorted portfolios are reported in Table 9. We find that the default risk premium is economically and statistically significant mainly in countries where shareholders face considerable frictions in attempting to renegotiate the outstanding debt (*High Renegotiation Failure*) as well as in countries where creditors' recovery rate is high. This evidence is in line with the arguments of Favara et al. (2012), showing that when shareholders' bargaining power and their ability to extract rents from creditors are low, then the former require a significant default risk premium, which is close to 10% p.a.. To the contrary, in those countries where shareholders' bargaining power is high and the judicial process favors debt renegotiation, the default risk premium is lower and statistically insignificant, since shareholders' expected

[21] Available on Andrei Shleifer's website: http://scholar.harvard.edu/shleifer/.

payoffs in default are higher, and hence default risk carries a lower price. These results hold for both value-weighted and equally-weighted portfolios.[22]

[Table 9 here]

To further examine the shareholder advantage hypothesis at the firm level, we also construct double-sorted portfolios on the basis of CHS and firm tangibility. As Garlappi et al. (2008) and Garlappi and Yan (2011) argue, shareholders' bargaining power decreases with asset tangibility, proxied by the ratio of property, plant and equipment to total assets. This is because the more tangible the assets are, the easier and less costly it is for creditors to liquidate them in the case of bankruptcy. The corresponding results from these double-sorted portfolios, which are reported in Table 9, strongly support the shareholder advantage hypothesis. In particular, the default risk premium among firms with highly tangible assets is twice as high as the corresponding premium among firms with low tangibility. Actually, in the case of equally-weighted portfolios, the premium becomes insignificant among firms with low tangibility.

Though our results strongly support the shareholder bargaining power hypothesis of Garlappi et al. (2008) at the firm level and Favara et al. (2012) at the country level, in the Supplementary Appendix we also examine alternative country-level characteristics as potential drivers of the international default risk premium. First, following GPS, we examine whether country-level investor overconfidence, as proxied by Hofstede's (2001) individualism index, has an effect on the price of default risk. Moreover, we examine whether the documented premium is affected by the depth of the local stock market, as proxied by its total trading volume relative to the country's GDP, or by the degree of information asymmetry between firm managers and investors, as captured by the Accounting Standards Index of La Porta et al. (1998). The corresponding results show that none of these alternative country-level characteristics has

[22] The explanation we put forward for the difference in the reported default risk premia implies that the price of default risk is high and significant only in the countries with high creditor protection and low shareholder bargaining power. However, this argumentation does not exclude the possibility that the spread between firms' default probabilities could also be larger in these countries, thus contributing to the reported default risk premium differential.

a considerable effect on the default risk premium, since this remains significantly positive among countries with both high and low values of these characteristics.

6. Systematic vs. Idiosyncratic Default Risk

Our benchmark asset pricing results utilize CHS values estimated from LOGIT models to classify firms as high versus low default risk. However, a growing strand of the literature (see Anginer and Yildizhan, 2014; Friewald et al., 2014; and Hilscher and Wilson, 2015) argues that, in equilibrium, investors should require a premium for being exposed to systematic rather than firm-specific default risk. This is because systematic default risk is non-diversifiable; default events are typically correlated and their cost depends on their timing. In fact, Hilscher and Wilson (2015) introduce the concept of "failure beta", defined as the sensitivity of a firm's default probability to the median cross-sectional default probability, and they show that it is a meaningful proxy for systematic default risk. Motivated by these arguments, in this section we decompose firms' total default risk into its systematic and idiosyncratic components and examine which of the two is priced in our international sample.

To this end, we follow the regression decomposition approach of Anginer and Yildizhan (2014), estimating the following regression using a 48-month rolling window:

$$CHS_{i,t} = a_{i,t} + \beta_{i,t} MCHS_t + \varepsilon_{i,t}, \quad (5)$$

where $CHS_{i,t}$ is the default risk measure for firm *i* in month *t* and $MCHS_t$ is the median cross-sectional value of CHS in month *t*. The slope regression coefficient $\beta_{i,t}$ is a proxy for the systematic default risk of firm *i* in month *t*, since it captures the sensitivity of the firm's default risk to changes in aggregate default risk. Moreover, the idiosyncratic default risk component of firm *i* in month *t* is given by the sum of the intercept and the corresponding residual value. We perform this decomposition among firms in both the C6 and the C14 countries.

Having computed these systematic and idiosyncratic default risk measures, we alternatively sort firms on the basis of each measure, classify them into portfolios and compute their post-ranking returns. The results are presented in the Supplementary Appendix. Since we use a window of 48 months to estimate $\beta_{i,t}$, the test period now becomes 2004-2014.

In line with the arguments of Anginer and Yildizhan (2014), we find that the systematic component of default risk carries a significant premium. In particular, the spread strategy that is long the quintile portfolio with the highest systematic default risk firms and short the quintile portfolio with the lowest systematic default risk firms, Q5-Q1, yields a premium of 10.65% (10.29%) p.a. in the case of value-weighted (equally-weighted) portfolios in the C6 countries. Similar is the evidence in the C14 countries, although the premium is marginally insignificant in the case of value-weighted portfolios. Adjusting for market, size, value, and momentum factor exposures, the Q5-Q1 strategy yields a significant FFC alpha in most of the cases examined, and hence the magnitude of the default risk premium remains intact.

To the contrary, sorting stocks on the basis of their idiosyncratic default risk estimates, we do not find a positive relation between this measure of default risk and post-ranking portfolio returns. The spread strategy between the highest and the lowest idiosyncratic default risk quintile portfolios, Q5-Q1, yields a premium that is close to zero and insignificant in both the C6 and the C14 countries. Using the FFC model to adjust portfolio returns, we get very similar results. In sum, we find that consistent with the predictions of standard asset pricing theory, the idiosyncratic component of firms' default risk is not priced in the cross-section of stock returns.

7. Conclusions

Motivated by the lack of consensus on the pricing of default risk in the US market, this study examines this issue in a large sample of firms from 14 developed (ex US) markets and makes a number of contributions. First, we construct the largest dataset of non-US firm bankruptcies that has been examined in the literature. Second, utilizing this dataset, we estimate OOS firm

default probabilities from country- and bankruptcy law-specific hazard models à la Campbell et al. (2008), and show that this default risk proxy has a clearly superior ability to forecast bankruptcies relative to Merton's (1974) MDD measure, both in-sample and out-of-sample. Third, we find a significant default risk premium in our international sample. The positive relation between default risk and stock returns is robust to different portfolio weighting schemes, data filters, and holding period definitions, and remains intact after controlling for a series of firm characteristics. Fourth, we find that the systematic component of default risk drives this positive relation rather than the idiosyncratic one.

Our results are in contrast to the conclusion of EGZ and GPS that a default risk puzzle exists in international markets too, which is derived on the basis of MDD and Moody's KMV EDF, respectively. Showing that MDD is not a sufficient statistic for default probability and that it is inferior to CHS for bankruptcy forecasting, we derive a different conclusion because CHS disagrees with MDD predominantly on the identification of the lowest default risk firms.

Finally, our international dataset allows us to examine what are the country-level characteristics that drive the default premium. To this end, we find that the premium is relatively higher in countries where creditor protection is stronger and shareholder bargaining power is lower, in line with the arguments of Favara et al. (2012). Furthermore, consistent with the shareholder advantage hypothesis of Garlappi et al. (2008), we find that the default risk premium is more pronounced among firms with high asset tangibility.

Echoing the concerns of Chava and Purnanandam (2010), our results indicate that the distress anomaly could be specific to the US market. 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 considering less developed markets as well as extending the time period to study the behavior of the default risk premium across different economic conditions. Another important research direction is to delve further into the drivers of the default risk premium outside the US market. Of particular interest is the question whether proposed explanations for

the anomalous returns of US distressed stocks, such as differences in corporate liquidity (Medhat, 2014) and lottery-like payoffs of distressed stocks (Conrad et al., 2014) can also help us understand the behavior of distressed stocks in non-US markets.

References

Altman, E. I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The Journal of Finance 23, 589–609.

Anginer, D., Yildizhan, C., 2014. Is there a distress risk anomaly? Corporate bond spreads as a proxy for default risk, University of Michigan Working Paper Series.

Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2009. Credit ratings and the cross–section of stock returns. Journal of Financial Markets 12, 469–499.

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

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. Journal of Political Economy 81, 637-659.

Blume, M. E., Stambaugh, R. F., 1983. Biases in computed returns: An application to the size effect. Journal of Financial Economics 12, 387–404.

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

Campbell, J. Y., Hilscher, J., Szilagyi, J., 2011. Predicting financial distress and the performance of distressed stocks. Journal of Investment Management 9, 14-34.

Chan, K., Chen, N., 1991. Structural and return characteristics of small and large firms. The Journal of Finance 46, 1467–1484.

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

Chava, S., Purnanandam, A. K., 2010. Is default risk negatively related to stock returns? Review of Financial Studies 23, 2523–2559.

Cohen, R. B., Polk, C., Vuolteenaho, T., 2003. The value spread. Journal of Finance 58, 609–641.

Conrad, J., Kapadia, N., Xing, Y., 2014. Death and jackpot: Why do individual investors hold overpriced stocks? Journal of Financial Economics 113, 455-475.

Correia, M., Richardson, S., Tuna, I., 2012. Value investing in credit markets. Review of Accounting Studies 17, 572-609.

Crosbie, P., Bohn, J., 2003. Modeling default risk, available from: www.ma.hw.ac.uk/~mcneil/F79CR/Crosbie_Bohn.pdf.

Da, Z., Gao, P., 2010. Clientele change, liquidity shock, and the return on financially distressed stocks. Journal of Financial and Quantitative Analysis 45, 27-48.

Davydenko, S. A., 2008. When do firms default? A study of the default boundary, University of Toronto Working Paper Series.

DeFond, M., Hung, M., Trezevant, R., 2007. Investor protection and the information content of annual earnings announcements: International evidence. Journal of Accounting and Economics 43, 37–67.

Dichev, I. D., 1998. Is the risk of bankruptcy a systematic risk? The Journal of Finance 53, 1131–1147.

Djankov, S., Hart, O., McLiesh, C., Shleifer, A., 2008. Debt enforcement around the world. Journal of Political Economy 116, 1105–1150.

Eisdorfer, A., Goyal, A., Zhdanov, A., 2013. Distress anomaly and shareholder risk: International evidence. University of Connecticut Working Paper Series.

Fama, E. F., French, K. R., 1996. Multifactor explanations of asset pricing anomalies. The Journal of Finance 51, 55–84.

Fama, E. F., French, K. R., 2012. Size, value, and momentum in international stock returns. Journal of Financial Economics 105, 457–472.

Favara, G., Schroth, E., Valta, P., 2012. Strategic default and equity risk across countries. The Journal of Finance 67, 2051-2095.

Foster, F. D., Smith, T., Whaley, R. E., 1997. Assessing the goodness-of-fit of asset pricing models: The distribution of the maximal R^2. The Journal of Finance 52, 591–607.

Friewald, N., Wagner, C., Zechner, J., 2014. The cross-section of credit risk premia and equity returns. The Journal of Finance 69, 2419–2469.

Gao, P., Parsons, C. A., Shen, J., 2015. The global relation between financial distress and equity returns, University of Notre Dame Working Paper Series.

Garlappi, L., Shu, T., Yan, H., 2008. Default risk, shareholder advantage and stock returns. Review of Financial Studies 21, 2743–2778.

Garlappi, L., Yan, H., 2011. Financial distress and the cross-section of equity returns. The Journal of Finance 66, 789-822.

George, T. J., Hwang, C.-Y., 2010. A resolution of the distress risk and leverage puzzles in the cross section of stock returns. Journal of Financial Economics 96, 56–79.

Griffin, J., Lemmon, M., 2002. Book to market equity, distress risk, and stock returns. The Journal of Finance 57, 2317–2336.

Hackbarth, D., Haselmann, R., Schoenherr, D., 2015. Financial distress, stock returns, and the 1978 Bankruptcy Reform Act. Review of Financial Studies 28, 1810-1847.

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

Hilscher, J., Wilson, M., 2015. Credit ratings and credit risk: Is one measure enough?. Management Science, forthcoming.

Hofstede, G., 2001. Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations. 2nd edition, Sage Publications, Beverly Hills, CA.

Kaiser, K. M. J., 1996. European bankruptcy laws: Implications for corporations facing financial distress. Financial Management 25, 67-85.

Kapadia, N., 2011. Tracking down distress risk. Journal of Financial Economics 102, 167-182.

La Porta, R., Lopez-de Silanes, F., Shleifer, A., Vishny, R. W., 1998. Law and finance. Journal of Political Economy 106, 1113–1155.

Lehman, B.N., 1990. Fads, martingales, and market efficiency. Quarterly Journal of Economics 105, 1-28.

Lo, A. W., MacKinlay, A. C., 2001, A non-random walk down Wall Street, Princeton University Press, New Jersey.

Medhat, M., 2014. Liquidity risk and distressed equity, Copenhagen Business School Working Paper.

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

Moody's Investor Services, 2011. Corporate default and recovery rates 1920-2010, available from efinance.org.cn/cn/FEben/Corporate%20Default%20and%20Recovery%20Rates, 1920-2010.pdf.

Newey, W. K., West, K. D., 1987. A simple positive-definite heteroscedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

O'Doherty, M. S., 2012. On the conditional risk and performance of financially distressed stocks. Management Science 58, 1502-1520.

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

Pinkowitz, L., Williamson, R., 2001. Bank power and cash holdings: Evidence from Japan. Review of Financial Studies 14, 1059-1082.

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

Vassalou, M., Xing, Y., 2004. Default risk in equity returns. The Journal of Finance 59, 831–868.

Wood, P. R., 2007. Principles of international insolvency. Sweet & Maxwell, London.

Table 1
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 and over the full sample period (1992-2013). This information is reported for 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	463	0.43				2	1,798	0.11	5	1,166	0.43	9	3,427	0.26
1994							0	468	0.00				0	1,889	0.00	3	1,175	0.26	3	3,532	0.08
1995							1	482	0.21	1	342	0.29	1	2,012	0.05	4	1,200	0.33	7	4,036	0.17
1996	1	256	0.39	0	383	0.00	4	472	0.85	2	351	0.57	1	2,080	0.05	8	1,215	0.66	16	4,757	0.34
1997	1	304	0.33	2	413	0.48	1	536	0.19	1	410	0.24	8	2,136	0.37	6	1,375	0.44	19	5,174	0.37
1998	2	328	0.61	0	441	0.00	2	659	0.30	1	477	0.21	7	2,311	0.30	11	1,496	0.74	23	5,712	0.40
1999	1	362	0.28	4	579	0.69	1	770	0.13	4	539	0.74	3	2,861	0.10	16	1,464	1.09	29	6,576	0.44
2000	3	496	0.60	4	748	0.54	1	845	0.12	3	640	0.47	11	2,990	0.37	7	1,383	0.51	29	7,101	0.41
2001	8	734	1.09	3	875	0.34	3	879	0.34	16	742	2.16	11	3,047	0.36	22	1,347	1.63	63	7,625	0.83
2002	6	1,214	0.49	3	926	0.32	10	870	1.15	29	776	3.74	29	3,174	0.91	24	1,336	1.80	101	8,297	1.22
2003	6	1,243	0.48	1	1,070	0.09	10	824	1.21	16	744	2.15	18	3,240	0.56	16	1,301	1.23	67	8,422	0.80
2004	5	1,254	0.40	4	1,197	0.33	4	776	0.52	9	705	1.28	11	3,293	0.33	10	1,267	0.79	43	8,493	0.51
2005	6	1,364	0.44	1	1,336	0.07	3	735	0.41	4	689	0.58	8	3,404	0.24	9	1,342	0.67	31	8,869	0.35
2006	7	1,485	0.47	6	1,964	0.31	2	747	0.27	6	705	0.85	2	3,523	0.06	7	1,493	0.47	30	9,917	0.30
2007	7	1,609	0.44	5	2,328	0.21	3	787	0.38	13	766	1.70	6	3,651	0.16	5	1,622	0.31	39	10,763	0.36
2008	20	1,747	1.14	7	2,480	0.28	0	803	0.00	9	832	1.08	32	3,678	0.87	33	1,663	1.98	101	11,203	0.90
2009	22	1,795	1.23	6	2,531	0.24	8	782	1.02	24	832	2.88	32	3,600	0.89	38	1,594	2.38	130	11,134	1.17
2010	4	1,767	0.23	6	2,554	0.23	7	758	0.92	10	817	1.22	5	3,533	0.14	13	1,507	0.86	45	10,935	0.41
2011	9	1,802	0.50	10	2,672	0.37	9	758	1.19	3	814	0.37	2	3,560	0.06	10	1,592	0.63	43	11,198	0.38
2012	10	1,845	0.54	11	2,777	0.40	8	736	1.09	10	791	1.26	4	3,534	0.11	17	1,562	1.09	60	11,244	0.53
2013	8	1,805	0.44	15	2,715	0.55	1	701	0.14	4	754	0.53	3	3,446	0.09	11	1,472	0.75	42	10,894	0.39
1992-2013	126	21,410	0.59	88	27,989	0.31	80	14,850	0.54	165	12,729	1.30	196	62,760	0.31	289	30,748	0.94	944	170,484	0.55

Table 2
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), 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 firms (act) as well as for bankrupt firms (bank) in the month prior to their filing (*t-1*). The statistics are reported for Australia, Canada, France, Germany, Japan and the UK (the C6 countries) over the period 1992-2013. 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	-0.10	-0.25	0.25	0.63	0.00	-0.11	-10.16	-11.59	0.72	1.12	0.17	0.14	2.12	1.50	-0.96	-1.69
Median	-0.02	-0.14	0.17	0.71	-0.01	-0.08	-10.47	-11.92	0.68	1.09	0.07	0.05	1.45	0.56	-0.92	-1.86
St.Dev	0.24	0.31	0.24	0.24	0.16	0.17	2.03	1.39	0.39	0.43	0.26	0.23	1.80	2.11	1.20	1.15
All firm/months (N=256,918); Bankruptcy Group (N=126)																
Panel B: Canada																
Mean	-0.10	-0.39	0.26	0.64	0.00	-0.18	-10.46	-12.46	0.89	1.59	0.14	0.15	2.35	2.25	0.08	-1.25
Median	-0.02	-0.29	0.17	0.74	-0.01	-0.25	-10.50	-12.92	0.80	1.51	0.05	0.05	1.64	0.75	0.21	-1.51
St.Dev	0.25	0.42	0.26	0.25	0.18	0.25	2.29	2.10	0.56	0.64	0.22	0.24	1.97	2.58	1.43	1.23
All firm/months (N=335,867); Bankruptcy Group (N=88)																
Panel C: France																
Mean	0.01	-0.07	0.47	0.70	0.00	-0.04	-9.52	-11.93	0.44	0.67	0.10	0.07	2.06	2.67	2.86	1.95
Median	0.02	-0.06	0.47	0.78	-0.05	-0.04	-9.78	-12.20	0.39	0.60	0.07	0.03	1.56	1.36	2.93	1.67
St.Dev	0.06	0.10	0.25	0.27	0.10	0.13	2.14	1.33	0.23	0.32	0.10	0.11	1.57	2.40	0.91	0.83
All firm/months (N=178,198); Bankruptcy Group (N=80)																
Panel D: Germany																
Mean	-0.02	-0.15	0.44	0.76	-0.01	-0.07	-9.41	-11.67	0.50	1.10	0.12	0.16	2.19	1.46	2.28	1.26
Median	0.01	-0.07	0.43	0.85	-0.01	-0.12	-9.56	-11.92	0.43	1.10	0.06	0.06	1.67	0.54	2.40	1.07
St.Dev	0.14	0.27	0.27	0.23	0.12	0.19	1.99	1.50	0.32	0.46	0.17	0.22	1.69	2.00	1.06	0.85
All firms/months (N=152,742); Bankruptcy Group (N=165)																
Panel E: Japan																
Mean	0.01	-0.02	0.54	0.82	0.00	-0.02	-9.95	-11.33	0.41	0.74	0.17	0.11	1.30	1.26	6.36	5.90
Median	0.02	-0.01	0.56	0.91	-0.01	-0.05	-10.09	-11.52	0.37	0.77	0.13	0.08	1.02	0.68	6.35	5.59
St.Dev	0.04	0.05	0.23	0.20	0.09	0.15	1.56	1.15	0.19	0.25	0.13	0.10	0.94	1.30	0.68	0.74
All firms/months (N=753,115); Bankruptcy Group (N=196)																
Panel F: United Kingdom																
Mean	-0.02	-0.17	0.38	0.73	0.00	-0.10	-9.84	-12.33	0.39	0.72	0.10	0.11	2.31	1.87	4.36	3.13
Median	0.02	-0.12	0.35	0.80	-0.01	-0.13	-9.94	-12.33	0.35	0.73	0.05	0.04	1.63	0.56	4.52	3.27
St.Dev	0.14	0.22	0.24	0.19	0.11	0.16	2.03	1.18	0.22	0.28	0.15	0.19	1.91	2.51	1.01	0.75
All firms/months (N=368,944); Bankruptcy Group (N=289)																
Panel G: All Countries																
Mean	-0.03	-0.16	0.41	0.73	0.00	-0.08	-9.96	-11.88	0.54	0.92	0.14	0.12	1.89	1.72	3.44	2.22
Median	0.01	-0.07	0.40	0.81	-0.01	-0.09	-10.08	-12.08	0.43	0.84	0.09	0.05	1.32	0.62	4.01	2.30
St.Dev	0.16	0.26	0.27	0.23	0.13	0.18	1.95	1.43	0.38	0.47	0.17	0.19	1.63	2.20	2.95	2.68
All firms/months (N=2,045,784); Bankruptcy Group (N=944)																

Table 3
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 a set of predictors (listed and defined below) 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. CASHMTA is the 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, whereas PRICE is the log stock price. Estimated coefficients are in bold, whereas *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	**-0.029**	**-1.347** ***	**-4.879** ***	**-0.729** **	**1.080**	**-0.987** ***	**19.13** ***
	[-0.09]	[-3.67]	[-3.41]	[-2.27]	[0.81]	[-3.26]	(0.00)
TLMTA	**2.765** ***	**2.941** ***	**0.745**	**1.772** ***	**4.709** ***	**1.846** ***	**40.23** ***
	[7.58]	[7.44]	[1.24]	[5.10]	[7.96]	[7.34]	(0.00)
EXRET	**-1.848** ***	**-1.402** **	**0.247**	**-0.093**	**-0.899**	**-1.048** **	**7.17**
	[-2.97]	[-2.11]	[0.26]	[-0.14]	[-1.40]	[-2.11]	(0.31)
RSIZE	**-0.062**	**0.317** ***	**-0.373** ***	**-0.214** ***	**-0.217** ***	**-0.157** ***	**31.90** ***
	[-0.89]	[3.59]	[-4.24]	[-3.92]	[-4.15]	[-4.19]	(0.00)
SIGMA	**1.019** ***	**0.022**	**0.991** **	**1.004** ***	**2.075** ***	**0.907** ***	**32.21** ***
	[4.42]	[0.11]	[2.10]	[5.44]	[7.09]	[3.78]	(0.00)
CASHMTA	**-1.622** ***	**-0.843** *	**-2.938** *	**-0.241**	**-2.622** ***	**-2.378** ***	**15.57** **
	[-2.58]	[-1.92]	[-1.67]	[-0.51]	[-3.01]	[-4.12]	(0.02)
MB	**-0.048**	**-0.044**	**0.004**	**0.009**	**0.243** ***	**-0.001**	**21.23** ***
	[-0.97]	[-0.86]	[0.08]	[0.18]	[3.82]	[-0.04]	(0.00)
PRICE	**0.169**	**-0.821** ***	**-0.141**	**-0.006**	**0.423** ***	**-0.275** ***	**54.09** ***
	[1.40]	[-4.79]	[-0.73]	[-0.05]	[3.62]	[-3.83]	(0.00)
CONSTANT	**-9.582** ***	**-6.055** ***	**-12.016** ***	**-10.466** ***	**-17.074** ***	**-8.687** ***	
	[-15.76]	[-6.77]	[-9.99]	[-16.07]	[-16.05]	[-13.38]	
Observations	227,492	291,601	144,618	134,225	632,063	274,108	
Failures	115	86	70	152	190	244	
Pseudo-R^2	0.068	0.092	0.094	0.065	0.083	0.071	

Table 4
Logit Regressions including Merton's Distance-to-Default and Accuracy Ratios

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 3 for a description of these variables) in Panel B or *(iii)* only the CHS default risk indicators in Panel C. The LOGIT models in Panels A-C are estimated using only the firm-month observations and failures 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. To construct the MDD measure, we follow the methodology of Vassalou and Xing (2004) (see Section 3.1 for details). ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively. Panel D reports the average accuracy ratios of the CHS and MDD default risk measures for each of the C6 countries. The accuracy ratio is given by the ratio of each measure's area under curve divided by the area under curve of the "perfect foresight measure", which could ex ante assign the highest default risk rank exactly to those firms that subsequently defaulted. We follow the methodology of Vassalou and Xing (2004) to compute areas under curve (see Section 3.3 for details).

Predictors 12-month lag	AUSTRALIA	CANADA	FRANCE	GERMANY	JAPAN	UNITED KINGDOM
***Panel A**: Merton (1974) Distance-to-Default*						
MDD	**2.739** ***	**2.416** ***	**2.955** ***	**2.905** ***	**3.104** ***	**2.617** ***
	[9.33]	[6.61]	[7.08]	[14.36]	[16.43]	[13.08]
Pseudo-R^2	0.044	0.033	0.047	0.066	0.041	0.039
***Panel B**: Merton (1974) Distance-to-Default + CHS Default Risk Indicators*						
MDD	**0.991** *	**0.251**	**1.225**	**1.606** ***	**0.783** **	**0.402**
	[1.84]	[0.44]	[1.49]	[4.44]	[2.45]	[1.17]
Pseudo-R^2	0.079	0.078	0.093	0.084	0.085	0.079
***Panel C**: CHS Default Risk Indicators*						
Pseudo-R^2	0.077	0.078	0.089	0.073	0.083	0.078
Observations	179,723	215,544	102,149	104,591	485,069	180,814
Failures	76	50	39	148	169	156
***Panel D**: Accuracy Ratios*						
CHS	0.651	0.720	0.581	0.693	0.467	0.750
MDD	0.571	0.665	0.459	0.618	0.312	0.671

Table 5
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 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 USD 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. We use the Developed Markets Global ex US Fama-French market, size, value, and momentum factors, sourced from K. French's online data library; see Fama and French (2012, p. 459-460) for their construction details. The lower part of each panel reports the (equally-weighted) 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 2000-2014. ***, ** 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	**-2.66**	**-3.01**	**1.06**	**2.54**	**6.48**	**9.75**	**11.80**	**13.86** ***	**14.46** **
		[-0.51]	[-0.48]	[0.19]	[0.44]	[1.01]	[1.35]	[1.35]	[2.71]	[2.26]
	ew	**4.49**	**3.37**	**5.32**	**6.98**	**8.91**	**10.48**	**17.86** **	**10.24** **	**13.37** **
		[0.77]	[0.51]	[0.79]	[0.96]	[1.19]	[1.37]	[2.05]	[2.43]	[2.41]
CAPM alpha	vw	**-5.11** *	**-6.16** **	**-2.55** ***	**-1.21**	**2.49**	**5.52**	**7.48**	**12.41** **	**12.59** **
		[-1.96]	[-2.28]	[-3.42]	[-0.95]	[1.12]	[1.64]	[1.44]	[2.47]	[2.11]
	ew	**2.30**	**0.39**	**1.65**	**2.95**	**4.90**	**6.54** *	**13.88** ***	**8.87** **	**11.58** **
		[0.58]	[0.09]	[0.52]	[0.98]	[1.54]	[1.94]	[2.63]	[2.43]	[2.32]
FFC alpha	vw	**-3.82** **	**-5.88** ***	**-1.77** **	**-1.14**	**-0.30**	**1.01**	**5.68**	**8.13** **	**9.50** *
		[-2.07]	[-2.74]	[-2.14]	[-1.20]	[-0.13]	[0.43]	[1.20]	[2.16]	[1.67]
	ew	**0.37**	**-1.40**	**-0.09**	**1.78**	**3.20**	**5.29** **	**13.52** ***	**9.92** ***	**13.15** ***
		[0.14]	[-0.53]	[-0.05]	[0.91]	[1.55]	[2.55]	[3.88]	[2.95]	[3.00]
average # of firms		823	823	1646	1646	1646	823	823		
average sigma		0.40	0.47	0.51	0.53	0.56	0.60	0.72		
average RSIZE		-9.54	-9.73	-9.57	-9.61	-10.05	-10.66	-11.36		
average CHS		0.00%	0.01%	0.02%	0.04%	0.08%	0.14%	0.50%		

(continued on next page)

Table 5 (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	**-2.14**	**-3.12**	**1.74**	**2.56**	**4.99**	**10.01**	**11.12**	**13.42** ***	**13.26** **
		[-0.42]	[-0.49]	[0.30]	[0.43]	[0.76]	[1.39]	[1.33]	[3.03]	[2.34]
	ew	**4.85**	**3.21**	**5.52**	**6.98**	**9.07**	**10.37**	**17.67** **	**9.99** ***	**12.82** ***
		[0.85]	[0.53]	[0.83]	[0.97]	[1.21]	[1.36]	[2.06]	[2.66]	[2.72]
CAPM alpha	vw	**-4.87** **	**-6.53** ***	**-1.95** **	**-1.25**	**0.93**	**5.82** *	**6.82**	**12.26** ***	**11.69** **
		[-2.15]	[-2.98]	[2.12]	[-1.15]	[0.52]	[1.91]	[1.46]	[2.83]	[2.24]
	ew	**2.27**	**0.10**	**1.76**	**2.94**	**5.03** *	**6.42** **	**13.68** ***	**8.86** ***	**11.41** ***
		[0.66]	[0.03]	[0.63]	[1.05]	[1.69]	[2.07]	[2.85]	[2.88]	[2.80]
FFC alpha	vw	**-3.31** **	**-6.47** ***	**0.23**	**-0.50**	**-0.84**	**1.25**	**5.23**	**7.86** ***	**8.54** **
		[-2.38]	[-3.84]	[0.22]	[-0.41]	[-0.45]	[0.57]	[1.30]	[2.80]	[2.02]
	ew	**0.62**	**-1.34**	**1.12**	**1.98**	**3.46** *	**4.91** **	**13.22** ***	**9.43** ***	**12.60** ***
		[0.26]	[-0.58]	[0.64]	[1.02]	[1.72]	[2.44]	[4.30]	[3.44]	[3.78]
average # of firms		1028	1028	2056	2056	2056	1028	1028		
average sigma		0.39	0.44	0.48	0.51	0.55	0.60	0.72		
average RSIZE		-9.18	-9.16	-9.01	-9.24	-9.78	-10.44	-11.17		
average CHS		0.01%	0.01%	0.02%	0.04%	0.08%	0.13%	0.52%		

Table 6
Robustness Tests

This table reports the results of three robustness tests regarding data filters, and the beginning of the portfolio holding period. Results are reported 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 expressed in USD terms in excess of the USD risk-free rate. Returns are reported for both value-weighted (vw) and equally-weighted (ew) portfolios. The first robustness test ("Return of Defaulting Stocks=−100%") repeats the analysis of Table 5 setting the returns of filing firms to −100% during their filing month. The second robustness test ("Additional Data Filters") repeats the analysis of Table 5 excluding in addition stocks with a zero ex-dividend monthly return and stocks with incomplete data on the market and accounting variables used in the LOGIT model in the prior 12 months. The third robustness test ("No Gap Between Formation & Holding Period") repeats the analysis of Table 5 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*. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	Value-weighted Portfolios			Equally-weighted Portfolios		
Modifications	Q1	Q5	Q5-Q1	Q1	Q5	Q5-Q1
Panel A: C6 Countries						
Return of Defaulting Stocks = -100%	**-2.93**	**10.83**	**13.76** ***	**3.87**	**12.86**	**8.99** **
	[-0.52]	[1.42]	[2.70]	[0.63]	[1.60]	[2.13]
Additional Data Filters	**0.45**	**11.53**	**11.08** **	**6.08**	**15.62** *	**9.54** **
	[0.09]	[1.44]	[2.32]	[1.00]	[1.87]	[2.11]
No Gap Between Formation & Holding Period	**-3.75**	**11.66**	**15.41** ***	**3.96**	**14.67** *	**10.71** **
	[-0.65]	[1.53]	[2.80]	[0.63]	[1.85]	[2.45]
Panel B: C14 Countries						
Return of Defaulting Stocks = -100%	**-2.56**	**10.73**	**13.29** ***	**3.97**	**12.86**	**8.89** **
	[-0.45]	[1.43]	[3.00]	[0.68]	[1.61]	[2.36]
Additional Data Filters	**0.58**	**11.76**	**11.18** ***	**6.32**	**15.98** *	**9.66** **
	[0.12]	[1.48]	[2.60]	[1.09]	[1.93]	[2.36]
No Gap Between Formation & Holding Period	**-3.00**	**11.57**	**14.57** ***	**4.10**	**14.59** *	**10.49** ***
	[-0.53]	[1.57]	[3.08]	[0.69]	[1.86]	[2.79]

Table 7
Fama-MacBeth Regressions

This table reports the results from Fama-MacBeth regressions on the relation between Campbell et al.'s (2008, CHS) default risk measure and subsequent stock returns. For each month of our sample we run cross-sectional regressions of excess stock returns on lagged CHS estimates and a set of firm characteristics that are also lagged. These include beta, log size, book-to-market value ratio (B/M), prior year stock return (MOMENTUM), prior month stock return (REVERSAL), PRICE, SIGMA, NIMTA, TLMTA and CASHMTA. Each firm characteristic is normalized by its standard deviation. Beta has been calculated using past 60 months' stock returns. Models 5 and 6 include country dummies. The coefficients are reported as time-series averages of the estimates from the cross-sectional regressions. The t-statistics, which are reported in brackets, are based on the Newey-West heteroskedasticity and autocorrelation consistent standard errors. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
CHS	**0.0086** ***	**0.0047** ***	**0.0036** ***	**0.0048** ***	**0.0084** ***	**0.0048** ***
	[7.23]	[4.60]	[3.60]	[5.05]	[7.20]	[5.34]
BETA	-	**0.0002**	**-0.0012**	**-0.0006**	-	**-0.0007**
		[0.11]	[-1.01]	[-0.52]		[-0.67]
LN(MV)	-	**-0.0071** ***	**-0.0044** ***	**-0.0051** ***	-	**-0.0016** **
		[-5.09]	[-4.39]	[-5.94]		[-2.10]
B/M	-	**0.0016** *	**0.0015** *	**0.0011**	-	**0.0018** **
		[1.69]	[1.73]	[1.45]		[2.42]
MOMENTUM	-	-	**0.0011**	**0.0021**	-	**0.0021**
			[0.78]	[1.53]		[1.46]
REVERSAL	-	-	**-0.0016** **	**-0.0013** *	-	**-0.0011** **
			[-2.35]	[-1.91]		[-1.98]
PRICE	-	-	**-0.0056** ***	**-0.0064** ***	-	**-0.0119** ***
			[-3.94]	[-5.02]		[-10.64]
SIGMA	-	-	-	**-0.0030** ***	-	**-0.0033** ***
				[-4.54]		[-4.01]
NIMTA	-	-	-	**0.0017** **	-	**0.0020** ***
				[1.99]		[3.19]
TLMTA	-	-	-	**0.0013**	-	**0.0004**
				[1.06]		[0.51]
CASHMTA	-	-	-	**0.0039** ***	-	**0.0031** ***
				[4.05]		[4.27]
CONSTANT	**0.0063**	**0.0249** ***	**0.0232** ***	**0.0232** ***	**0.0108**	**0.0134** **
	[1.07]	[3.92]	[3.81]	[3.00]	[1.18]	[2.00]
Country Dummies	No	No	No	No	Yes	Yes
Observations	1,928,527	1,444,725	1,436,565	1,435,710	1,928,527	1,435,710

Table 8
Comparison of CHS and MDD-Sorted Portfolio Returns

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 5. 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 2000-2014. ***, ** 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	**-2.56**	**-2.65**	**1.05**	**2.66**	**6.56**	**10.16**	**12.04**	**14.03** ***	**14.60** **
		[0.50]	[-0.43]	[0.19]	[0.47]	[1.03]	[1.42]	[1.39]	[2.78]	[2.31]
	ew	**4.75**	**3.64**	**4.85**	**6.88**	**8.72**	**10.80**	**18.26** **	**10.34** **	**13.51** **
		[0.85]	[0.58]	[0.75]	[0.98]	[1.18]	[1.44]	[2.10]	[2.39]	[2.35]
MDD	vw	**2.90**	**2.61**	**0.94**	**0.67**	**0.83**	**2.94**	**5.01**	**1.21**	**2.11**
		[0.47]	[0.45]	[0.18]	[0.12]	[0.13]	[0.36]	[0.57]	[0.27]	[0.43]
	ew	**13.80**	**9.63**	**5.01**	**4.59**	**6.45**	**7.68**	**15.14** *	**-0.86**	**1.34**
		[1.59]	[1.13]	[0.87]	[0.78]	[1.00]	[1.00]	[1.66]	[-0.21]	[0.25]
average # of firms		770	767	1518	1510	1521	761	743		
average sigma		0.69	0.62	0.42	0.40	0.47	0.57	0.77		
average RSIZE		-10.54	-10.20	-9.18	-9.21	-9.97	-10.57	-11.10		
average CHS		0.10%	0.04%	0.04%	0.04%	0.08%	0.16%	0.32%		
Panel B: C14 Countries										
CHS	vw	**-1.98**	**-2.72**	**1.71**	**2.67**	**5.00**	**10.39**	**11.29**	**13.49** ***	**13.27** **
		[-0.39]	[-0.43]	[0.29]	[0.45]	[0.76]	[1.46]	[1.35]	[3.06]	[2.34]
	ew	**5.23**	**3.70**	**5.32**	**7.01**	**9.04**	**10.85**	**18.08** **	**9.96** ***	**12.85** ***
		[0.95]	[0.64]	[0.82]	[1.00]	[1.22]	[1.44]	[2.11]	[2.60]	[2.60]
MDD	vw	**2.52**	**1.44**	**1.27**	**0.76**	**1.60**	**2.51**	**4.30**	**1.11**	**1.78**
		[0.43]	[0.27]	[0.23]	[0.13]	[0.25]	[0.29]	[0.49]	[0.27]	[0.41]
	ew	**13.11**	**9.70**	**4.98**	**5.00**	**6.78**	**9.20**	**15.14** *	**0.77**	**2.02**
		[1.60]	[1.19]	[0.89]	[0.83]	[1.02]	[1.19]	[1.67]	[0.21]	[0.43]
average # of firms		963	959	1898	1893	1902	947	928		
average sigma		0.66	0.59	0.39	0.40	0.47	0.56	0.75		
average RSIZE		-10.32	-9.84	-8.69	-8.86	-9.59	-10.21	-10.75		
average CHS		0.12%	0.04%	0.03%	0.04%	0.09%	0.16%	0.30%		

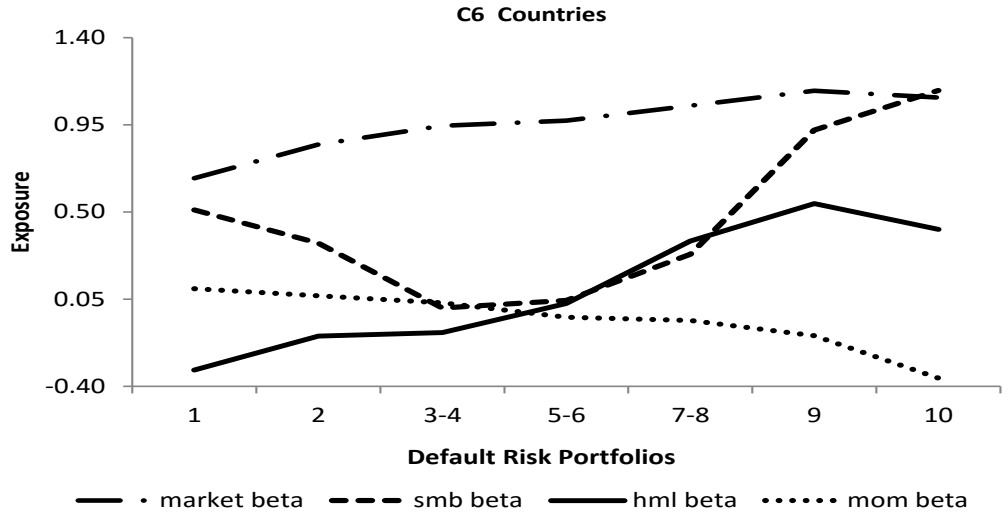
Table 9
Double-Sorted Portfolios

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 country/firm characteristics: *(i)* RENEGOTIATION FAILURE, which is an index that summarizes a number of characteristics of debt enforcement procedures that protect creditors from shareholders' strategic default (see Djankov et al., 2008, and Favara et al., 2012, for details), *(ii)* CREDITOR RECOVERY RATE, which is an inverse measure of the shareholders' benefits to engage in strategic default. In particular, this index takes into account not only the order in which secured creditors are paid, but also the overall estimated costs of the insolvency procedure as well as its duration, and *(iii)* TANGIBILITY, which is the (firm-level) ratio of property, plant and equipment to total assets. Panel A reports results based on value-weighted global portfolio returns whereas Panel B reports results based on equal-weighted global portfolio returns. The OOS CHS default risk measures are recursively estimated as described in Section 3 and the caption of Table 5. 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), and we also independently sort stocks into ascending order according to the value of each country/firm characteristic in December of year $t-1$ and allocate them into tercile portfolios (Low, Medium, High). 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 country/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. Average excess portfolio returns are annualized and bolded; their associated t-statistics are reported in square brackets. The examined period is 2000-2014. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

		RENEGOTIATION FAILURE		CREDITOR RECOVERY RATE		TANGIBILITY OF ASSETS	
CHS	ALL	High	Low	High	Low	High	Low
Panel A: Value-weighted Global Portfolios Based on C14 Countries							
T3	**7.56**	**8.02**	**3.03**	**6.41**	**6.08**	**10.85**	**3.68**
	[1.12]	[1.04]	[0.44]	[0.91]	[0.82]	[1.34]	[0.42]
T1	**-1.71**	**0.09**	**0.87**	**-3.42**	**2.27**	**-3.92**	**-3.77**
	[-0.29]	[0.01]	[0.18]	[-0.58]	[0.39]	[-0.58]	[-0.51]
Spread (T3-T1)	**9.27** ***	**7.93** *	**2.16**	**9.83** **	**3.81**	**14.77** ***	**7.45** **
	[2.70]	[1.87]	[0.78]	[2.09]	[1.33]	[3.65]	[2.11]
Panel B: Equally-weighted Global Portfolios Based on C14 Countries							
T3	**12.50**	**14.15**	**7.94**	**12.73**	**11.39**	**18.18**	**8.30**
	[1.59]	[1.58]	[1.14]	[1.60]	[1.42]	[0.82]	[0.82]
T1	**4.50**	**3.96**	**5.42**	**3.48**	**6.61**	**5.34**	**3.39**
	[0.75]	[0.47]	[1.10]	[0.56]	[0.95]	[0.82]	[0.41]
Spread (T3-T1)	**8.00** ***	**10.19** ***	**2.52**	**9.25** **	**4.78**	**12.84** ***	**4.91**
	[2.65]	[4.05]	[0.73]	[2.39]	[1.51]	[3.53]	[1.24]

Figure 1
Default Risk Portfolios' Factor Loadings

This figure presents the market, size (SMB), value (HML) and momentum (MOM) factor loadings (betas) of value-weighted 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 2000-2014. 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 5. For the countries that feature too few bankruptcies, we run recursively a LOGIT model for each bankruptcy law regime, see caption of Table 5 for details.



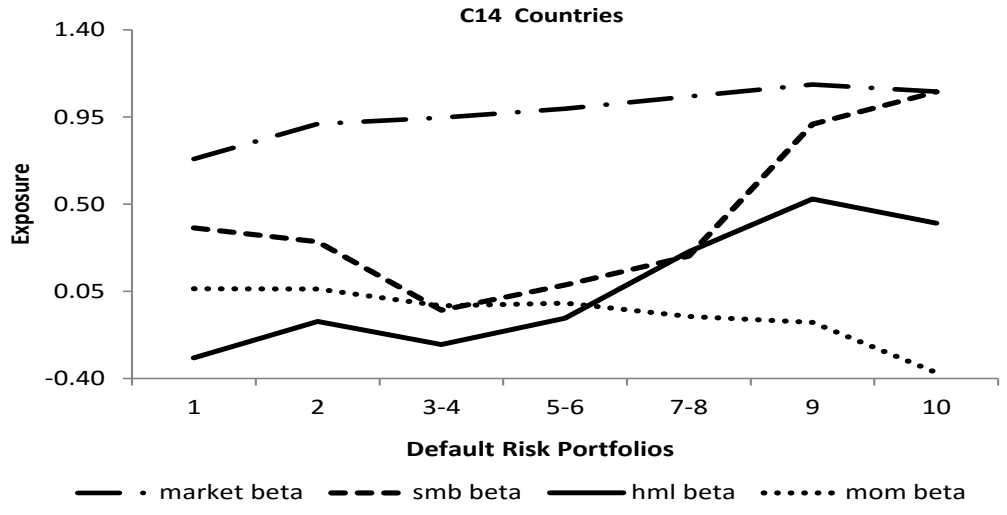
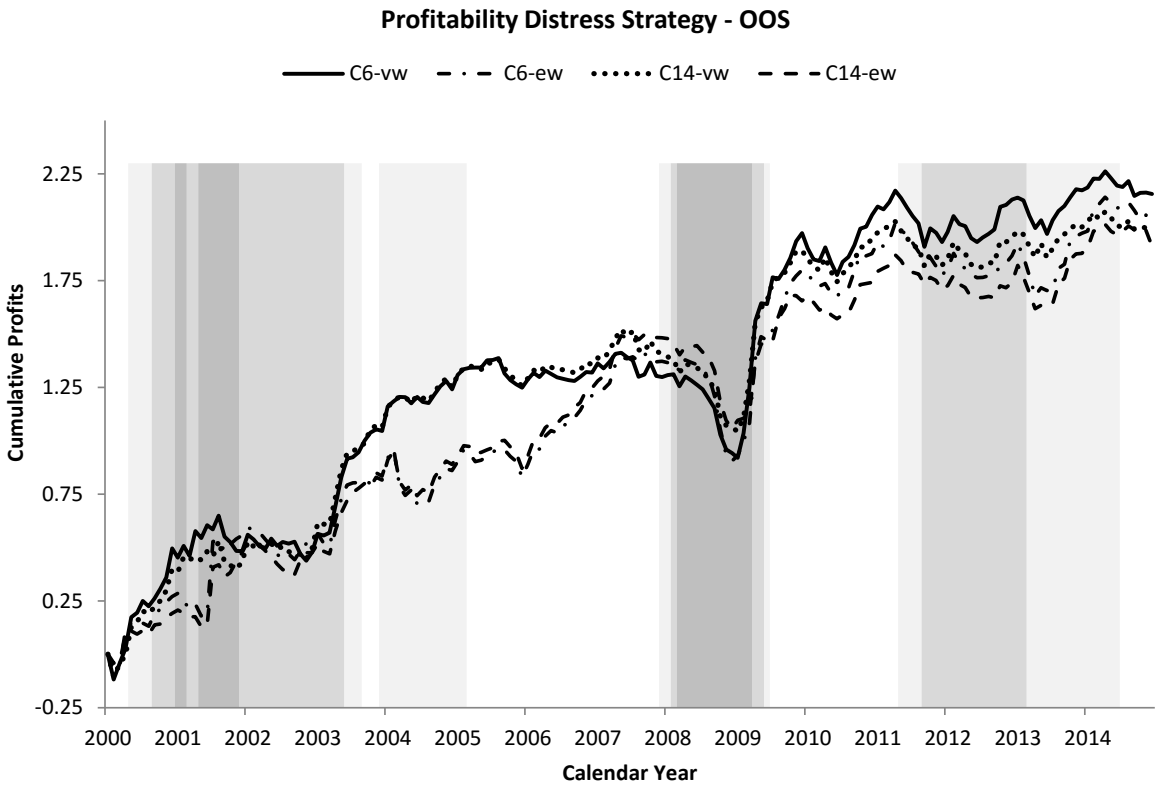


Figure 2
Profitability of Default Risk Spread Strategies

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. We use 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 5, and the examined period is 2000-2014. 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.



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

Online Supplementary Appendix

1. Alternative Factors

The benchmark results reported in the main body of the paper utilized the Developed Markets Global *ex US* Fama-French factors for risk-adjusting portfolio returns. In this section, we examine the robustness of the benchmark results to using two alternative sets of risk factors.

1.1 MSCI ex US Indices

We firstly use market, size, and value factor returns, which are computed from the corresponding MSCI World *ex US* Indices, sourced from Thomson Datastream. These indices are expressed in USD terms and they are inclusive of dividends. The excess market return is computed as the difference between the total return on the "MSCI World ex US Index" and the risk-free rate. The SMB 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 HML 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 past performance-based MSCI indices, we are unable to create a momentum factor, and thus we employ the FF 3-factor model in this set of robustness tests.

The corresponding results are reported in Table A.1. The portfolio alphas estimated using this alternative set of factors are very similar to the ones derived using the Fama-French factors in our benchmark results (see Table 5 in the main body of the paper). Most

importantly, the magnitude and the significance of the documented default risk premium remain intact. In particular, the spread strategy that is long the quintile portfolio with the highest default risk stocks and short the quintile portfolio with the lowest default risk stocks, Q5-Q1, yields a CAPM alpha of 12.51% p.a. (t-stat: 2.90) in the case of value-weighted portfolio returns and 9.01% p.a. (t-stat: 2.96) in the case of equally-weighted portfolio returns in the C14 countries. Very similar are the results in the C6 countries. Adjusting further for size and value premia, the FF alpha of the spread strategy Q5-Q1 is reduced in the case of value-weighted portfolio returns, but remains economically and statistically significant. Consistent with our benchmark results, the value and size premia are related to the default risk premium but only partially.

[Table A.1 here]

1.2 Constructed Factors

We alternatively construct our own market, size, value, and momentum factor returns, using the universe of stocks from the markets that we examine in this study. The advantage of this approach is that it perfectly aligns the universe of stocks that we use to construct these factors with the universe of stocks used to construct the default risk-sorted portfolios, whose performance we examine.[1]

To this end, the excess market return in month *t* is computed as the value-weighted dollar return of all stocks in month *t* minus the corresponding risk-free rate. The SMB factor return is computed by sorting stocks on the basis of their June market value, and calculating the value-weighted spread return between the 30% smallest and 30% largest stocks. These portfolios are rebalanced on an annual basis. The HML factor return is computed by sorting stocks on the basis of their book-to-market value ratio calculated in June of year *y*, using

[1] We would like to thank an anonymous referee for this suggestion.

book values reported at the fiscal year end of year *y-1*, and calculating the spread return between the 30% highest and 30% lowest book-to-market value portfolios. These portfolios are again rebalanced on an annual basis. Finally, the MOM factor return is computed by sorting stocks in month *t* on the basis of their cumulative returns from month *t-12* to month *t-1*, and calculating the spread return between the 30% top winner and 30% bottom loser stock portfolios. In this case, portfolios are rebalanced on a monthly basis.

The risk-adjusted performance of the CHS-sorted portfolios using this set of factors is reported in Table A.2. The results are very similar to the ones derived using the benchmark Fama-French factors. The magnitude and the significance of the default risk premium remain intact using this alternative risk-adjustment. In terms of CAPM alpha, the quintile portfolio with the highest default risk stocks outperforms the quintile portfolio with the lowest default risk stocks by almost 13% p.a. in the case of value-weighted portfolios and more than 9% p.a. in the case of equally-weighted portfolios. Moreover, risk-adjusting portfolio returns via the FFC model reduces the magnitude of the default risk premium by approximately 2% p.a. relative to the CAPM. Nevertheless, the premium remains significant.

[Table A.2 here]

2. Alternative Approaches to Estimate MDD

In the main body of the paper, we have followed the approach of Vassalou and Xing (2004) and Bharath and Shumway (2008) in constructing Merton's (1974) Distance-to-Default (MDD). This approach involves using the mean of prior year's implied asset value return series as a proxy for the expected return of firms' assets. However, this approach may induce noise or build a momentum effect into our MDD estimates.[2] To alleviate the concern that the

[2] We would like to thank an anonymous referee for this remark.

MDD-sorted portfolio returns are affected by this methodological choice, we compute MDD in two alternative ways.

First, we follow Campbell et al. (2008, p. 2937) and set the expected return equal to a constant risk premium of 6% p.a. *plus* the prevailing risk-free rate. This proxy for the equity risk premium remains constant throughout the sample period and is assumed to be the same across all stocks. In this way, we avoid building in a momentum effect or inducing noise in the MDD estimates from time-varying equity premium estimates. Second, we follow the alternative approach employed by Bharath and Shumway (2008, p. 1358) and set the expected return equal to the risk-free rate.

On the basis of each of these two alternative proxies for the expected return of firms' assets, we compute the corresponding MDD measures. Using each of these two alternative sets of MDD estimates, we sort stocks into portfolios and examine their post-ranking performance. Panel A of Table A.3 reports the performance of MDD-sorted portfolios when the fixed equity premium is used, whereas Panel B of Table A.3 reports the performance of MDD-sorted portfolios when the risk-free rate is used.

[Table A.3 here]

In both cases, the results are very similar to the ones derived for the MDD-sorted portfolios under the benchmark approach of computing MDD reported in Table 8 in the main body of the paper. In particular, we find that, if anything, a U-shape relation between default risk and portfolio returns emerges. As a result, the corresponding spread strategies using either quintile or decile portfolios yield premia that are very close to zero and insignificant. This finding is consistent for both value-weighted and equally-weighted portfolio returns in the C6 and C14 countries.

3. Hybrid MDD-based Default Risk Measures

In the main body of the paper, we have found that sorting stocks into portfolios on the basis of their MDD estimates does not lead to a significant default risk premium. We have attributed the different conclusions between the CHS- and the MDD-sorted portfolios to the disagreement of these two measures in classifying stocks as high versus low default risk. In particular, we have argued that MDD is an inferior proxy to CHS because Merton's (1974) model fails to incorporate firm characteristics that may lead firms to file for bankruptcy and that are empirically important to capture default risk.

Motivated by these arguments, and the in-sample and out-of-sample bankruptcy forecasting comparison results reported in the main body of the paper, this section examines whether combining MDD estimates with the default risk indicators of Campbell et al. (2008) to construct a hybrid MDD-based default risk proxy could yield a positive default risk premium. In other words, we examine whether including firm characteristics that are useful empirical bankruptcy indicators, and that Merton's model obviously misses out, could enhance the informational content of MDD with respect to future stock returns.[3]

To this end, we firstly compute a hybrid MDD default risk measure by recursively estimating a LOGIT model using as regressors MDD and one of the default risk indicators. In particular, we alternatively use cash holdings (CASHMTA) and the market-to-book value ratio (MB) as the additional regressor. This choice is motivated by the argument that Merton's model ignores firms' liquidity position as well as their growth opportunities. Secondly, we include both CASHMTA and MB as additional regressors. Finally, motivated by the evidence in Table 4 showing that combining MDD with all CHS default risk indicators yields the model with the highest in-sample explanatory power, we also compute a hybrid MDD measure that combines MDD with all CHS indicators.

[3] We would like to thank an anonymous Associate Editor for this suggestion.

Using each of these hybrid MDD measures, we sort stocks into portfolios and re-run our benchmark out-of-sample asset pricing tests. Table A.4 reports the portfolio performance for each hybrid measure. These results show that combining MDD with CASHMTA or MB alone to construct a hybrid measure does not lead to considerably different asset pricing implications relative to the benchmark results derived from MDD-sorted portfolios. The same is true if we combine both CASHMTA and MB with MDD to compute the corresponding hybrid measure. However, if we combine MDD with all CHS default risk indicators, this hybrid default risk measure yields an economically and statistically significant default risk premium, which is very similar to the benchmark CHS-sorted portfolio results.

[Table A.4 here]

On the basis of this evidence, we argue that combining MDD with a number of firm characteristics that Merton's model clearly does not capture, and that can considerably enhance its inferior bankruptcy forecasting ability, leads to a hybrid measure that aligns default risk with future stock returns in our international sample. In other words, this evidence supports the argument that Merton's model misses out a series of firm characteristics that are empirically important for bankruptcy forecasting, and that once these characteristics are combined with MDD, one can construct a hybrid measure that yields the theoretically expected positive relationship between default risk and stock returns.

4. US Market Evidence

This section re-examines the pricing of default risk in the US market during the period 2000-2014 that we consider in our study. In particular, we address the question whether the positive relation that we document for our sample of 14 developed ex US markets differs from the puzzling evidence provided for the US market in the prior literature (see e.g., Campbell et al., 2008) only because of the more recent sample period that we cover, or

whether the puzzling negative relation between default risk and stock returns is still there post-2000.

To this end, we compute the OOS-CHS and MDD default risk proxies for US firms post-1999. We follow the approach of Vassalou and Xing (2004) to compute MDD, and we rely on the recursive LOGIT coefficients of Campbell et al. (2008) to compute the CHS default risk proxy.[4] On the basis of each of these two measures, we sort stocks into portfolios and examine their post-ranking performance during the period 2000-2014. For ease of comparison, we implement exactly the same filtering criteria as the ones used by Campbell et al. (2008) in constructing portfolios and computing returns.

Panel A of Table A.5 reports the performance of CHS-sorted portfolios for US stocks during the period 2000-2014. We find that the strong negative relation between default risk and stock returns reported in Campbell et al. (2008) has disappeared in the post-2000 period. In particular, we find no evidence that the highest default risk portfolios yield significantly lower excess or risk-adjusted returns relative to the lowest default risk portfolios. Nevertheless, these results also show that there is no positive default premium either. Hence, the puzzle remains in the post-2000 period too. Therefore, the different conclusions we derive from the international sample that we examine in the main body of the paper versus the US market are not solely driven by the fact that we consider a more recent sample period. Even though the default risk-stock return relationship has recently become less puzzling in the US market, we still find no evidence of the conjectured positive relationship that we confirm in our international sample.

[Table A.5 here]

For completeness, we also report the corresponding results on the basis of MDD for the post-2000 period. Panel B of Table A.5 reports the performance of MDD-sorted

[4] We are grateful to Jens Hilscher for sharing with us these coefficients.

portfolios. In line with the evidence for CHS-sorted portfolios, we find that the significant negative spread between the highest and the lowest default risk portfolios has become insignificant or even disappeared in the post-2000 period. Nevertheless, we still fail to find a positive relation. Therefore, we conclude that neither CHS nor MDD can yield a positive default risk premium in the US market post-2000.

5. Alternative Country-level Characteristics

The main body of the paper tests and confirms shareholder bargaining power and the strength of creditor rights as drivers of the international default risk premium. In this section, we examine the ability of alternative country-level characteristics to affect the magnitude of this premium. In particular, we examine whether this premium is contingent upon: i) the degree of country-level investor overconfidence, as proxied by Hofstede's (2001) individualism index and used by Gao et al. (2015), ii) the liquidity conditions in the local stock market, proxied by the ratio of the average total value of traded stocks to GDP, which is provided by the World Bank's Development Indicators and has been used in La Porta et al. (2006) inter alia, and iii) the degree of information asymmetry between firm managers and investors, as proxied by the Accounting Standards Index of La Porta et al. (1998). The country-level ratios of stock market trading volume to GDP are sourced from Rafael La Porta's website, whereas the Accounting Standards Index is taken from Andrei Shleifer's website.

Equipped with these country-level characteristics, we construct double-sorted portfolios on the basis of the CHS measure and each of these characteristics. The post-ranking performance of these double-sorted portfolios is reported in Table A.6. The main finding that emerges is that the default risk premium remains positive and significant among countries that feature both high and low values of these characteristics. Therefore, we conclude that the international default risk premium is not driven by the country-level degree

of investor overconfidence, stock market liquidity conditions or transparency of accounting statements.

[Table A.6 here]

6. Hedging Innovations in Aggregate Default Risk

This section examines the exposure of the Fama-French factor returns and the CHS-sorted quintile portfolio returns to innovations in aggregate default risk. With respect to the Fama-French factors, this analysis is motivated by the evidence in Table 5 in the main body of the paper, showing that the default risk premium is reduced once we adjust for these factors, and the corresponding findings in Figure 1, showing that the returns of the highest default risk portfolios exhibit higher market, SMB, and HML factor loadings relative to the returns of the lowest default risk portfolios. With respect to the CHS-sorted quintile portfolios, we test whether their returns are differentially affected by changes in aggregate default risk. In particular, we examine whether the returns of the highest default risk portfolio are more negatively affected by an increase in aggregate default risk, and whether the lowest default risk portfolio can provide a hedge against this adverse macro shock.

To test these conjectures, we follow Kapadia (2011) and estimate contemporaneous regression models of changes in aggregate default risk on the Fama-French factor returns and the CHS-sorted quintile portfolio excess returns. In line with Kapadia (2011) and Anginer and Yildizhan (2014), we proxy aggregate default risk in month *t* by the median CHS default probability computed across firms in the same month. Table A.7 presents the corresponding results for the C6 (Panel A) and the C14 countries (Panel B).

[Table A.7 here]

The results from Model 1 show that excess market, SMB, and HML factor returns are significantly negatively related to contemporaneous innovations in aggregate default risk.

This finding indicates that these three factors are exposed to default risk. Therefore, part of the market, size, and value premium, respectively, can be regarded as compensation for exposure to systematic default risk. This result also implies that short positions on these factors would enable an investor to hedge against increases in aggregate default risk.

Model 2 utilizes the quintile portfolios with the lowest (Q1) and the highest (Q5) default risk stocks, as classified on the basis of the CHS measure. Interestingly, we find that the returns of the highest default risk quintile portfolio (Q5) are negatively related to changes in aggregate default risk. In other words, an adverse aggregate shock is associated with negative returns for high default risk stocks. On the other hand, the returns of the lowest default risk quintile portfolio (Q1) are positively associated with changes in aggregate default risk. As a result, the lowest default risk stocks provide a good hedge against these adverse aggregate shocks. This finding can help explain why the value-weighted portfolios containing the lowest default risk stocks yield negative premia (see Table 5 in the main body of the paper). In line with standard asset pricing theory, risk averse investors may still hold these stocks, despite their negative premia, because they can use them to hedge against adverse aggregate economic shocks that affect their marginal utility. These findings are also consistent with the evidence reported in Section 6 in the main body of the paper, showing that sorting firms on the basis of the CHS measure is equivalent to sorting them on the basis of their systematic default risk component.

The previous conclusions carry through even when we successively control for excess market returns in Model 3, and SMB and HML factor returns in Model 4. However, the magnitude and the significance of the coefficients are modified. This is expected, since we already know from Figure 2 that the returns of the default risk portfolios and the Fama-French factors are significantly correlated. Finally, Model 5 utilizes the spread strategy Q1-Q5, and finds a significant positive relation between its returns and contemporaneous

innovations in aggregate default risk. In line with the previous arguments, a risk averse investor can hedge adverse aggregate default risk shocks by buying the lowest and selling short the highest default risk stocks. The significant hedging ability of the Q1-Q5 spread strategy can also rationalize the average negative return that it yields (i.e., the premium of the reverse, Q5-Q1 strategy). A risk averse investor may be willing to pay this premium for being hedged against increases in aggregate default risk.

7. Do the Fama-French Factors Predict Changes in Future Failure Rates?

Motivated by the evidence that the Fama-French factor returns are correlated with contemporaneous innovations in aggregate default risk, in this section we examine whether these factors also contain predictive ability with respect to unexpected changes in firms' failure rates. In line with the arguments of Kapadia (2011), information about a future increase in firm bankruptcies would reduce current stock prices, yielding negative excess market returns. Similarly, if small and value stocks are more exposed to aggregate default risk relative to big and growth stocks, respectively, this information would yield negative SMB and HML factor returns. In this way, current factor returns may contain information regarding changes in future failure rates.

To examine this issue, we estimate 12-month ahead predictive regressions of future changes in the failure rate on current factor returns.[5] Following Kapadia (2011), we use annual failure rates because these are less noisy and more robust to seasonality relative to monthly rates. We compute annual failure rates by aggregating monthly bankruptcies, in the following way:

$$AFRate_{t+1,t+12} = \frac{1}{N_t} \sum_{i=t+1}^{t+12} f_i, \qquad \text{(A.1)}$$

[5] We would like to thank an anonymous referee for this suggestion.

where f_t is the total number of bankruptcies in month *t*, and N_t is the number of live firms in month *t*. We compute annual failure rates across firms in the C6 and the C14 countries. The annual failure rate growth is computed as the percentage change in the annual failure rate in month *t+12* relative to the annual failure rate in month *t*.

Since we examine whether factor returns can predict unexpected changes in failure rates, we also control for the lagged annual failure rate growth, the risk-free rate (RF), the term spread (TERM) and the default spread (DEF). The last three variables act as proxies for macroeconomic conditions that may drive changes in failure rates. In the absence of global versions for TERM and DEF, we utilize their US market values sourced from the updated dataset of Welch and Goyal (2008).

Table A.8 presents the results of these predictive regressions for the C6 (Panel A) and the C14 countries (Panel B). In sum, we find that excess market and SMB factor returns significantly predict unexpected annual changes in bankruptcy rates. Moreover, their coefficients carry the expected negative signs. When there is news about an increase in future bankruptcies, current stock prices drop, and the prices of small cap stocks decrease more than the prices of big cap stocks. This finding remains intact when we control for the lagged failure rate growth in Model 1 as well as for the three macroeconomic proxies in Model 2. On the other hand, we find no evidence that HML factor returns can help predict changes in bankruptcy rates. Given the evidence in the previous section, we conclude that HML factor returns are related to aggregate default risk in a contemporaneous rather than in a predictive fashion.

[Table A.8 here]

8. Out-of-Sample Bankruptcy Forecasting Ability Comparison: Further Tests

In this section, we present additional tests to further assess the out-of-sample bankruptcy forecasting ability of the CHS and the MDD default risk measures. In particular, we classify firms into portfolios on the basis of each measure and then compute the frequency of subsequent actual bankruptcies in each portfolio. We repeat this analysis for both the C6 and the C14 countries. Table A.9 shows that 41.1% (39.9%) of the actual bankruptcies occurred among firms that were *ex ante* classified into the 5^{th} highest percentile of the CHS distribution across the C6 (C14) countries. To the contrary, the corresponding percentage of actual bankruptcies among firms that were ex ante classified into the 5^{th} highest percentiles of the MDD distribution is 32.1% (30.8%). This striking difference illustrates the superior ability of CHS relative to MDD, to ex ante classify as extremely high default risk a notably higher portion of the firms that subsequently filed for bankruptcy.

[Table A.9 here]

Providing further evidence, we construct double-sorted portfolios on the basis of CHS and MDD and compute again the frequency of actual bankruptcies that occurred among firms in different percentile classifications of these two measures. Corroborating the univariate results, we find that the classification of firms into the 5^{th} highest CHS percentile is much more informative with respect to subsequent bankruptcy events relative to the corresponding classification according to MDD. For example, for firms that were classified into the 5^{th} highest MDD percentile and would appear to be very risky, almost no bankruptcy (less than 1%) occurred among firms that were simultaneously classified in the lowest 60^{th} percentile according to CHS. In other words, if a firm was not classified as relatively risky (upper 40^{th} percentile) according to CHS, being classified in the 5^{th} highest percentile according to MDD carried no information for forecasting bankruptcy. To the contrary, there was a non-negligible

portion of bankruptcies (3.6%) among firms that were classified in the 5th highest CHS percentile but considered as safe (lowest 60th percentile) according to MDD.

Table A.10 contains information that is equivalent to Table A.9, but instead of reporting the frequency of bankruptcies that occurred in each classification, it shows the average proportion of bankruptcy filings to the total number of firms per portfolio per year. The univariate sorts clearly show that CHS is superior in ex ante characterizing as risky those portfolios that exhibited a higher proportion of filings, and as safe those portfolios that exhibited an almost zero proportion of filings. Apart from the stronger monotonic increase in the average proportion of filings that we observe as we move from the lowest to the highest CHS default risk classifications, the proportion spread between the highest and lowest classifications is also much higher for CHS than for MDD. Similarly informative are the proportion spreads computed from double-sorted portfolios. In particular, the spread between the highest and lowest CHS classifications is higher across all MDD classifications relative to the corresponding MDD-based spreads across CHS classifications. In sum, CHS is able to distinguish between high and low default risk firms out-of-sample in a much sharper way relative to MDD.

[Table A.10 here]

9. Systematic and Idiosyncratic Default Risk-Sorted Portfolio Performance

In this section, we report the performance of the portfolios sorted on the basis of the systematic and idiosyncratic components of the CHS default risk measure. The approach used to decompose CHS into its systematic and idiosyncratic components is described in Section 6 of the main body of the paper, where the reported results are also discussed. Table A.11 presents the performance of portfolios constructed on the basis of systematic default risk,

whereas Table A.12 reports the corresponding performance of idiosyncratic default risk-sorted portfolios.

[Tables A.11 and A.12 here]

10. Bankruptcy Filing Data Sources

Table A.13 provides an overview of our sources for the bankruptcy filing data, which include commercial data providers, government institutions, stock exchanges, and other researchers.

[Table A.13 here]

References

Anginer, D., Yildizhan, C., 2014. Is there a distress risk anomaly? Corporate bond spreads as a proxy for default risk, University of Michigan Working Paper Series.

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

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

Gao, P., Parsons, C. A., Shen, J., 2015. The global relation between financial distress and equity returns. University of Notre Dame Working Paper Series.

Hofstede, G., 2001. Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations. 2nd edition, Sage Publications, Beverly Hills, CA.

Kapadia, N., 2011. Tracking down distress risk. Journal of Financial Economics 102, 167-182.

La Porta, R., Lopez-de Silanes, F., Shleifer, A., Vishny, R. W., 1998. Law and finance. Journal of Political Economy 106, 1113–1155.

La Porta, R., Lopez-de Silanes, F., Shleifer, A., 2006. What works in securities laws? The Journal of Finance 61, 1–32.

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

Vassalou, M., Xing, Y., 2004. Default risk in equity returns. The Journal of Finance 59, 831–868.

Welch, I., Goyal, A., 2008. A comprehensive look at the empirical performance of equity premium prediction. Review of Financial Studies 21, 1455–1508.

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

This table reports 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 caption of Table 5. 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). At the end of December of year t-1, we sort stocks in ascending order on the basis of their default risk and allocate them into decile and quintile portfolios in each case. 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 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. 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. The 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. The 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 examined period is 2000-2014. ***, ** 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										
CAPM Alpha	vw	**-4.50**	**-5.42**	**-1.85**	**-0.49**	**3.30**	**6.46** *	**8.48**	**12.69** **	**12.98** **
		[-1.46]	[-1.57]	[-1.17]	[-0.29]	[1.36]	[1.68]	[1.48]	[2.55]	[2.17]
	ew	**2.94**	**1.18**	**2.54**	**3.90**	**5.85**	**7.45** *	**14.75** **	**9.04** **	**11.81** **
		[0.66]	[0.51]	[0.67]	[1.04]	[1.46]	[1.81]	[2.55]	[2.52]	[2.39]
FF alpha	vw	**-6.32** ***	**-6.92** **	**-3.22** **	**-2.23**	**0.31**	**1.43**	**2.65**	**9.04** **	**8.97** *
		[-2.66]	[-2.35]	[-2.29]	[-1.38]	[0.14]	[0.53]	[0.61]	[2.38]	[1.92]
	ew	**-0.69**	**-3.22**	**-1.80**	**-0.45**	**1.75**	**3.73**	**10.50** **	**9.07** ***	**11.19** **
		[-0.19]	[-0.81]	[-0.57]	[-0.14]	[0.50]	[1.07]	[2.27]	[2.66]	[2.39]
Panel B: C14 Countries										
CAPM Alpha	vw	**-4.22**	**-5.78** *	**-1.24**	**-0.53**	**1.73**	**6.77** *	**7.79**	**12.51** ***	**12.01** **
		[-1.54]	[-1.95]	[-0.73]	[-0.30]	[0.79]	[1.90]	[1.48]	[2.90]	[2.27]
	ew	**2.97**	**0.89**	**2.64**	**3.87**	**5.96**	**7.33** *	**14.55** ***	**9.01** ***	**11.58** ***
		[0.75]	[0.22]	[0.76]	[1.09]	[1.57]	[1.87]	[2.70]	[2.96]	[2.87]
FF alpha	vw	**-6.03** ***	**-7.35** ***	**-2.16**	**-2.39**	**-0.76**	**1.90**	**2.00**	**9.00** ***	**8.03** **
		[-2.83]	[-2.75]	[-1.50]	[-1.38]	[-0.34]	[0.72]	[0.49]	[2.77]	[2.00]
	ew	**-0.65**	**-3.08**	**-1.26**	**-0.26**	**1.99**	**3.23**	**10.17** **	**8.57** ***	**10.82** ***
		[-0.19]	[-0.93]	[-0.43]	[-0.08]	[0.60]	[0.96]	[2.39]	[2.87]	[2.79]

Table A.2
Out-of-Sample Global Default Risk Portfolios- Our Own Factors

This table reports 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. The construction of the portfolios is described in the caption of Table 5. 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). At the end of December of year t-1, we sort stocks in ascending order on the basis of their default risk and allocate them into decile and quintile portfolios in each case. 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 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. Alphas are annualized and bolded; their associated t-statistics are reported in square brackets. To compute CAPM and FFC alphas we construct market, size, value, and momentum factor returns from the same universe of stocks as the one used to construct portfolios for the C6 and C14 countries, respectively (see Section 1.2 in this Appendix for details). The examined period is 2000-2014. ***, ** 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										
CAPM Alpha	vw	**-4.69** *	**-5.49** **	**-1.66** **	**-0.28**	**3.46** *	**6.50** **	**8.50**	**12.86** ***	**13.19** **
		[-1.91]	[-2.09]	[-2.02]	[-0.22]	[1.66]	[2.01]	[1.61]	[2.58]	[2.21]
	ew	**2.65**	**0.98**	**2.48**	**3.90**	**5.85**	**7.49** **	**14.89** ***	**9.38** **	**12.24** **
		[0.70]	[0.24]	[0.82]	[1.37]	[1.23]	[2.26]	[2.80]	[2.55]	[2.45]
FFC alpha	vw	**-4.80** *	**-5.26** *	**-1.23**	**-0.40**	**2.80**	**4.83** **	**6.44** *	**11.08** ***	**11.24** ***
		[-1.87]	[-1.86]	[-1.54]	[-0.31]	[1.48]	[2.16]	[1.77]	[3.05]	[2.77]
	ew	**0.95**	**-0.95**	**0.29**	**1.47**	**3.00** **	**4.30** ***	**11.03** ***	**7.66** **	**10.08** **
		[0.23]	[-0.25]	[0.16]	[1.11]	[2.20]	[2.60]	[3.70]	[2.05]	[2.22]
Panel B: C14 Countries										
CAPM Alpha	vw	**-4.50** *	**-5.99** ***	**-1.33**	**-0.61**	**1.62**	**6.51** **	**7.51**	**12.49** ***	**12.01** **
		[-1.96]	[-2.64]	[-0.76]	[-0.68]	[1.01]	[2.24]	[1.60]	[2.90]	[2.30]
	ew	**2.62**	**0.56**	**2.35**	**3.59**	**5.68** **	**7.06** **	**14.36** ***	**9.12** ***	**11.74** ***
		[0.75]	[0.16]	[0.90]	[1.41]	[2.07]	[2.42]	[3.03]	[3.00]	[2.91]
FFC alpha	vw	**-4.42** *	**-6.32** **	**-0.63**	**-0.66**	**1.11**	**4.42** **	**5.32** *	**10.55** ***	**9.74** ***
		[-1.93]	[-2.46]	[-0.95]	[-0.68]	[0.68]	[2.11]	[1.67]	[3.42]	[2.95]
	ew	**0.91**	**-1.30**	**0.40**	**1.23**	**2.61** **	**3.63** **	**10.49** ***	**7.26** **	**9.58** **
		[0.25]	[-0.43]	[0.26]	[0.95]	[1.97]	[2.47]	[4.23]	[2.25]	[2.44]

Table A.3
Alternative MDD Estimates and Portfolio Returns

This table reports average excess returns for portfolios sorted on the basis of two alternative estimates of Merton's (1974) Distance-to-Default measure (MDD). In Panel A, we present results based on our first alternative MDD measure. For this measure, instead of using prior year's stock returns as a proxy for the expected return of firm's assets for constructing MDD, we alternatively follow Campbell et al. (2008) and set the expected return equal to a constant risk premium of 6% p.a. *plus* the prevailing risk-free rate. In Panel B, we present results based on our second alternative MDD measure. For this measure, we follow Bharath and Shumway (2008) and set the expected return equal to the risk-free rate. We use these two alternative MDD measures of default risk to construct portfolios. At the end of December of year t-1, we sort stocks in ascending order on the basis of their default risk and allocate them into decile and quintile portfolios in each case. 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 are annualized and bolded; their associated t-statistics are reported in square brackets. The examined period is 2000-2014. ***, ** 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: Equity premium 6% + Risk-free rate										
C6 Countries	vw	**2.25**	**2.66**	**0.64**	**-0.40**	**1.07**	**5.56**	**5.25**	**2.04**	**3.00**
		[0.41]	[0.59]	[0.12]	[-0.07]	[0.16]	[0.75]	[0.59]	[0.50]	[0.60]
	ew	**13.05**	**10.50**	**5.22**	**4.77**	**5.97**	**7.66**	**15.17**	**-0.28**	**2.12**
		[1.63]	[1.35]	[0.85]	[0.83]	[0.92]	[1.00]	[1.64]	[-0.07]	[0.43]
C14 Countries	vw	**3.33**	**4.37**	**0.58**	**0.37**	**0.80**	**5.10**	**4.62**	**0.57**	**1.28**
		[0.69]	[0.83]	[0.11]	[0.06]	[0.12]	[0.68]	[0.50]	[0.14]	[0.23]
	ew	**12.24**	**10.75**	**5.53**	**5.21**	**6.37**	**8.52**	**15.34 ***	**1.26**	**3.11**
		[1.61]	[1.42]	[0.90]	[0.88]	[0.96]	[1.10]	[1.67]	[0.38]	[0.69]
Panel B: Risk-free rate										
C6 Countries	vw	**2.95**	**2.22**	**0.58**	**0.03**	**1.45**	**5.08**	**6.14**	**2.71**	**3.18**
		[0.58]	[0.46]	[0.13]	[0.01]	[0.22]	[0.68]	[0.72]	[0.68]	[0.63]
	ew	**10.82**	**12.99 ***	**5.11**	**4.76**	**5.95**	**8.11**	**15.02 ***	**-0.41**	**4.20**
		[1.32]	[1.66]	[0.84]	[0.81]	[0.92]	[1.05]	[1.66]	[-0.11]	[1.21]
C14 Countries	vw	**5.03**	**3.75**	**0.19**	**0.64**	**1.26**	**5.39**	**4.03**	**0.63**	**-1.00**
		[0.96]	[0.74]	[0.03]	[0.11]	[0.18]	[0.72]	[0.44]	[0.15]	[-0.19]
	ew	**9.65**	**12.68 ***	**5.62**	**5.20**	**6.37**	**9.08**	**15.08 ***	**0.67**	**5.44 ***
		[1.25]	[1.69]	[0.95]	[0.87]	[0.96]	[1.18]	[1.67]	[0.21]	[1.69]

Table A.4
Hybrid MDD Measures and Portfolio Returns

This table reports average excess returns for portfolios sorted on the basis of several hybrid estimates of Merton's (1974) Distance-to-Default measure (MDD). The hybrid estimates are based on reduced-form hazard models that include MDD plus a set of CHS indicators. In particular, the first hybrid estimate is based on a LOGIT model that only includes MDD and CASHMTA (ratio of cash and short-term assets to the sum of market value of equity and total liabilities) as bankruptcy indicators. The second hybrid estimate is based on a LOGIT model that only includes MDD and MB (market-to-book value ratio) as bankruptcy indicators. The third hybrid estimate is based on a LOGIT model that only includes MDD, CASHMTA (defined above) and MB (defined above) as bankruptcy indicators. The fourth hybrid estimate is based on a LOGIT model that includes MDD plus the full set of the CHS indicators (namely, NIMTA- net income scaled by the sum of the market value of equity and total liabilities; TLMTA- total liabilities scaled by the sum of the 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- 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- annualized standard deviation of a firm's daily log stock returns in the prior three months, as defined in Section 2.2; CASHMTA- defined above; MB-defined above; and PRICE- log stock price). We compute the corresponding default risk measures from each of these hybrid models, and use them to construct portfolios. At the end of December of year t-1, we sort stocks in ascending order on the basis of their default risk and allocate them into decile and quintile portfolios in each case. 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 are annualized and bolded; their associated t-statistics are reported in square brackets. The examined period is 2000-2014. ***, ** 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
C14 Countries										
MDD+CASHMTA	vw	**5.28**	**2.90**	**0.42**	**0.05**	**2.82**	**3.66**	**5.68**	**0.68**	**0.40**
		[1.18]	[0.59]	[0.07]	[0.01]	[0.50]	[0.52]	[0.70]	[0.18]	[0.08]
	ew	**10.63** *	**7.45**	**5.57**	**9.50**	**6.25**	**6.25**	**13.67**	**0.92**	**3.04**
		[1.90]	[1.09]	[0.82]	[1.51]	[0.85]	[0.78]	[1.58]	[0.26]	[0.67]
MDD+MB	vw	**6.56**	**7.62** *	**-0.37**	**0.35**	**1.77**	**2.36**	**7.11**	**-2.43**	**0.55**
		[1.17]	[1.65]	[-0.07]	[0.01]	[0.26]	[0.32]	[0.96]	[-0.61]	[0.10]
	ew	**8.05**	**11.20** *	**3.80**	**7.93**	**8.48**	**6.17**	**14.61** *	**0.77**	**6.56**
		[1.22]	[1.73]	[0.59]	[1.25]	[1.12]	[0.74]	[1.69]	[0.17]	[1.23]
MDD+CASHMTA+MB	vw	**4.30**	**4.89**	**1.04**	**0.37**	**1.31**	**3.73**	**4.34**	**-0.44**	**0.04**
		[0.88]	[1.01]	[0.19]	[0.07]	[0.21]	[0.53]	[0.53]	[-0.12]	[0.01]
	ew	**9.62** *	**8.44**	**5.99**	**6.36**	**8.52**	**6.31**	**14.65** *	**1.45**	**5.03**
		[1.67]	[1.25]	[0.86]	[1.02]	[1.25]	[0.78]	[1.71]	[0.45]	[1.26]
MDD+Campbell's et al. (2008) Indicators	vw	**-2.05**	**-2.00**	**1.85**	**2.54**	**6.03**	**7.58**	**9.73**	**10.85** ***	**11.78** *
		[-0.38]	[-0.34]	[0.31]	[0.43]	[0.92]	[1.10]	[1.09]	[2.83]	[1.95]
	ew	**5.35**	**4.37**	**5.27**	**7.13**	**10.32**	**11.00**	**14.55**	**7.91** **	**9.20** **
		[0.95]	[0.74]	[0.83]	[1.01]	[1.44]	[1.47]	[1.63]	[2.14]	[1.97]

Table A.5
US Market Evidence

This table presents results on the pricing of default risk in the US during our sample period (2000-2014). In particular, it 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 (Panel A) and on the basis of estimates of Merton's (1974) Distance-to-Default measure (MDD) (Panel B). The OOS CHS measures are recursively estimated using a LOGIT model identical to the one described in Section 3 for non-US stocks and for the case of C6 countries. We follow the methodology of Vassalou and Xing (2004) to estimate MDD for each US 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. 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. ***, ** 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: CHS (2000-2014)										
Excess Return	vw	**3.42**	**2.46**	**4.81**	**3.48**	**7.22**	**2.52**	**3.87**	**-0.95**	**0.45**
		[0.58]	[0.45]	[1.08]	[0.72]	[1.28]	[0.30]	[0.41]	[-0.20]	[0.06]
	ew	**8.02**	**8.09**	**9.31 ***	**10.84 ****	**10.71 ***	**10.36**	**6.92**	**0.58**	**-1.10**
		[1.40]	[1.30]	[1.72]	[2.05]	[1.78]	[1.37]	[0.73]	[0.13]	[-0.21]
CAPM Alpha	vw	**-0.91**	**-1.67**	**1.32 ****	**-0.30**	**2.72**	**-3.68**	**-3.34**	**-3.29**	**-2.43**
		[-0.38]	[-0.97]	[1.97]	[-0.34]	[1.02]	[-1.49]	[-0.63]	[-0.87]	[-0.34]
	ew	**3.33**	**3.32**	**4.91 ****	**6.57 ****	**6.16 ***	**5.00**	**0.83**	**-0.41**	**-2.50**
		[1.33]	[1.28]	[2.24]	[2.26]	[1.78]	[1.23]	[0.15]	[-0.10]	[-0.55]
FFC Alpha	vw	**-0.72**	**-1.72**	**0.98**	**-0.40**	**2.14**	**-2.64**	**-4.22**	**-3.04**	**-3.49**
		[-0.35]	[-1.50]	[1.24]	[-0.60]	[0.86]	[-1.07]	[-0.90]	[-0.82]	[-0.56]
	ew	**1.12**	**1.16**	**2.09 ***	**3.50 *****	**3.40 ***	**3.34**	**-0.76**	**0.15**	**-1.88**
		[0.71]	[0.70]	[1.94]	[2.77]	[1.95]	[1.38]	[-0.20]	[0.05]	[-0.51]
Panel B: MDD (2000-2014)										
Excess Return	vw	**4.69**	**3.73**	**4.10**	**6.20**	**6.34**	**4.67**	**4.34**	**0.12**	**-0.35**
		[0.69]	[0.93]	[0.90]	[1.17]	[1.09]	[0.63]	[0.45]	[0.02]	[-0.05]
	ew	**11.33 ***	**9.52 ***	**9.25 ****	**10.46 ****	**10.87 ***	**11.57**	**11.52**	**1.12**	**0.19**
		[1.77]	[1.87]	[2.00]	[2.01]	[1.73]	[1.58]	[1.20]	[0.30]	[0.04]
CAPM Alpha	vw	**-0.78**	**0.76**	**0.58**	**1.84**	**1.64**	**-0.85**	**-2.24**	**-2.32**	**-1.46**
		[-0.22]	[0.48]	[1.01]	[0.84]	[0.54]	[-0.17]	[-0.37]	[-0.36]	[-0.17]
	ew	**6.34 ***	**5.51 ****	**5.38 ****	**6.13 ****	**6.12 ***	**6.47**	**5.48**	**0.05**	**-0.86**
		[1.74]	[2.17]	[2.53]	[2.22]	[1.80]	[1.43]	[0.91]	[0.02]	[-0.21]
FFC Alpha	vw	**2.57**	**1.24**	**1.01 ****	**0.86**	**-0.38**	**-1.54**	**-4.78**	**-4.74**	**-7.35**
		[1.16]	[0.81]	[2.30]	[0.52]	[-0.24]	[-0.47]	[-1.28]	[-1.21]	[-1.62]
	ew	**5.22 ****	**3.22 ****	**3.01 *****	**2.90 ****	**2.52 ***	**3.13**	**1.78**	**-1.76**	**-3.44**
		[2.16]	[2.02]	[2.74]	[2.10]	[1.67]	[1.44]	[0.56]	[-0.90]	[-1.27]

Table A.6
Double-Sorted Portfolios with Alternative Country-Level Characteristics

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 country characteristics: *(i)* INDIVIDUALISM, which captures the degree of country-level investors' overconfidence, as proxied by Hofstede's (2001) individualism index; *(ii)* STOCK MARKET LIQUIDITY, which captures liquidity conditions in the local stock market, proxied by the ratio of the average total value of traded stocks to GDP (as provided by the World Bank's Development Indicators); and *(iii)* ACCOUNTING STANDARDS, which captures the degree of information asymmetry between firm managers and investors, as proxied by the Accounting Standards Index of La Porta et al. (1998). Panel A reports results based on value-weighted global portfolio returns whereas Panel B reports results based on equal-weighted global portfolio returns. The OOS CHS default risk measures are recursively estimated as described in Section 3 and the caption of Table 5. We sort stocks in 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), whereas we also independently sort stocks in ascending order according to the value of each country characteristic in December of year $t-1$ and allocate them into tercile portfolios (Low, Medium, High). 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 country 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. Average excess portfolio returns are annualized and bolded; their associated t-statistics are reported in square brackets. The examined period is 2000-2014. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

		INDIVIDUALISM		STOCK MARKET LIQUIDITY		ACCOUNTING STANDARDS INDEX	
CHS	ALL	High	Low	High	Low	High	Low
Panel A: Value-weighted Global Portfolios Based on C14 Countries							
T3	**7.56**	**7.96**	**6.63**	**8.08**	**6.38**	**7.95**	**6.96**
	[1.12]	[1.11]	[1.04]	[1.02]	[1.06]	[1.09]	[1.10]
T1	**-1.71**	**1.93**	**-2.27**	**1.70**	**-2.77**	**1.40**	**-2.28**
	[-0.29]	[0.36]	[-0.68]	[0.27]	[-0.49]	[0.23]	[-0.39]
Spread (T3-T1)	**9.27** ***	**6.03** *	**8.90** ***	**6.38** *	**9.15** ***	**6.55** *	**9.24** ***
	[2.70]	[1.73]	[2.73]	[1.80]	[2.80]	[1.73]	[2.81]
Panel B: Equally-weighted Global Portfolios Based on C14 Countries							
T3	**12.50**	**14.53** *	**9.96**	**14.75**	**8.67**	**14.83** *	**8.15**
	[1.59]	[1.66]	[1.46]	[1.63]	[1.29]	[1.70]	[1.23]
T1	**4.50**	**7.06**	**3.48**	**6.53**	**3.29**	**6.87**	**3.26**
	[0.75]	[0.87]	[0.61]	[0.87]	[0.57]	[0.85]	[0.59]
Spread (T3-T1)	**8.00** ***	**7.47** ***	**6.48** *	**8.22** ***	**5.38** *	**7.96** ***	**4.89** *
	[2.65]	[3.02]	[1.92]	[3.40]	[1.65]	[3.37]	[1.89]

Table A.7
Hedging Innovations in Aggregate Default Risk

This table presents the results from contemporaneous regressions of monthly changes in aggregate default risk on the monthly excess market, size (SMB) and value (HML) factor returns as well as the returns of OOS-CHS default risk-sorted value-weighted quintile portfolios. Q1 denotes the quintile portfolio containing the stocks with the lowest default risk estimates, whereas Q5 denotes the quintile portfolio containing the stocks with the highest default risk estimates. Q1-Q5 denotes the spread between the returns of the Q1 and Q5 portfolios. Aggregate default risk in month *t* is proxied by the median CHS default probability computed across firms in the same month. We report these results for 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). The examined period is 2000-2014. T-statistics computed from Newey-West standard errors are reported in square brackets. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Panel A: C6 Countries	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*
Intercept	**0.02** ***	**0.02** ***	**0.02** ***	**0.03** ***	**0.03** ***
	[3.32]	[3.10]	[3.19]	[3.72]	[3.68]
Excess Market	**-1.12** ***	-	**0.06**	**-1.47** **	**-0.88** ***
	[-5.43]		[0.14]	[-2.32]	[-5.32]
SMB	**-2.73** ***	-	-	**-2.90** ***	**-2.50** ***
	[-6.30]			[-4.25]	[-6.19]
HML	**-0.88** **	-	-	**-0.52** *	**-0.42**
	[-2.44]			[-1.65]	[-1.37]
Q1	-	**0.30**	**0.28**	**0.88** **	-
		[1.09]	[0.75]	[2.13]	
Q5	-	**-1.09** ***	**-1.11** ***	**-0.26**	-
		[-3.47]	[-3.45]	[-0.78]	
Q1-Q5	-	-	-	-	**0.55** **
					[2.32]
R-Squared	0.41	0.29	0.29	0.45	0.44

Panel B: C14 Countries	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*
Intercept	**0.02** ***	**0.02** ***	**0.02** ***	**0.03** ***	**0.02** ***
	[3.27]	[3.46]	[3.48]	[3.93]	[3.83]
Excess Market	**-0.97** ***	-	**0.11**	**-1.39** **	**-0.70** ***
	[-5.66]		[0.25]	[-2.14]	[-5.41]
SMB	**-2.42** ***	-	-	**-2.44** ***	**-2.03** ***
	[-6.16]			[-3.96]	[-5.44]
HML	**-0.73** **	-	-	**-0.22**	**-0.13**
	[-2.19]			[-0.74]	[-0.44]
Q1	-	**0.57** **	**0.51**	**1.18** ***	-
		[2.08]	[1.27]	[2.59]	
Q5	-	**-1.20** ***	**-1.24** ***	**-0.45**	-
		[-3.91]	[-3.84]	[-1.28]	
Q1-Q5	-	-	-	-	**0.76** ***
					[2.75]
R-Squared	0.39	0.31	0.31	0.45	0.44

Table A.8
Predicting Changes in Failure Rates

This table presents the results from 12-month ahead predictive regressions of annual failure rate growth on excess market, size (SMB) and value (HML) factor returns as well as the lagged failure rate growth, the risk-free rate (RF), the US term spread (TERM) and the US default spread (DEF). The annual failure rate growth is computed as the percentage change in the annual failure rate in month *t+12* relative to the annual failure rate in month *t*. The annual failure rate is computed by aggregating monthly bankruptcies (see equation A.1 in this Appendix). We report these results for 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). The examined period is 2001-2014. t-statistics computed from Newey-West standard errors are reported in square brackets. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Panel A: C6 Countries	*Model 1*	*Model 2*
Intercept	**0.17**	**-0.32**
	[1.17]	[-0.83]
Excess Market	**-3.90** ***	**-3.42** ***
	[-4.99]	[-4.82]
SMB	**-6.04** ***	**-4.55** **
	[-2.91]	[-2.38]
HML	**1.78**	**0.31**
	[0.69]	[0.17]
Lagged Failure Rate Growth	**-0.01**	**-0.08**
	[-0.11]	[-0.49]
RF	-	**138.83** *
		[1.78]
TERM	-	**-1.53**
		[-0.19]
DEF	-	**26.33**
		[1.21]
R-Squared	0.13	0.24

Panel B: C14 Countries	*Model 1*	*Model 2*
Intercept	**0.16**	**-0.70**
	[1.12]	[-1.64]
Excess Market	**-3.81** ***	**-3.27** ***
	[-4.51]	[-4.71]
SMB	**-6.05** ***	**-4.54** **
	[-2.98]	[-2.48]
HML	**1.21**	**-0.09**
	[0.52]	[-0.05]
Lagged Failure Rate Growth	**-0.06**	**-0.24**
	[-0.65]	[-1.49]
RF	-	**179.27** **
		[2.16]
TERM	-	**3.23**
		[0.36]
DEF	-	**43.58** *
		[1.87]
R-Squared	0.13	0.24

Table A.9
Frequency of Bankruptcies per Default Risk Portfolio

This table reports the frequency of actual bankruptcies in each default risk portfolio. Firms are alternatively classified into portfolios on the basis of Campbell's et al. (2008, CHS) default risk measure and Merton's (1974) Distance-to-Default (MDD), estimated at the end of year *t-1*. We separately construct portfolios for stocks in the C6 countries (Australia, Canada, France, Germany, Japan and the United Kingdom) and the C14 countries (the C6 countries plus Denmark, Finland, Hong Kong, New Zealand, Portugal, Spain, Sweden and Taiwan). Panel A (Panel C) reports the frequency of actual bankruptcies in year *t* in each CHS- and MDD-based portfolio for the case of C6 countries (C14 countries). We also construct double-sorted portfolios on the basis of CHS and MDD and report the frequency of actual bankruptcies that occurred among firms in different percentile classifications for these two measures. These results are reported separately for C6 countries (Panel B) and C14 countries (Panel D). The two default risk indicators used in our analysis are constructed as follows: For the CHS measure, 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. For the MDD measure, we follow the methodology of Vassalou and Xing (2004) to estimate distance-to-default for each firm in our sample (see Section 3 for details).

Panel A: Univariate Sorts C6

	<20 (LOW)	20-40	40-60	60-80	80-90	90-95	>95 (HIGH)	TOTAL
CHS	0.038	0.045	0.055	0.154	0.166	0.131	0.411	1.000
MDD	0.071	0.052	0.105	0.105	0.169	0.178	0.321	1.000

Panel B: Double Sorts C6

	CHS Default Risk Measure							
MDD	<20 (LOW)	20-40	40-60	60-80	80-90	90-95	>95 (HIGH)	TOTAL
<20 (LOW)	0.005	0.007	0.002	0.017	0.010	0.012	0.019	0.071
20-40	0.007	0.005	0.010	0.010	0.010	0.002	0.010	0.052
40-60	0.019	0.012	0.014	0.021	0.024	0.007	0.007	0.105
60-80	0.000	0.007	0.014	0.029	0.017	0.021	0.017	0.105
80-90	0.005	0.012	0.007	0.038	0.031	0.019	0.057	0.169
90-95	0.002	0.000	0.002	0.019	0.033	0.031	0.090	0.178
>95 (HIGH)	0.000	0.002	0.005	0.021	0.043	0.038	0.211	0.321
TOTAL	0.038	0.045	0.055	0.154	0.166	0.131	0.411	

Panel C: Univariate Sorts C14

	<20 (LOW)	20-40	40-60	60-80	80-90	90-95	>95 (HIGH)	TOTAL
CHS	0.035	0.044	0.060	0.153	0.166	0.142	0.399	1.000
MDD	0.071	0.069	0.089	0.115	0.171	0.177	0.308	1.000

Panel D: Double Sorts C14

	CHS Default Risk Measure							
MDD	<20 (LOW)	20-40	40-60	60-80	80-90	90-95	>95 (HIGH)	TOTAL
<20 (LOW)	0.002	0.007	0.004	0.018	0.011	0.011	0.018	0.071
20-40	0.013	0.002	0.011	0.018	0.009	0.004	0.011	0.069
40-60	0.011	0.011	0.016	0.018	0.022	0.004	0.007	0.089
60-80	0.002	0.011	0.016	0.029	0.020	0.022	0.016	0.115
80-90	0.004	0.011	0.007	0.033	0.035	0.020	0.060	0.171
90-95	0.002	0.000	0.002	0.020	0.027	0.033	0.093	0.177
>95 (HIGH)	0.000	0.002	0.004	0.018	0.042	0.047	0.195	0.308
TOTAL	0.035	0.044	0.060	0.153	0.166	0.142	0.399	

Table A.10
Proportion of Filings per Default Risk Portfolio

This table reports the average proportion of bankruptcy filings in year *t* to the total number of firms in each default risk portfolio constructed at the end of year *t-1*. Firms are alternatively classified into portfolios on the basis of Campbell's et al. (2008, CHS) default risk measure and Merton's (1974) Distance-to-Default (MDD). We separately construct portfolios for stocks in the C6 countries (Australia, Canada, France, Germany, Japan and the United Kingdom) and the C14 countries (the C6 countries plus Denmark, Finland, Hong Kong, New Zealand, Portugal, Spain, Sweden and Taiwan). Panel A (Panel C) reports the average proportion of filings in each CHS- and MDD-based portfolio for the case of C6 countries (C14 countries). We also construct double-sorted portfolios on the basis of CHS and MDD and report the average proportion of filings in different percentile classifications for these two measures. These results are reported separately for C6 countries (Panel B) and C14 countries (Panel D). The two default risk indicators used in our analysis are constructed as follows: For the CHS measure, 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. For the MDD measure, we follow the methodology of Vassalou and Xing (2004) to estimate distance-to-default for each firm in our sample (see Section 3 for details).

Panel A: Univariate Sorts C6

	<20 (LOW)	20-40	40-60	60-80	80-90	90-95	>95 (HIGH)	HIGH-LOW	t-stat
CHS	0.07	0.09	0.11	0.32	0.67	1.04	3.37	3.30	[7.57]
MDD	0.13	0.11	0.21	0.22	0.69	1.49	2.58	2.45	[7.33]

Panel B: Double Sorts C6

	CHS Default Risk Measure								
MDD	<20 (LOW)	20-40	40-60	60-80	80-90	90-95	>95 (HIGH)	HIGH-LOW	t-stat
<20 (LOW)	0.04	0.07	0.02	0.19	0.26	0.68	1.41	1.37	[2.37]
20-40	0.03	0.05	0.09	0.19	0.61	0.00	1.76	1.73	[1.64]
40-60	0.14	0.09	0.15	0.23	0.79	0.76	1.64	1.51	[1.66]
60-80	0.00	0.07	0.14	0.21	0.30	0.99	0.99	0.99	[3.10]
80-90	0.27	0.39	0.14	0.58	0.67	0.78	2.65	2.38	[3.47]
90-95	0.60	0.00	0.13	0.73	1.42	1.92	4.24	3.64	[3.50]
>95 (HIGH)	0.00	0.18	0.44	1.30	1.90	1.65	5.26	5.26	[8.08]
HIGH-LOW	-0.04	0.12	0.43	1.11	1.64	0.97	3.85		
t-stat	[-1.49]	[0.69]	[1.37]	[2.70]	[3.67]	[1.79]	[7.37]		

Panel C: Univariate Sorts C14

	<20 (LOW)	20-40	40-60	60-80	80-90	90-95	>95 (HIGH)	HIGH-LOW	t-stat
CHS	0.05	0.08	0.11	0.28	0.60	1.00	2.86	2.80	[7.52]
MDD	0.11	0.12	0.16	0.21	0.63	1.34	2.17	2.06	[7.34]

Panel D: Double Sorts C14

	CHS Default Risk Measure								
MDD	<20 (LOW)	20-40	40-60	60-80	80-90	90-95	>95 (HIGH)	HIGH-LOW	t-stat
<20 (LOW)	0.02	0.05	0.03	0.20	0.30	0.45	0.89	0.87	[2.25]
20-40	0.05	0.02	0.09	0.24	0.59	0.57	2.43	2.38	[2.22]
40-60	0.07	0.07	0.13	0.16	0.61	0.39	1.21	1.14	[1.82]
60-80	0.04	0.10	0.13	0.21	0.30	0.86	0.82	0.78	[2.99]
80-90	0.25	0.33	0.13	0.46	0.63	0.72	2.38	2.13	[3.50]
90-95	0.42	0.00	0.10	0.72	1.01	1.73	3.84	3.42	[4.02]
>95 (HIGH)	0.00	0.15	0.36	0.85	1.74	1.96	4.13	4.13	[7.61]
HIGH-LOW	-0.02	0.10	0.33	0.65	1.44	1.50	3.23		
t-stat	[-1.04]	[0.71]	[1.32]	[2.04]	[4.07]	[2.66]	[7.18]		

Table A.11
Systematic Default Risk Portfolios

This table reports average excess returns 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 *systematic component* of Campbell's et al. (2008, CHS) default risk measure. The decomposition of the CHS default risk measure is carried out using the approach of Anginer and Yildizhan (2014). In particular, we run the following regression using a 48-month rolling window: $CHS_{i,t} = a_{i,t} + \beta_{i,t} MCHS_t + \varepsilon_{i,t}$, where $CHS_{i,t}$ is the default risk measure for firm i in month t and $MCHS_t$ is the median cross-sectional value of CHS in month t. The slope regression coefficient $\beta_{i,t}$ is a proxy for the systematic default risk of firm i in month t, since it captures the sensitivity of the firm's default risk to changes in aggregate default risk. We perform this decomposition among firms in both 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). The CHS default risk measure is estimated as analytically described in the caption of Table 5. At the end of December of year *t-1*, we sort stocks in ascending order on the basis of their systematic default risk and allocate them into decile and quintile portfolios. We form the spread strategy Q5-Q1 that is long the quintile portfolio with the highest systematic default risk stocks (Q5) and short the quintile portfolio with the lowest systematic default risk stocks (Q1). We also form the spread strategy P10-P1 that is long the decile portfolio with the highest systematic default risk stocks (P10) and short the decile portfolio with the lowest systematic 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 examined period is 2004-2014. ***, ** 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	**-1.79**	**0.99**	**3.80**	**4.85**	**6.76**	**13.20**	**6.72**	**10.65** *	**8.51**
		[-0.24]	[0.19]	[0.72]	[0.82]	[1.50]	[1.50]	[0.74]	[1.74]	[1.29]
	ew	**6.55**	**2.81**	**7.52**	**8.30**	**11.63**	**13.50**	**16.45** *	**10.29** *	**9.90**
		[0.88]	[0.49]	[1.38]	[1.15]	[1.33]	[1.44]	[1.65]	[1.77]	[1.48]
FFC Alpha	vw	**-9.04** ***	**-6.15** ***	**-2.22** **	**-1.08**	**0.27**	**5.88**	**1.06**	**10.86** *	**10.10**
		[-2.56]	[-4.19]	[-2.07]	[-1.38]	[0.18]	[1.01]	[0.25]	[1.71]	[1.37]
	ew	**0.50**	**-3.14**	**2.34**	**3.08** *	**5.83** ***	**8.59** ***	**13.26** ***	**12.24** ***	**12.76** **
		[0.20]	[-1.47]	[1.15]	[1.90]	[2.63]	[3.09]	[3.12]	[2.84]	[2.24]
Panel B: C14 Countries										
Excess Return	vw	**4.18**	**1.57**	**3.90**	**5.25**	**6.36**	**9.91**	**9.17**	**8.34**	**4.99**
		[0.56]	[0.30]	[0.71]	[0.84]	[0.92]	[1.27]	[0.99]	[1.63]	[0.89]
	ew	**11.74**	**3.88**	**7.72**	**9.10**	**11.59**	**13.58**	**15.94** *	**6.95** *	**4.20**
		[1.40]	[0.63]	[1.42]	[1.27]	[1.35]	[1.47]	[1.65]	[1.68]	[0.86]
FFC Alpha	vw	**-2.47**	**-4.41** ***	**-2.32** **	**-0.92**	**0.17**	**2.25**	**3.96**	**7.90**	**6.43**
		[-1.35]	[-2.99]	[-2.49]	[-1.00]	[0.10]	[0.60]	[0.71]	[1.49]	[1.08]
	ew	**5.76** *	**-1.32**	**2.29**	**3.56** **	**5.81** ***	**8.13** ***	**12.48** ***	**8.08** ***	**6.72** **
		[1.78]	[-0.80]	[-1.46]	[2.43]	[2.80]	[3.03]	[3.22]	[3.16]	[1.98]

Table A.12
Idiosyncratic Default Risk Portfolios

This table reports average excess returns 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 *idiosyncratic component* of Campbell's et al. (2008, CHS) default risk measure. The decomposition of the CHS default risk measure is carried out using the approach of Anginer and Yildizhan (2014). In particular, we run the following regression using a 48-month rolling window: $CHS_{i,t} = a_{i,t} + \beta_{i,t} MCHS_t + \varepsilon_{i,t}$, where $CHS_{i,t}$ is the default risk measure for firm i in month t and $MCHS_t$ is the median cross-sectional value of CHS in month t. The idiosyncratic default risk component of firm i in month t is given by the sum of the intercept and the corresponding residual value. We perform this decomposition among firms in both 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). The CHS default risk measure is estimated as analytically described in the caption of Table 5. At the end of December of year *t-1*, we sort stocks in ascending order on the basis of their idiosyncratic default risk and allocate them into decile and quintile portfolios. We form the spread strategy Q5-Q1 that is long the quintile portfolio with the highest idiosyncratic default risk stocks (Q5) and short the quintile portfolio with the lowest idiosyncratic default risk stocks (Q1). We also form the spread strategy P10-P1 that is long the decile portfolio with the highest idiosyncratic default risk stocks (P10) and short the decile portfolio with the lowest idiosyncratic 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 examined period is 2004-2014. ***, ** 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	**7.71**	**6.94**	**5.36**	**2.45**	**4.56**	**7.82**	**6.03**	**0.61**	**-1.68**
		[0.89]	[0.95]	[1.04]	[0.46]	[0.76]	[1.08]	[0.72]	[0.20]	[-0.48]
	ew	**15.87**	**12.12**	**8.06**	**6.28**	**7.53**	**9.94**	**17.23** *	**-0.41**	**1.36**
		[1.62]	[1.32]	[1.15]	[1.14]	[1.05]	[1.29]	[1.95]	[-0.14]	[0.45]
FFC Alpha	vw	**0.65**	**-1.01**	**-1.69**	**-3.33** ***	**-1.75**	**2.38**	**2.75**	**3.26**	**2.10**
		[0.16]	[-0.34]	[-1.36]	[-3.61]	[-1.64]	[1.23]	[1.38]	[0.93]	[0.54]
	ew	**10.98** ***	**6.51** **	**1.16**	**0.87**	**2.89** **	**4.97** ***	**13.99** ***	**0.74**	**3.01**
		[3.03]	[2.12]	[0.63]	[0.40]	[2.14]	[3.30]	[4.40]	[0.33]	[1.34]
Panel B: C14 Countries										
Excess Return	vw	**8.37**	**5.53**	**5.09**	**4.48**	**4.79**	**6.83**	**5.69**	**0.38**	**-2.68**
		[0.95]	[0.79]	[0.89]	[0.85]	[0.76]	[0.96]	[0.64]	[0.15]	[-0.65]
	ew	**15.39**	**12.00**	**8.87**	**7.40**	**8.47**	**11.10**	**18.41** **	**1.06**	**3.02**
		[1.60]	[1.33]	[1.26]	[1.27]	[1.16]	[1.37]	[2.00]	[0.31]	[0.71]
FFC Alpha	vw	**0.05**	**-1.72**	**-2.30** ***	**-1.31**	**-0.95**	**1.18**	**1.19**	**2.48**	**1.14**
		[0.01]	[-0.75]	[-3.06]	[-1.26]	[-0.76]	[0.71]	[0.41]	[0.93]	[0.25]
	ew	**10.59** ***	**6.08** **	**1.90**	**2.73**	**3.53** **	**5.60** **	**14.07** ***	**1.49**	**3.48**
		[2.95]	[2.25]	[1.58]	[1.29]	[2.28]	[2.53]	[3.47]	[0.58]	[1.06]

Table A.13
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 (e.g. whether data have been hand-collected).

Country	*Period*	*Contact Person*	*Institution*	*Contact Information*	*Bankruptcy Source Information*
Australia	1996-2013	S. Jones	Department of Accounting, University of Sydney, Australia	tel.: +61 2 9351 7755 e-mail: s.jones@econ.usyd.edu.au	
		T. McLeen	Delisted.com.au	e-mail: admin@delisted.com.au	Hand-collected from website
Canada	1996-2013	D. Kennedy	School of Accountancy, University of Waterloo, Canada	tel.: +1 519 888 4752 e-mail: dkennedy@uwaterloo.ca	Hand-collected from media and press releases
		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 new CCAA procedure
Denmark	2000-2013	None	NASDAQ OMX	web: www.nordic. nasdaqomxtrader.com	Hand-collected from website; features only bankruptcy filings leading to a delisting
		None	Bureau van Dyck	tel.: +44 9 020 7549 5000	
France	1993-2013	A. Holmes	Duns & Bradstreet (D&B)	tel.: +44 0 1628 492677 e-mail: holmesa@dnb.com	Hand-collected from French bankruptcy courts
		None	Bureau van Dyck	tel.: +44 9 020 7549 5000	
Finland	1996-2013	H. Hämäläinen[1]	Office of the Bankruptcy Ombudsman, Finland	tel.: +35 810 3665111 web: www.konkurssiasiamies.fi	
		None	Bureau van Dyck	tel.: +44 9 020 7549 5000	
Germany	1995-2013	None	Hoppenstedt Database	web: www.hoppenstedt.de	
		None	Bureau van Dyck	tel.: +44 9 020 7549 5000	
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 private and public firms
Japan	1993-2013	C.Y. Shirata	Department of Accounting, University of Tsukuba Tokyo, Japan	e-mail: shirata@mbaib. gsbs.tsukuba.ac.jp	Bankruptcy data from Teikoku Database
New Zealand	1996-2013	P. Davey[1]	Ministry of Economic Development	tel.: +64 4 472 0030 web: www.med.govt.nz	Bankruptcy data contain private and public firms with substantial shareholdings; filing date from website
Portugal	1996-2013	C. Albuquerque Correia	Comissão do Mercado de Valores Mobiliários (CMVM)	e-mail cmvm@cmvm.pt	
Spain	1996-2013	None	Comisión Nacional del Mercado de Valores (CNMV)	web: www.cnmv.es	Hand-collected data from website
		None	Bureau van Dyck	tel.: +44 9 020 7549 5000	
Sweden	1998-2013	B. Ståhl	Kronofogden (Swedish Enforcement Authority)	email: kronofogdemy ndigheten@kronofogden.se	
		None	Bureau van Dyck	tel.: +44 9 020 7549 5000	
Taiwan	1996-2013	C. Shao-Wei	Taiwanse Economic Journal (TEJ)	e-mail: tina@tej.com.tw web: www.tej.com.tw	
United Kingdom	1992-2013	M. Staunton	London Business School	e-mail: m.staunton@london.edu	London Business School Share Price Database