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

Kevin Aretz*, Chris Florackis† and Alexandros Kostakis‡

Abstract

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Keywords: Default risk; Bankruptcy; Asset pricing tests; International markets;
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This study constructs a unique dataset of bankruptcy filings for a large sample of non-U.S. firms in 14 developed markets and sheds new light on the cross-sectional relation between default risk and stock returns. Using the flexible approach of Campbell et al. (2008) to estimate default risk probabilities, this is the first study to offer conclusive evidence supporting the existence of a significantly positive default risk premium in international markets, in both economic and statistical terms. This finding is robust to different portfolio weighting schemes, data filters, sample periods and holding period definitions, and holds using both in-sample estimates of default probabilities during the period 1992-2010 and out-of-sample estimates during the period 2000-2010. We also show that the default risk premium is contingent upon a series of firm characteristics.

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1. Introduction

The cross-sectional relation between default risk and stock returns, the so-called default risk premium, has been a subject of intense debate in the literature. Since the vast majority of defaults occur during recessions (Campbell et al., 2011, Moody's, 2011), i.e., when investors' marginal utility is high, standard asset pricing theory predicts that highly distressed stocks should yield higher premia relatively to less distressed ones. In stark contrast to this intuition, prior empirical studies for the U.S. market usually report a flat, negative or even hump-shaped relation between stock returns and several well-established proxies for default risk.[1] Adjusting for market, size, value and momentum premia this relation becomes even less positive. This puzzling finding has been termed as the "distress anomaly" (Campbell et al., 2008).

In a recent insightful study, Gao et al. (2012, pp. 2-3) claim that "investigation of the distress anomaly among U.S. firms […] has failed to produce a consensus about even the basic [default risk-stock return relation], let alone its interpretation." As a result, they argue that it is high time to shift the focus to new data for non-U.S. firms. Using international data over the period 1992-2010, they find a flat relation between stock returns and Moody's KMV Expected Default Frequency (EDF), which becomes significantly negative only among small capitalization stocks. They also document that there is no relation between the default risk

[1] Among the first studies to examine the pricing of default risk is Dichev (1998), who uses Altman's (1968) Z-score and Ohlson's (1980) O-score, two accounting-based proxies, showing that these measures are not positively related to stock returns. Similarly, Griffin and Lemmon (2002) use the O-score to show that, after controlling for the book-to-market ratio, there is no evidence that default risk is priced. More recently, George and Hwang (2010) report a negative relation between stock returns and default risk measured by the O-score after excluding stocks trading at low prices. Departing from the use of accounting models, Vassalou and Xing (2004) extract default risk estimates from the Merton (1974) model and find that a positive return differential exists between stocks with high and low exposures to their default risk measure, but this return differential is significant only for small and value firms. Using market-based default probability estimates from the proprietary model of Moody's KMV, Garlappi et al. (2008) and Garlappi and Yan (2011) find a hump-shaped relation between default risk and stock returns, while Anginer and Yildizhan (2010) obtain a flat relation using corporate credit spreads. On the other hand, Avramov et al. (2009) show that stock returns significantly increase with S&P senior debt credit ratings, implying a negative relationship between returns and default risk, to the extent that credit ratings effectively capture default risk. Probably the most comprehensive evidence comes from Campbell et al. (2008), who measure default risk using a dynamic hazard model with both accounting and market variables. They document a strongly negative relation between default risk and stock returns, which becomes even more significant after accounting for size, value and momentum premia. Aretz (2012) confirms the evidence of Campbell et al. (2008, 2011). So far, only Chava and Purnanandam (2010) have shown that expected stock returns implied from accounting valuation models increase with a broad set of default risk measures.

premium and creditor protection at the country level, as suggested by Garlappi et al. (2008) and Garlappi and Yan (2011). They also find that country-level individualism, which is a proxy of investor overconfidence that explains other asset pricing anomalies according to Chui et al. (2010), is significantly negatively related to the distress premium.

In the spirit of Gao et al. (2012), we use a new international dataset to shed more light on the "distress anomaly". However, contrary to their study, we do not use a structural estimate of default risk to analyze the default risk premium for non-U.S. firms. Instead, we collect bankruptcy filings for 14 countries, excluding the U.S., over the period 1992-2010. We use these data to construct default risk estimates following the reduced-form approach of Campbell et al. (2008, 2011). While we unavoidably examine a smaller set of countries relative to Gao et al. (2012), we benefit from using a potentially more flexible and better-calibrated default risk measure.[2,3] In addition, our estimates of the Campbell et al. (2008) default risk (hereafter, CDR) measure should more efficiently incorporate cross-country differences in the bankruptcy filing process, induced by bankruptcy laws and institutional settings.[4] Consistent with this idea, the LOGIT models used to create the CDR measure produce estimates that considerably vary across countries. At the very least, estimating CDR measures for non-U.S. firms allows us to provide evidence complementary to that of Gao et al. (2012).

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[2] Computing the CDR measure in-sample and imposing exactly the same restrictions as in Gao et al. (2012), our dataset features more than 1.6 million firm-month observations from 14 countries (excluding the U.S.) during the period 1992-2010, relative to 3.4 million observations from 39 countries (including the U.S.) in their study. However, it is comforting that our dataset includes many countries that exhibit relatively low correlations with the U.S., rendering them good candidates for an out-of-sample study (see Foster et al., 1997).

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

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

Our evidence is notably different from that of Gao et al. (2012). Estimating country-specific LOGIT models to compute out-of-sample (OOS) default probabilities for firms in Australia, Canada, France, Germany, Japan and the U.K. (hereafter, the C6 countries) over the sample period 2000-2010, we find a significantly positive relation between default risk and stock returns, both statistically and economically. In particular, the spread strategy that goes long the highest default risk decile portfolio and goes short the lowest one yields an average return of 14.19% p.a. (t-stat: 1.87) in the case of value-weighted portfolios and an average return of 12.13% p.a. (t-stat: 2.11) in the case of equally-weighted portfolios. Furthermore, we estimate bankruptcy regime-specific LOGIT models to compute OOS default probabilities also 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 results. Adjusting for market risk does not materially affect these findings. Nevertheless, once we adjust for size and value premia, the relation becomes flatter and insignificant, suggesting that the latter factors explain away the default risk premium found among non-U.S. firms.

We verify that our results are robust to several modifications to our research design. In particular, we report that our results do not depend on whether or not we allow for a gap between the portfolio formation date and the beginning of the holding period. In principle, allowing for a 1- or 2-month gap is important to rule out that microstructure-based liquidity shocks bias upward the returns of distressed stocks (Da and Gao, 2010). Our results also remain intact if we set the returns of defaulting stocks to minus 100%, taking into account the potential effect of missing delisting returns (Gao et al., 2012). Finally, we still find a significantly positive default risk-stock return relation even if we impose exactly the same data filters as in Gao et al. (2012). Our results continue to hold when we repeat the portfolio formation exercises calculating default probabilities using in-sample (IS) LOGIT model estimates from the full sample period 1992-2010.[5] Therefore, our benchmark results are not driven by potential parameter instability in our OOS default risk estimates. This is an interesting finding, contradicting the evidence of a negative default risk premium provided by Gao et al. (2012) in the same period using the EDF measure as a proxy of default risk. Furthermore, plotting the cumulative profits of the spread strategy that goes short the lowest OOS CDR decile portfolio and goes long the highest OOS CDR decile portfolio, the lion share of profits occur after the surge in bankruptcies in 2001 and 2002. Since the IS estimates are fairly close to the OOS estimates after 2002, this result implies that, if anything, parameter instability may potentially reduce, rather than increase, the magnitude of the default risk premium.

Why do our results differ from those in Gao et al. (2012)? To address this question, we compare our CDR estimates with the corresponding estimates of Merton's (1974) Distance-to-Default (MDD), created using the approach of Vassalou and Xing (2004). The latter is a very close proxy of the EDF measure (Bharath and Shumway, 2008, and Correia et al., 2012), which is neither publicly available nor replicable. Equipped with this default risk measure, we repeat the portfolio formation exercises using alternatively the CDR or MDD measure as sorting variable only for those firm-month observations for which both measures are available. While the CDR measure remains positively and significantly related to post-ranking portfolio returns, MDD yields a U-shaped relation. In particular, for the C6 countries, the highest MDD decile portfolio attracts a value-weighted (equally-weighted) excess return of 2.48% (18.31%) p.a. and the lowest one an excess return of 6.94% (22.39%) p.a., producing a negative but insignificant spread between the two equal to -4.46% (-4.07%).

Examining the source of discrepancy between these two measures, we find that CDR and MDD mostly disagree on characterizing low default risk firms. More specifically, while the proportion of stocks in both the highest three CDR *and* MDD deciles is on average 55%, the

[5] While the use of the IS estimates induces a look-ahead bias, it should be noted that the majority of studies using the Campbell et al. (2008) default risk measure also employ the IS estimates reported in their study. Several examples include Song (2008) and Conrad et al. (2012).

corresponding proportion in the lowest three CDR *and* MDD deciles is only 38%. Moreover, we find some evidence that the small overlap in the lower deciles is partially driven by unlevered firms. While MDD assigns zero default risk to these firms because it assumes that a default occurs only if the asset value drops below a fraction of the debt value (see Crosbie and Bohn, 1999, and Vassalou and Xing, 2004), their CDR is much higher. A second reason for the small overlap could be that MDD abstracts from default-triggering events other than an economic insolvency. For example, Davydenko (2008) shows that, while most defaulting firms are insolvent *and* illiquid, a fraction of them are only illiquid. Similarly, the EDF measure used by Gao et al. (2012) also abstracts from bankruptcies triggered by liquidity issues, while the CDR measure we use takes them into account.

We also provide extensive evidence on theories suggested to explain cross-sectional variations in the default risk-stock return relation.[6] We construct double-sorted portfolios on the CDR measure and a series of firm characteristics. Overall, the default risk premium is found to be relatively higher among big capitalization and growth stocks, stocks that are traded at high prices and exhibit high return volatility as well as among firms that are followed by analysts and that are characterized by high asset tangibility and low leverage. Therefore, the default risk premium we document cannot be attributed to microstructure biases and it does not exclusively derive from small capitalization or value firms. Moreover, our results support

[6] 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, producing an upward concave relation between default risk and stock returns. George and Hwang (2010) and Johnson et al. (2011) argue that capital structure choice variables can create an endogenous negative relation between default risk and stock returns. However, Johnson et al. (2011) point out that the negative relation derived from the model of George and Hwang (2010) is between default risk and the expected *asset* return, while the relation between default risk and the expected *equity* return remains positive. Aretz (2012) shows that if default risk arises through the possibility of a catastrophic event manifesting itself as a hump in the left tail of the asset payoff distribution, then a higher default risk can yield a lower expected return. O'Doherty (2010) argues that it is the inability to precisely estimate firm value that causes distressed firms to have low market betas, and hence low expected returns (see also Johnson, 2004). Moreover, given that most distressed stocks trade at very low prices, it is also possible that microstructure effects bias the returns of highly distressed stocks (see Blume and Stambaugh, 1983, and Boguth et al., 2011). Finally, a negative default risk premium could be the result of mispricing that persists due to limits to arbitrage (see Campbell et al., 2008).

the shareholder advantage hypothesis of Garlappi et al. (2008) and Garlappi and Yan (2011), since the default risk premium is less pronounced among firms with low tangibility.

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

2. Data

2.1 Bankruptcy Data

Table 1 offers an overview of our sources for the bankruptcy filing data, which include commercial data providers, government institutions, stock exchanges and other researchers.[7] We have merged data from more than one source in a number of cases to extend the length of the sample period. For most countries, the data extend from January 1996 to December 2009, although for some countries (UK and Japan) they begin slightly earlier (1992 and 1993, respectively) and they stop slightly earlier for France (2007) and Canada (2008). Even though we were sometimes able to obtain richer data, at the very least they contain the identity of the filing firm and the filing date. The dataset includes filings under any legal procedure (except where noted). Since we often lack information on how long firms spent in re-organization, we drop firms after their initial bankruptcy filing in our sample period.

[Table 1 here]

Table 2 reports the number of bankruptcy filings, the number of firms with complete data and the proportion of bankruptcy filings for each country and year. To save space, filing and descriptive statistics are reported for the C6 countries.[8] This table shows that our sample is initially heavily tilted towards Japan and the U.K., with around 70% of all observations

[7] The data obtained from government institutions often include filings for both public and private firms, without distinguishing between the two. To extract the public filings from these data, we have used a name-matching algorithm comparing the company names featured in the government data with those contained in a list featuring all public firms covered by Datastream.
[8] The complete set of descriptive statistics is available upon request.

coming from these two countries in 1996. However, the sample becomes more balanced from 1999 onwards, with Japanese and U.K. firms making up only 50% of the sample. Also noteworthy is the significant increase in the number of observations for Australia and Canada, which is attributable to WorldScope dramatically expanding its coverage of these countries over the sample period.

[Table 2 here]

Table 2 also shows that the frequency of bankruptcy filings varies across countries; filings are more frequent in countries where the bankruptcy system strongly favors managers or creditors (Germany and the U.K.) relative to countries where employees welfare is more important (France and Japan). In addition, the frequencies of bankruptcy filings are strongly correlated across the C6 countries. For the period 2000-2010, the average pairwise correlation is 0.392. However, the correlation is markedly higher for countries that are geographically close, such as France and Germany (0.743). Moreover, there is at least one bankruptcy filing in each country sample from 1997 onwards. However, since we require a sufficient number of bankruptcy filings for the estimation of LOGIT models and the calculation of default probabilities, we perform our benchmark OOS asset pricing tests during the period 2000-2010. This choice ensures that there are at least five bankruptcy filings in each country sample before the beginning of the test period. Nevertheless, we also perform a battery of robustness tests using different sample periods to ensure that this choice does not affect our conclusions.

2.2 Default Risk Indicators

We use the same variables as in Campbell et al. (2008) to estimate default risk. 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 more accurately a firm's prospects.

Leverage is measured using the ratio of total liabilities to the market value-adjusted version of total assets (TLMTA).[9] Since the lack of liquidity can also force a firm to file for bankruptcy (Davydenko, 2008), we proxy for internal slack using the ratio of cash holdings plus short-term assets to the market value-adjusted version of total assets (CASHTMA). Moreover, we use the market-to-book ratio (MB) to measure growth opportunities. To make sure that book values of equity close to zero do not yield extreme values when used in the denominator of MB, we follow Cohen et al. (2003) in adding 10% of the difference between the market and the book value of equity to the latter. In the few cases where this adjustment does not generate a positive book value of equity, we follow Campbell et al. (2008) and set it equal to one unit of the local currency. To avoid extreme MB values, we further winsorize them at the 5th and 90th percentiles of their distribution for each country and month.

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

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

where $r_{i,k}$is the log return of firm i on day k, and N is the number of days in the 3-month estimation interval.[10] $SIGMA$ 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 ratio of a firm's market value to the total market value of firms in the same country and month. Campbell et al. (2008) also use log share price (PRICE)

[9] 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 usage of the book value of total assets decreases the ability of NIMTA and TLMTA to forecast bankruptcy.

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

as a default risk indicator mainly to capture the inability of distressed firms to engage in reverse stock splits, implying that such firms often have low share prices. They winsorize this variable below \$15/16 and above \$15. Given that the above thresholds vaguely correspond to the first and the third quartiles of the U.S. share price distribution, we also winsorize share prices using the first and the third quartiles of the local share price distributions in each country. We collectively refer to NIMTA, TLMTA, EXRET, RSIZE, SIGMA, CASHMTA, MB and PRICE as default risk indicators in the remainder. Apart from the previously described winsorization of PRICE and MB, we alleviate the effect of outliers by also winsorizing the rest default risk indicators at the 5^{th} and 95^{th} percentiles, computed for each country-month.

As an alternative default risk measure, we also use the Merton (1974) Distance-to-Default (MDD). To compute the MDD measure, we require the market value of equity, the default-triggering asset value and the risk-free rate of return. Following Crosbie and Bohn (1999) and Vassalou and Xing (2004), we set the default-triggering asset value equal to the book value of short-term debt plus one-half times the book value of long-term debt. We also use the local 3-month interest rate as a proxy of the risk-free rate of return.

Market data are sourced from Thomson Datastream. We only consider shares traded in local currency, and we exclude non-primary issues. The accounting data are from WorldScope. 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 relative to the U.S. (DeFond et al., 2007), we assume that the accounting items are available to investors six months after the fiscal year end. To avoid excluding firms shortly before their filing date, we also assume that investors use outdated data for up to twelve months if more recent data are unavailable.

Table 3 reports descriptive statistics for the default risk indicators from 1997 to 2009, separately for filing and non-filing firms from the C6 countries. The table suggests that the firms filing for bankruptcy are in general less profitable (NIMTA), more levered (TLMTA) and more volatile (SIGMA) than the rest firms. In addition, they tend to have lower stock returns (EXRET), market-to-book ratios (MB) and stock prices (PRICE) relative to non-filing firms. However, deviating from Campbell et al. (2008), bankrupt firms hold on average more, not less, cash (CASHTMA), with firms in France and Japan being an exception.

[Table 3 here]

A more detailed inspection of Table 3 reveals considerable differences between filing and non-filing firms across individual countries. For example, firms filing for bankruptcy in France or Japan are only slightly less profitable in the filing month relative to non-filing firms. In particular, the difference in their mean and median NIMTA is only -0.07 in France and -0.04 in Japan, but it is much higher in the rest countries. A potential explanation could be that company laws in France and Japan mandate a compulsory bankruptcy filing if net worth drops below a certain threshold, and hence firms in France and Japan are forced to file for bankruptcy earlier than those in other countries (LaPorta et al., 1998). Similarly, German bankruptcy law requires firms to file for bankruptcy once the market value of its assets drops below the book value of liabilities; failing to comply with this law can subject managers to criminal charges (Davydenko and Franks, 2008). The threat of criminal charges may explain why firms in Germany do not use up their internal slack to delay filing for bankruptcy and, as a result, they enter bankruptcy with substantially more cash holdings (0.19) than firms in the rest countries, with the exception of Canada (0.20).

Table 3 also documents that the stock returns (EXRET) of bankrupt firms in France and the U.K. are not as negative during the filing month as in the rest countries. On the one hand, secured creditors in France are not ranked first in the distribution of residual value, implying that a bankruptcy filing may not necessarily imply a total loss of investment value to French shareholders (Davydenko and Franks, 2008, and Altman and Hotchkiss, 2011). On the other hand, absolute priority rules are strictly adhered to in the U.K. (Franks and Sussman, 2005), and hence relatively high stock returns of bankrupt firms in the U.K. may indicate that the prices of these firms have adjusted long before the filing date. In line with this argument, we subsequently show that, over a 12-month forecasting horizon, low stock returns are indeed a very good predictor of bankruptcy in the U.K. Finally, filing firms tend to attract significantly lower share prices (PRICE) in capital market-based systems, such as Australia, Canada and the U.K., relative to bank-based systems, such as Germany and France, which could possibly be due to cross-regime differences in capital market efficiency.[11]

Overall, the univariate analysis 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 different country bankruptcy codes or institutional features and the subsequent analysis shows that these variations also exist in the ability of default risk indicators to forecast bankruptcies.

2.3 Size, Value and Momentum Factors

Apart from market risk, our asset pricing tests also adjust portfolio returns for size, value and momentum factor exposures, using the Fama-French-Carhart (FFC) 4-factor asset pricing model. To this end, we construct the corresponding factors for each asset universe we examine, using the following simple approach. The market portfolio consists of all stocks in a given set of countries (the C6, the C14 countries or each of the four bankruptcy regimes) in each month. Moreover, in June of year t, we create size, BM and momentum median breakpoints for all stocks in each set of countries. Size is the share price times shares outstanding at the end of June. BM is the book-to-market value ratio of each firm reported in December of year $t-1$. Momentum is defined as the compounded stock return of each firm over the prior eleven months, excluding the most recent month. Using the median breakpoints for each characteristic, we assign firms into two portfolios. We do not use double-sorted portfolios to ensure

[11] The cross-country differences in the stock prices are hard to see, because the table reports averages of winsorized log prices measured in local currencies.

that all portfolios are well-diversified. The SMB (HML) factor is defined as the spread between the portfolio with the smallest capitalization (highest BM ratio) stocks and the portfolio with the biggest capitalization (lowest BM ratio) stocks. Portfolios are held from July in year t to June in year $t + 1$, at which point they are rebalanced. On the other hand, we rebalance momentum portfolios every month, as it is standard in the literature. The MOM factor is defined as the spread between the portfolio of stocks with the highest past year returns and the portfolio of stocks with the lowest past year returns. All factor returns are value-weighted and they are denominated in U.S. dollar terms.

3. Forecasting Bankruptcies Around the World

3.1 The Bankruptcy Forecasting Models

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, and Hillegeist at al., 2004). This hazard model specifies the probability of bankruptcy as:

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

where $Y_{i,m}$ is a dummy variable that equals one if firm i files for bankruptcy in month m and zero otherwise and $\boldsymbol{X_{i,m-12}}$ is a vector containing the values of the default risk indicators for firm i in month $m - 12$.[12] We call the default probability estimated from the above model the CDR measure.

We firstly estimate the LOGIT model in (1) for each of the C6 countries over the full sample period, using 12-month lagged default risk indicators. Combining the estimated coefficients with the default risk indicators for each firm in December of year $t - 1$, we calculate the corresponding IS default probability that we assign to every month in year t. For the remaining eight countries that feature too few (i.e. less than 40) total bankruptcy filings in the

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

entire sample to be analyzed separately, we compute in the same way IS default risk measures for each firm by pooling data for each bankruptcy law regime and estimating the LOGIT model over the full sample period for each of these regimes. Following Wood (2007), we define that Australia, Canada, Hong Kong, New Zealand and the U.K. belong to the common law regime, France, Spain and Portugal belong to the Napoleonic regime, Denmark, Finland, Germany and Sweden belong to the Roman-Germanic regime, while Taiwan and Japan belong to the mixed regime.

While IS default probability estimates are informative, they were obviously not available to investors in real time, and hence they would induce a look-ahead bias in our asset pricing tests. As a result, we also compute OOS default probabilities estimating recursively each of the LOGIT models. We face the following tradeoff when choosing the initial window of estimation. On the one hand, OOS default probabilities should be as accurate as possible, implying that they should be estimated over sufficiently long windows. On the other, asset pricing tests should cover a long enough period, suggesting that the initial window of estimation should be rather short. We finally opt for an initial window using data up to December 1999. This choice ensures that each recursive window includes at least five bankruptcy filings (Australia) and still allows us to perform asset pricing tests using eleven years of monthly returns. Nevertheless, we also run several robustness tests to show that this choice does not materially affect our conclusions. In line with Campbell et al. (2008), having estimated each LOGIT model using in each recursion data until December of year $t-1$, we combine these parameter estimates with December values for default risk indicators to compute OOS default probabilities for each firm and each month in the following year t.

In addition, we compare the CDR measure with a well-known structural predictor of bankruptcy, the MDD measure. By its very nature, MDD is estimated OOS, and hence we compare it only to the OOS version of CDR. We follow Vassalou and Xing (2004) in calculating MDD. In particular, we use as initial guess of the firm’s asset volatility its stock return volatility, calculated from daily data over the prior twelve months. Using this initial guess together with the market value of equity, the default-triggering asset value and the risk-free rate, we derive the firm's asset value from the Black and Scholes (1973) call option formula on each trading day over the prior twelve months. The time-series of asset values allow us to derive a new estimate of the firm's asset volatility. We iterate this process until the asset volatility estimate converges. Finally, upon convergence, we plug the most recent implied asset value, $V_{i,t}$, the estimated asset volatility, $\sigma_{i,t}$, the mean return of the implied asset value series, $\mu_{i,t}$, and the default-triggering asset value, $X_{i,t}$, into the following formula:

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

As with the CDR measure, MDD also captures default risk 12 months ahead.

3.2 *Results of the In-Sample LOGIT Models*

Table 4 reports the results of full-sample estimations of the LOGIT model in (1) using 12-month lagged values of the default risk indicators for each of the C6 countries. For the sake of brevity, we do not show the results for the bankruptcy law regimes, but these are readily available upon request. In general, the reported results confirm the initial findings from the descriptive statistics in Table 3. In particular, default probability tends to increase with total liabilities (TLMTA) and stock return volatility (SIGMA), while it tends to decrease with profitability (NIMTA), excess returns (EXRET), relative size (RSIZE) and cash holdings (CASHTMA). Based on their significance levels, TLMTA, EXRET and SIGMA are the most important default risk indicators. Stock price (PRICE) is related to default probability with an ambiguous sign, while MB is found to be insignificant in most cases. Using the same variables in a LOGIT model to forecast failures (bankruptcies, delistings or defaults) among U.S. firms, Campbell et al. (2008) report a pseudo-R^2 of 11.4% for a 12-month forecasting horizon (see their Table 4). Keeping in mind that we do not have data on delistings or defaults, the pseudo-R^2s in our Table 4 suggest that these default risk indicators exhibit a higher forecasting power in Japan (12.5%), a roughly similar one in Canada (10.6%) and the U.K. (8.4%) and a lower one in Australia (4.4%), France (5.3%) and Germany (6.9%).

The results reported in Table 4 also suggest that there are strong variations in the coefficient estimates of the default risk indicators across countries. These variations are often, though not always, consistent with the findings from the descriptive statistics in Table 3. For example, NIMTA is never significant in distinguishing between bankrupt and non-bankrupt firms in countries with a legally-binding net worth constraint (France, Germany and Japan). Moreover, CASHMTA attracts the lowest significance level in Germany. To test whether the cross-country variations in coefficient estimates are statistically significant, we pool the country data and estimate a single LOGIT model with a complete set of country interaction terms (unrestricted model). We then drop the country interaction terms associated with each default risk indicator in turn (restricted model), re-estimate the model and deduct the log-likelihood of the restricted model from that of the unrestricted model. Under the null hypothesis of no cross-country variations in coefficients, twice this difference is distributed as a chi-square variable with five degrees of freedom. The final column of Table 4 shows that the resulting statistic implies the rejection of the null hypothesis of no cross-country variations in the coefficients for all default risk indicators, except for EXRET and MB.

[Table 4 here]

Next, we compare the bankruptcy forecasting ability of the LOGIT model advocated by Campbell et al. (2008) with that of the MDD measure. To this end, Table 5 presents the results from LOGIT models including either only the MDD measure (Panel A), or the MDD measure together with the default risk indicators (Panel B) or only the default risk indicators (Panel C). These models are estimated using only firm-month observations for which both MDD and all default risk indicators are available. Panel A suggests that, on its own, MDD is a significant predictor of bankruptcies and its coefficient carries the correct sign. However, the results reported in Panel B indicate that adding the default risk indicators substantially decreases the magnitude of the MDD coefficient in all countries, and it becomes insignificant in Australia, France and the U.K. Comparing pseudo-R^2s, we find that adding the default risk indicators more than doubles the models' forecasting power, with the exception of Germany.[13] However, this twofold increase in the pseudo-R^2s does not imply that MDD and the default risk indicators contain similar amount of independent information about future bankruptcies. Considering the pseudo-R^2s generated when only the default risk indicators are used as explanatory variables (Panel C), there is strong evidence that the default risk indicators subsume the bankruptcy-relevant information contained in MDD.

[Table 5 here]

4. The Global Default Risk Premium

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

In this section we examine the relation between CDR estimates and post-ranking stock portfolio returns. We sort stocks in ascending order on the basis of their CDR estimates in December of each year $t-1$ and assign them to quantile portfolios. In our benchmark results, we follow Da and Gao (2010) and calculate portfolio returns from February of year t to January of year $t+1$, i.e., we allow a one month gap between portfolio formation and the start of the 12-month holding period.[14] Since non-U.S. stock return data can be of lower quality relative to the well examined U.S. return data, we impose several data filters. In particular, in our benchmark results we exclude year t returns for a stock if its market capitalization or its price in December of year $t-1$ is lower than the 5^{th} percentile of the corresponding distribution

[13] It is perhaps not too surprising that the MDD measure performs almost as well as the default risk indicators in Germany. A major shortcoming of MDD is that it ignores cash reserves in forecasting bankruptcies. However, given that bankruptcy laws in Germany force a firm to file for bankruptcy once its net worth drops below a certain threshold, this limitation may not be too important for German firms.
[14] As Da and Gao (2010) show, the negative returns of distressed stocks reverse in the short-term due to a market microstructure-induced liquidity shock. This feature may bias upwards the returns of distressed stocks. Since CDR also depends on a firm's stock return in December of year $t-1$, allowing for a gap between the portfolio formation month and the start of the holding period is particularly important when using this default risk measure as a portfolio sorting variable.

across all stocks in the same market. These filters are useful to alleviate the effect of market microstructure biases, such as the bid-ask bounce. We calculate both equally-weighted (ew) and value-weighted (vw) portfolio returns. Moreover, we report average excess portfolio returns as well portfolio alphas, i.e., portfolio returns adjusted for market risk (CAPM alphas) or, alternatively, for market, size (SMB), value (HML) and momentum (MOM) factor exposures according to the Fama-French-Carhart 4-factor model (FFC alphas). All reported returns and alphas are calculated for a U.S.-based investor and are annualized.

We report in Table 6 the average premia of portfolios sorted on the basis of OOS CDR estimates from January 2000 to December 2010, for the C6 (Panel A) and C14 countries (Panel B), respectively. We construct portfolios for the same quantiles of CDR distribution as in Campbell et al. (2008), namely, the 10th, 20th, 40th, 60th, 80th and 90th percentiles. Moreover, we further classify the stocks of the highest default risk portfolio into three sub-portfolios, using the 95th and 99th percentiles as cutoff points. Finally, we also calculate the return of a spread strategy that goes long the decile portfolio with the highest default risk stocks (P10) and goes short the decile portfolio with the lowest default risk stocks (P1).

[Table 6 here]

The results in Table 6 show that average excess returns and CAPM alphas increase almost monotonically across the default risk portfolios in both the C6 and the C14 countries. In the case of value-weighted portfolios, the spread return between the highest and the lowest default risk deciles (P10-P1) is equal to 14.19% p.a. in the C6 countries and 14.53% p.a. in the C14 countries, indicating the existence of a highly economically significant default risk premium in both cases. This premium is also found to be statistically significant at the 10% level in the C6 countries (t-stat: 1.87) and at the 5% level in the C14 countries (t-stat: 2.06).[15] The corresponding default risk premia are of similar magnitude when we use equally-weighted

[15] Heteroscedasticity and autocorrelation consistent (HAC) Newey-West (1987) standard errors are used for the calculation of t-stats.

portfolio returns (12.13% p.a. in the C6 and 12.35% p.a. in the C14 countries) and they are statistically significant at the 5% level in both cases. Adjusting for market risk, the magnitude and the significance of the default risk premium are not affected, indicating that this premium cannot be attributed to a difference in market betas between the highest and the lowest default risk portfolios. In particular, the CAPM alpha of the P10-P1 strategy is 14.28% (14.50%) p.a. in the C6 (C14) countries when value-weighted portfolio returns are used.

On the other hand, when we adjust portfolio returns for their size, value and momentum factor loadings, the default risk premium is considerably reduced and becomes insignificant in all cases examined. Figure 1 shows why adjusting for these additional common factors reduces the alpha of the spread strategy P10-P1. In particular, portfolios containing the most distressed stocks command much higher SMB and HML betas relative to portfolios containing the least distressed ones. Therefore, the 4-factor FFC model attributes the high excess returns reported for the portfolios containing the highest CDR stocks to the corresponding SMB and HML factor premia that were quite high in our sample period.

[Figure 1 here]

Next, we test the conjecture based on the theoretical work of Garlappi et al. (2008) and Garlappi and Yan (2011) that a positive default risk-stock return relation could reverse at very high default risk levels. To this end, inspecting the returns for the three sub-portfolios formed within decile portfolio P10, we find mixed evidence. Even though value-weighted portfolio returns do yield an inverse U-shaped relation, equally-weighted portfolio returns actually yield a U-shaped relation. In addition, unreported results show that the sub-portfolios' returns are never significantly different from one another, indicating that no robust conclusion can be derived for the exact shape of the default risk-stock return relation at high default risk levels.

While our results are certainly not driven by under-diversification (see the very high number of firms per portfolio), a potential concern is that they are attributable to estimation error in the initial LOGIT recursions, since these can be based on relatively few bankruptcy filings. The evidence provided in Panel A of Figure 2 addresses this concern. The figure plots the cumulative profits from a trading strategy going short one dollar the decile portfolio with the lowest OOS CDR stocks (P1) and invests this dollar in the decile portfolio with the highest OOS CDR stocks (P10). The figure reveals that the profits from this spread strategy are not derived from the early sample period, and hence they cannot be attributed to a potential estimation error of OOS CDR measures in the initial periods. Moreover, highly distressed stocks outperformed the non-distressed ones in the 2003-2007 bull market period, but they were more severely affected during the recent global financial crisis.[16] Therefore, ending our sample period in December 2010 and missing part of the subsequent bull market may actually underestimate the magnitude of the default risk premium.

[Figure 2 here]

As an additional check to rule out that estimation error drives our results, we repeat the portfolio formation exercises using IS CDR estimates. Notwithstanding the look-ahead bias that the IS CDR estimates induce, they should be more accurately estimated relative to the OOS ones and they allow us to consider a longer time period, almost identical to the one analyzed by Gao et al. (2012). Table 7 presents the results from repeating the asset pricing tests in Table 6 using now the IS CDR estimates from January 1992 to December 2010. The reported results suggest a positive relation between default risk and excess portfolio returns, which is monotonic with the exception of value-weighted portfolios in the C6 countries. The magnitude of the average spread return between the highest and the lowest default risk deciles (P10-P1) is somewhat lower relative to the benchmark results, and it is statistically significant in the case of equally-weighted portfolios. Adjusting for market risk does not reduce the magnitude of the default risk premium, but adjusting also for size, value and momentum premia using the 4-factor FFC model renders the premium insignificant, statistically and economically.

[16] Bull and bear markets in Figure 2 are characterized with respect to the dollar-denominated price level of the MSCI World ex US index.

[Table 7 here]

Panel B of Figure 2 helps us understand why the default risk premium is slightly lower using IS CDR estimates relative to OOS CDR estimates. In particular, the cumulative profits of the spread strategy that goes long the highest default risk decile portfolio and goes short the lowest default risk decile portfolio (P10-P1) are rather low until the year 2000. Thereafter, the cumulative profits of this strategy based on IS CDR estimates resemble the profits of the corresponding strategy based on OOS CDR estimates, confirming again the robustness of our benchmark results for the period 2000-2010.

Table 8 reports the results from a series of robustness checks regarding the default risk-stock return relation in the C6 (Panel A) and the C14 countries (Panel B). To save space, we only show the average excess returns for the extreme CDR-sorted decile portfolios P1 and P10 as well as their spread (P10-P1). Results for the rest portfolios are available upon request. Our first robustness test examines the relation between the OOS CDR measure and portfolio returns over the longest feasible period for the asset pricing tests, from January 1998 to December 2010, i.e. using an initial window to estimate the LOGIT models up to December 1997. The second robustness test examines the relation between the IS CDR measure and portfolio returns from January 2000 to December 2010, i.e. the period used for the benchmark OOS results. In the third robustness test, we set to -100% the returns of filing firms in the filing month to examine whether missing delisting returns could have overestimated the magnitude of the default risk premium in our benchmark results. The fourth robustness test imposes exactly the same data filters as in Gao et al. (2012) to ensure that the different conclusions we derive regarding the sign and the magnitude of the default risk premium with respect to their study are not driven by different data filters.[17] In the final robustness test, we do not impose

[17] In particular, Gao et al. (2012) additionally omit stocks with a zero ex-dividend return or less than 12 months of complete historical data on their main analysis variables. It should be noted that Gao et al. (2012) also control for country composition when creating portfolios to ensure that their results are not simply picking up return differences between firms in developed and developing countries. Given that they study 39 countries, including many small and developing ones, this constraint is sensible. On the other hand, since we focus on a smaller

any gap between the portfolio formation date (December of year $t-1$) and the beginning of the holding period, which now becomes January of year t. The sample period for the last three robustness tests is 2000-2010, as in the benchmark results.

[Table 8 here]

The results of the previously described tests show that, overall, there is a robust positive relation between default risk and stock returns. The spread strategy P10-P1 indicates the existence of a highly economically and statistically significant default risk premium in all cases when equally-weighted portfolios are considered, with the exception of using OOS CDR estimates in the period 1998-2010, when the premium marginally loses its statistical significance. When value-weighted portfolio returns are used, the default risk premium remains quite high and it is also statistically significant in half of the cases. Even when the default risk premium is not statistically significant at conventional levels, the t-statistics take values higher than 1.50 in most cases.[18] The corresponding CAPM and FFC alphas of these portfolios are similar to the benchmark results presented in Table 6. Adjusting for market risk does not affect the magnitude of the default risk premium. However, adjusting for the exposure of portfolio returns to size, value and momentum factors explains a large part of the default risk premium, since the returns of high default risk stocks predominantly covary positively with SMB and HML factor returns (results available upon request).

4.2 *Default Risk and Stock Returns across Bankruptcy Law Regimes*

In this subsection we examine the relation between the OOS CDR estimates and stock portfolio returns during the period from 2000 to 2010 for each of the four bankruptcy law regimes. Average excess portfolio returns, CAPM and FFC alphas are reported in Table 9 for the

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number of developed countries, we focus on large default risk spreads rather than similar country compositions in our main tests.

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

common law regime (Panel A), the Napoleonic law regime (Panel B), the Roman-Germanic law regime (Panel C) and the mixed regime (Panel D), respectively.

[Table 9 here]

For the stocks in the common law countries we derive an almost monotonic positive relation between default risk and portfolio returns, while the return of the spread strategy P10-P1 is highly economically and statistically significant when equally-weighted portfolios are used. While the magnitude of this premium is reduced once we adjust for market risk and FFC factors, it remains highly significant. The corresponding results from the rest bankruptcy law regimes are rather mixed. For the Napoleonic law regime, there is an almost monotonic positive relation between OOS CDR and equally-weighted portfolio returns, while the average spread return between the extreme decile portfolios P10-P1 is positive and strongly significant and remains so even after adjusting for market, size, value and momentum premia. On the other hand, in the case of value-weighted portfolio returns we get an inverted U-shape relation and the average spread return P10-P1 is insignificant. Examining firms from countries belonging to the Roman-Germanic law regime, we fail to find any discernible pattern between OOS CDR and either value-weighted or equally-weighted portfolio returns. Finally, the corresponding relation is remarkably U-shaped in the mixed regime (Taiwan and Japan), a noteworthy finding since we are not aware of any theoretical model that predicts such a relation.

4.3 Comparison of the CDR and the MDD measure

Our benchmark results indicate a robust positive default risk-stock return relation, which is markedly different from the evidence reported in Gao et al. (2012), who use Moody's KMV EDF measure to capture default risk. In this subsection we examine why our results differ so much. To this end, we repeat the portfolio formation exercise using as a sorting criterion the MDD measure, which is a close proxy of the proprietary EDF measure. For comparison purposes, we also report the corresponding results using our OOS CDR measure, but now these portfolios are constructed using firms for which both measures are available to ensure that the same sample of firms is examined. Equally- and value-weighted excess portfolio returns during the period 2000-2010 are reported in Table 10 for both default risk measures.

[Table 10 here]

The reported results confirm the almost monotonically positive relation between the OOS CDR measure and portfolio returns in this sample of firms too. In sharp contrast, when MDD is used as a sorting variable, a U-shaped relation between default risk and portfolio returns emerges. For example, portfolio P1 containing the firms from the C6 countries with the lowest MDD values yields an average excess value-weighted return of 6.94% p.a., portfolios P5 and P6 yield an average excess return of -.67% p.a., while portfolio P10 containing the firms with the highest MDD values yields an average excess return of 2.48% p.a. As a result, the average spread return P10-P1 is negative and equal to -4.46% p.a. but insignificant (t-stat: -.86). This finding is in line with the evidence provided in Gao et al. (2012).

The results reported in Table 10 derive from the fact that these two default risk measures disagree in the characterization of the least distressed firms. Although 55% of the firms in the highest three MMD decile portfolios (P8 to P10) are on average also present in the highest three CDR decile portfolios (P8 to P10), only 38% of the firms in the lowest three MDD decile portfolios (P1 to P3) are on average also present in the lowest three CDR deciles (P1 to P3). This disagreement between the two measures can be also seen from the average CDR values for the firms in each of the MDD-sorted portfolios reported in Table 10. In particular, while the firms in the highest three MDD decile portfolios (P8 to P10) also exhibit the highest average CDR values, this is not the case when we consider the lowest MDD decile portfolio (P1), which actually contains firms with higher than average CDR values. Consistent with this evidence, this portfolio yields a high excess return because it contains moderately distressed firms, as classified by our OOS CDR measure.

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

4.4 Double-sorted Portfolios

In this subsection, we utilize double-sorted portfolios to examine whether the magnitude of the previously documented default risk premium is contingent upon a series of firm characteristics. In this way, we can also evaluate in our international sample prior evidence for U.S. firms as well as the validity of theories proposed to explain cross-sectional variations in the default risk-stock return relation. For example, Garlappi et al. (2008) and Garlappi and Yan (2011) hypothesize that this relation is hump-shaped if shareholders have high bargaining power, allowing them to strategically default on their debt obligations and extract rents from creditors. George and Hwang (2010) and Johnson et al. (2011) show that the default risk-stock return relation can be negative if high deadweight costs of distress or asset volatility decrease optimal leverage, but raise systematic risk. Moreover, O'Doherty (2010) claims that distressed stocks attract low market betas, and hence low systematic risk because their asset values are difficult to be precisely estimated. Finally, Campbell et al. (2008) partly attribute the distressed risk anomaly they document for U.S. firms to mispricing arising due to limits to arbitrage and market microstructure biases, while Gao et al. (2012) find a significant negative relation between default risk and stock returns only among small capitalization stocks in their international sample. On the other hand, Vassalou and Xing (2004) find a significant default risk premium only for small and value U.S. stocks.

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

To construct double-sorted portfolios, we sort stocks into ascending order according to their OOS CDR estimated values in December of year $t-1$ and classify them into quintile portfolios (Q1 to Q5), while we also independently sort stocks into ascending order according to each of the examined firm characteristics in December of year $t-1$, which are all expressed in U.S. dollars to ensure comparability, and classify them into tercile portfolios (Low, Medium, High).[19] The intersection of these two classifications yields the double-sorted portfolios. Portfolios are held from February of year t to January of year $t+1$, allowing again for a one month gap between formation and the beginning of the holding period. We report in Table 11 the average excess returns for the extreme double-sorted portfolios as well as for the spread strategy (Q5-Q1) that goes long the quintile portfolio with the highest default risk stocks (Q5) and goes short the quintile portfolio with the lowest default risk stocks (Q1) within the High or the Low classification of each firm characteristic, respectively. To ease comparison, we also report in the column ALL the corresponding returns for the single-sorted quintile portfolios according to OOS CDR estimates. Table 11 reports the premia for value- and equally-weighted portfolios for firms in the C6 countries (Panels A and B, respectively) and the C14 countries (Panels C and D, respectively).

[Table 11 here]

The results from Table 11 are summarized as follows. The default risk premium is found to be relatively higher among big capitalization and growth stocks, stocks that are traded at high prices and exhibit high return volatility as well as among firms that are followed by analysts and they are characterized by high asset tangibility and low leverage. Therefore, the default risk premium documented in this study cannot be attributed to microstructure biases and it does not derive from small capitalization or value firms. To the contrary, in line with Gao et al. (2012), we find no or even a negative default risk-stock return relation among small stocks. The same is true for stocks traded at low prices in the C6 countries and firms that are not followed by analysts, supporting the argument of Campbell et al. (2008) that market microstructure, information asymmetry and limits to arbitrage may explain the absence of a default risk premium. On the other hand, high stock return volatility does not hinder default risk from being priced in our sample. Finally, our results support the shareholder advantage hypothesis of

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

Garlappi et al. (2008) and Garlappi and Yan (2011), since the default risk premium is less pronounced among firms with low tangibility, in whose case shareholders can more easily extract rents by strategically defaulting. These results hold for the C6 and the C14 countries.

5. Conclusions

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

Our conclusions are markedly different from those reported in the recent study of Gao et al. (2012), who also examine the default risk-stock return relation using a large sample of non-U.S. firms for a similar period. In contrast to our approach, they use the proprietary EDF measure that is calculated from Moody's KMV structural model. While this commercial default risk measure is not replicable, for comparison purposes we calculate the MDD measure from Merton's model, which is a close proxy of EDF. This comparison reveals that the CDR measure that we use often disagrees with MDD on characterizing low default risk firms. A reason for this disagreement is that, unlike the CDR measure which is more flexible, MDD assumes that default certainly occurs once the asset value drops below a fraction of the book value of debt. Another reason that might explain why our results differ from the ones reported in Gao et al. (2012) is that structural models focus exclusively on insolvency risk, abstracting from corporate liquidity issues. However, as Davydenko (2008) argues, in practice even solvent firms sometimes have to declare bankruptcy due to being illiquid. Therefore, structural models, including the one used by Moody's KMV, may classify firms with liquidity problems as low default risk firms. In addition, Bharath and Shumway (2008) question the ability of MDD to produce a sufficient statistic for the probability of default.

Finally, our rich international dataset can help us examine whether the magnitude of the default risk premium is contingent upon a series of firm characteristics. In brief, we find that the default risk premium is relatively higher among big capitalization and growth stocks, stocks that are traded at high prices and exhibit high return volatility as well as among firms that are followed by analysts and they are characterized by high asset tangibility and low leverage. Therefore, the default risk premium we document cannot be attributed to microstructure biases and it does not derive from small capitalization or value firms. Finally, our results support the shareholder advantage hypothesis of Garlappi et al. (2008), since the default risk premium is less pronounced among firms with low tangibility.

Echoing the concerns of Chava and Purnanandam (2010), the reported results also raise the possibility that the distress anomaly documented in the U.S. market could be sample-specific. Therefore, as the quality of international bankruptcy filing data is bound to improve in the future, there is scope for expanding the cross-section of firms by also considering less developed markets as well as extending the time period examined to study the behavior of the default risk premium across different economic and stock market conditions.

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Table 1
Bankruptcy Filing Data Sources

This table offers 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. The last column provides further useful information about the bankruptcy filing data.

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

Table 2
Number and Proportion of Bankruptcies per Country and Year

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

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

Table 3
Summary Statistics

This table presents summary statistics (means, medians and standard deviations) for each of the following variables: NIMTA (net income scaled by the sum of market value of equity and total liabilities), TLMTA (total liabilities scaled by the sum of market value of equity and total liabilities), EXRET (monthly log stock return of a firm minus that of the index of the market in which the firm is headquartered), RSIZE (log ratio of a firm's market value to the sum of market values for all firms in the same market and month), SIGMA (annualized standard deviation of a firm's daily log stock return in the prior three months, as defined in section 2.2), CASHMTA (ratio of cash and short-term assets to the sum of market value of equity and total liabilities), MB (market-to-book value ratio) and PRICE (log stock price). The statistics are reported for each country with more than 40 bankruptcies over the period 1997-2009, namely Australia, Canada, France, Germany, Japan and the UK (the C6 countries). In Panel G, we also provide the corresponding statistics for the pooled sample of firms in all C6 countries. In each Panel, the statistics are reported for active (act) and for bankrupt firms (bank), respectively.

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

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

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

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

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

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

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

Table 6
Out-of-Sample Global Default Risk Portfolios

This table reports average excess returns, CAPM alphas and four-factor alphas from the Fama-French-Carhart asset pricing model (FFC alphas) for portfolios constructed on the basis of out-of-sample (OOS) estimates of the Campbell et al. (2008) default risk (CDR) 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 CDR measures, a LOGIT model is recursively run for each of the C6 countries; see Section 3. For the rest countries that feature too few bankruptcies, we run recursively a LOGIT model for each bankruptcy law regime. We consider four bankruptcy law regimes: *Common Law* (Australia, Canada, Hong Kong, New Zealand and the U.K.), *Napoleonic* (France, Spain and Portugal), *Roman-Germanic* (Denmark, Finland, Germany and Sweden) and *Mixed* (Japan and Taiwan). The recursive LOGIT estimations start with an initial window including data up to December 1999. At the end of December of year *t-1*, we sort stocks in ascending order on the basis of their OOS CDR estimates and classify them to decile portfolios. We further partition the stocks of the highest default risk decile portfolio (P10) into three sub-portfolios, using the 95th and 99th percentiles as cutoff points. We also form the spread strategy (P10-P1) that goes long the decile portfolio with the highest default risk stocks (P10) and goes 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. Returns are calculated for a U.S.-based investor and they are reported for both value-weighted (vw) and equally-weighted (ew) portfolios. Average excess portfolio returns and alphas are annualized and bolded; their associated t-statistics are reported in square brackets. The lower part of each panel reports the average number of firms per portfolio, stocks' average standard deviation of returns (SIGMA), their average log relative size (RSIZE) and their average OOS CDR estimate. The examined period is January 2000-December 2010. ** and * denote statistical significance at 5% and 10% levels, respectively.

		Deciles								Percentiles		
		1	2	3-4	5-6	7-8	9	10	10-1	90-95	95-99	99-100
Panel A: C6 Countries												
Excess return	vw	**-5.23**	**-6.21**	**0.08**	**4.43**	**5.47**	**5.32**	**8.96**	**14.19** *	**6.78**	**12.66**	**4.34**
		[-0.77]	[-0.76]	[0.01]	[0.55]	[0.62]	[0.54]	[0.82]	[1.87]	[0.71]	[0.94]	[0.28]
	ew	**4.44**	**3.42**	**7.48**	**11.79**	**13.26**	**10.51**	**16.57**	**12.13** **	**11.63**	**20.23** *	**26.51**
		[0.56]	[0.40]	[0.85]	[1.16]	[1.30]	[1.09]	[1.64]	[2.11]	[1.16]	[1.76]	[1.39]
CAPM alpha	vw	**-4.86** ***	**-5.85** **	**0.37**	**4.73**	**5.85**	**5.77**	**9.42**	**14.28** **	**7.23**	**13.15**	**4.80**
		[-3.06]	[-2.47]	[0.11]	[1.06]	[1.18]	[1.01]	[1.44]	[1.96]	[1.28]	[1.53]	[0.45]
	ew	**4.80**	**3.79**	**7.84** *	**12.16** **	**13.64** **	**10.86** **	**16.88** **	**12.08** **	**11.99** **	**20.50** **	**26.71**
		[1.11]	[0.87]	[1.68]	[2.05]	[2.33]	[2.02]	[2.42]	[2.03]	[2.25]	[2.11]	[1.48]
FFC alpha	vw	**-0.51**	**-4.89** *	**-3.03**	**-0.58**	**-1.43**	**-6.15** *	**-3.83**	**-3.31**	**-6.64** **	**-0.03**	**-3.31**
		[-0.30]	[-1.85]	[-1.39]	[-0.21]	[-0.42]	[-1.69]	[-0.92]	[-0.76]	[-1.99]	[-0.01]	[-0.31]
	ew	**2.07**	**-0.17**	**0.09**	**1.41**	**2.22**	**-0.58**	**5.41**	**3.34**	**1.70**	**5.93**	**21.73**
		[0.53]	[-0.04]	[0.03]	[0.43]	[0.67]	[-0.20]	[1.09]	[0.74]	[0.43]	[0.98]	[0.96]
average # of firms		794	795	1,590	1,590	1,590	795	795		397	318	80
average SIGMA		0.41	0.46	0.47	0.53	0.57	0.59	0.65		0.60	0.67	0.80
average RSIZE		-9.41	-9.69	-9.19	-9.46	-10.05	-10.55	-11.04		-10.88	-11.14	-11.46
average CDR		0.00%	0.00%	0.01%	0.02%	0.04%	0.09%	0.50%		0.17%	0.39%	2.54%

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

		Deciles								Percentiles		
		1	2	3-4	5-6	7-8	9	10	10-1	90-95	95-99	99-100
Panel B: C14 Countries												
Mean excess return	vw	**-4.70**	**-5.73**	**0.57**	**4.84**	**5.69**	**5.59**	**9.83**	**14.53** **	**6.94**	**14.76**	**5.65**
		[-0.68]	[-0.69]	[0.07]	[0.60]	[0.63]	[0.57]	[0.91]	[2.06]	[0.69]	[1.17]	[0.38]
	ew	**4.91**	**3.45**	**7.85**	**11.12**	**13.18**	**11.46**	**17.26** *	**12.35** **	**11.49**	**21.18** *	**30.42** *
		[0.64]	[0.43]	[0.90]	[1.12]	[1.31]	[1.18]	[1.70]	[2.24]	[1.15]	[1.91]	[1.72]
CAPM alpha	vw	**-4.81** ***	**-5.85** **	**0.47**	**4.74**	**5.56**	**5.44**	**9.69**	**14.50** **	**6.80**	**14.61** *	**5.50**
		[-3.22]	[-2.33]	[0.13]	[1.17]	[1.20]	[1.01]	[1.54]	[2.14]	[1.21]	[1.89]	[0.54]
	ew	**4.80**	**3.33**	**7.73** *	**10.99** **	**13.06** **	**11.34** **	**17.15** ***	**12.35** **	**11.37** **	**21.08** **	**30.36** *
		[1.25]	[0.87]	[1.76]	[1.97]	[2.40]	[2.17]	[2.56]	[2.19]	[2.28]	[2.37]	[1.83]
FFC alpha	vw	**-1.62**	**-4.34** *	**-1.22**	**1.64**	**0.03**	**-3.69**	**-1.86**	**-0.24**	**-5.25**	**4.00**	**-4.56**
		[-1.27]	[-1.91]	[-0.49]	[0.66]	[0.01]	[-1.13]	[-0.44]	[-0.05]	[-1.25]	[0.73]	[-0.48]
	ew	**1.40**	**0.01**	**2.09**	**3.16**	**4.22**	**1.77**	**6.80**	**5.40**	**2.93**	**7.77**	**22.19**
		[0.40]	[0.00]	[0.67]	[0.87]	[1.18]	[0.56]	[1.41]	[1.19]	[0.75]	[1.40]	[1.21]
average # of firms		985	986	1,971	1,971	1,971	986	986		493	394	99
average SIGMA		0.42	0.45	0.46	0.51	0.56	0.59	0.66		0.62	0.69	0.82
average RSIZE		-9.19	-9.21	-8.68	-9.08	-9.75	-10.30	-10.86		-10.69	-10.96	-11.28
average CDR		0.00%	0.00%	0.01%	0.02%	0.04%	0.09%	0.48%		0.17%	0.38%	2.50%

Table 7
In-Sample Global Default Risk Portfolios

This table reports average excess returns, CAPM alphas and four-factor alphas from the Fama-French-Carhart asset pricing model (FFC alphas) for portfolios constructed on the basis of in-sample (IS) estimates of the Campbell et al. (2008) default risk (CDR) measure. We construct these portfolios for stocks in the C6 countries (Australia, Canada, France, Germany, Japan and the United Kingdom; Panel A) and the C14 countries (the C6 countries plus Denmark, Finland, Hong Kong, New Zealand, Portugal, Spain, Sweden and Taiwan; Panel B). To estimate IS CDR measures, a full sample LOGIT model is run for each of the C6 countries; see Section 3. For the rest countries that feature too few bankruptcies, we run a full sample LOGIT model for each bankruptcy law regime. We consider four bankruptcy law regimes: *Common Law* (Australia, Canada, Hong Kong, New Zealand and the U.K.), *Napoleonic* (France, Spain and Portugal), *Roman-Germanic* (Denmark, Finland, Germany and Sweden) and *Mixed* (Japan and Taiwan). At the end of December of year *t-1*, we sort stocks in ascending order on the basis of their IS CDR estimates and classify them to decile portfolios. We further partition the stocks of the highest default risk decile portfolio (P10) into three sub-portfolios, using the 95^{th} and 99^{th} percentiles as cutoff points. We also form the spread strategy (P10-P1) that goes long the decile portfolio with the highest default risk stocks (P10) and goes short the decile portfolio with the lowest default risk stocks (P1). We exclude stocks whose price or market capitalization is below the 5^{th} percentile of the corresponding country-month distribution at the portfolio formation date. Portfolios are held from February of year *t* to January of year *t+1*, at which point they are rebalanced. Returns are calculated for a U.S.-based investor and they are reported for both value-weighted (vw) and equally-weighted (ew) portfolios. Average excess portfolio returns and alphas are annualized and bolded; their associated t-statistics are reported in square brackets. The lower part of each panel reports the average number of firms per portfolio, stocks' average standard deviation of returns (SIGMA), their average log relative size (RSIZE) and their average IS CDR estimate. The examined period is January 1992-December 2010. ** and * denote statistical significance at 5% and 10% levels, respectively.

		Deciles								Percentiles		
		1	2	3-4	5-6	7-8	9	10	10-1	90-95	95-99	99-100
Panel A: C6 Countries												
Mean excess return	vw	**-0.68**	**1.17**	**1.61**	**2.58**	**3.92**	**3.20**	**6.49**	**7.17**	**7.28**	**4.39**	**2.37**
		[-0.12]	[0.23]	[0.35]	[0.57]	[0.74]	[0.49]	[0.76]	[1.35]	[0.84]	[0.50]	[0.18]
	ew	**1.06**	**1.60**	**5.28**	**7.68**	**6.94**	**9.09**	**10.94**	**9.88 ****	**7.65**	**12.18**	**22.30 ***
		[0.17]	[0.25]	[0.89]	[1.31]	[1.14]	[1.50]	[1.37]	[2.03]	[1.03]	[1.41]	[1.91]
CAPM alpha	vw	**-3.23 ****	**-1.03**	**-0.15**	**1.02**	**2.02**	**1.14**	**3.83**	**7.05**	**4.74**	**1.51**	**-1.01**
		[-1.99]	[-0.47]	[-0.06]	[0.33]	[0.58]	[0.27]	[0.76]	[1.36]	[0.87]	[0.29]	[-0.11]
	ew	**-1.52**	**-1.00**	**3.14**	**5.80**	**5.17**	**7.46**	**9.02**	**10.54 ****	**5.76**	**10.18**	**20.54 ***
		[-0.68]	[-0.32]	[0.85]	[1.45]	[1.20]	[1.61]	[1.60]	[2.05]	[1.14]	[1.64]	[1.94]
FFC alpha	vw	**-2.09 ***	**-4.30 ****	**-5.03 ****	**-4.75 ****	**-5.02 ****	**-7.16 ****	**-3.53**	**-1.44**	**-2.75**	**-4.77**	**-11.68 ***
		[-1.92]	[-2.05]	[-2.39]	[-1.98]	[-1.98]	[-2.47]	[-0.93]	[-0.38]	[-0.62]	[-1.30]	[-1.75]
	ew	**-3.61 ***	**-5.58 ****	**-4.15 ***	**-3.24**	**-4.17 ***	**-2.80**	**-0.10**	**3.51**	**-3.82**	**0.20**	**17.11**
		[-1.84]	[-2.40]	[-1.68]	[-1.30]	[-1.66]	[-1.01]	[-0.03]	[0.93]	[-1.19]	[0.05]	[1.14]
average # of firms		649	649	1,299	1,299	1,299	649	650		325	260	65
average SIGMA		0.38	0.43	0.43	0.44	0.47	0.51	0.59		0.55	0.61	0.71
average RSIZE		-9.02	-8.98	-8.83	-9.06	-9.50	-9.95	-10.65		-10.42	-10.82	-11.09
average CDR		0.00%	0.01%	0.01%	0.04%	0.07%	0.15%	0.47%		0.23%	0.56%	1.35%

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

		Deciles								Percentiles		
		1	2	3-4	5-6	7-8	9	10	10-1	90-95	95-99	99-100
Panel B: C14 Countries												
Mean excess return	vw	-0.17	1.90	2.98	3.00	3.20	4.36	5.28	5.46	5.70	5.07	2.45
		[-0.03]	[0.40]	[0.59]	[0.66]	[0.64]	[0.65]	[0.64]	[1.11]	[0.72]	[0.54]	[0.18]
	ew	1.88	2.02	5.32	7.64	7.95	9.80	11.56	9.68 **	8.73	12.42	22.26 *
		[0.34]	[0.34]	[0.94]	[1.31]	[1.30]	[1.60]	[1.45]	[2.33]	[1.21]	[1.45]	[1.90]
CAPM alpha	vw	-2.96	-0.52	0.90	1.20	1.08	1.97	2.29	5.25	2.83	1.95	-1.61
		[-1.60]	[-0.24]	[0.33]	[0.40]	[0.34]	[0.46]	[0.50]	[1.11]	[0.61]	[0.34]	[-0.17]
	ew	-0.74	-0.81	3.01	5.54	5.92	7.87 *	9.33 *	10.07 **	6.58	10.09 *	20.00 **
		[-0.36]	[-0.27]	[0.86]	[1.41]	[1.42]	[1.78]	[1.74]	[2.28]	[1.37]	[1.72]	[2.02]
FFC alpha	vw	-2.41 **	-3.34 *	-3.38 *	-3.79 *	-4.86 **	-5.46 *	-4.16	-1.74	-4.01	-3.23	-11.08
		[-2.17]	[-1.77]	[-1.88]	[-1.81]	[-2.06]	[-1.75]	[-1.14]	[-0.49]	[-1.11]	[-0.69]	[-1.62]
	ew	-3.53 *	-4.62 **	-3.60	-2.61	-2.77	-1.73	1.29	4.83	-2.15	1.97	15.72
		[-1.73]	[-2.06]	[-1.48]	[-1.04]	[-1.07]	[-0.63]	[0.31]	[1.20]	[-0.63]	[0.40]	[1.27]
average # of firms		790	790	1,580	1,580	1,580	790	791		395	316	79
average SIGMA		0.38	0.42	0.42	0.44	0.47	0.51	0.59		0.55	0.62	0.72
average RSIZE		-8.47	-8.60	-8.31	-8.73	-9.31	-9.79	-10.53		-10.29	-10.72	-11.02
average CDR		0.00%	0.01%	0.01%	0.04%	0.06%	0.13%	0.43%		0.20%	0.50%	1.27%

Table 8
Robustness Tests

This table reports the results of various robustness tests regarding the sample period and method of estimation of Campbell et al. (2008) default risk (CDR) measure as well as regarding data filters and the beginning of the portfolio holding period. The table reports results only for the extreme decile CDR-sorted stock portfolios (P1 and P10) and the spread strategy (P10-P1) that goes long the decile portfolio with the highest default risk stocks (P10) and goes short the decile portfolio with the lowest default risk stocks (P1). The average excess portfolio returns are annualized and bolded; their associated t-statistics are in square brackets. We construct these portfolios for stocks in the C6 countries (Australia, Canada, France, Germany, Japan and the United Kingdom; Panel A) and for stocks in the C14 countries (the C6 countries plus Denmark, Finland, Hong Kong, New Zealand, Portugal, Spain, Sweden and Taiwan; Panel B). Returns are calculated for a U.S.-based investor and they are reported for both value-weighted (vw) and equally-weighted (ew) portfolios. The column titled "Est" indicates whether the portfolios are constructed using out-of-sample (OOS) estimates of the CDR measure, as described in Table 6, or in-sample (IS) estimates, as described in Table 7. The first robustness test ("Sample period 1998-2010") replicates the results in Table 6 for the period 1998-2010. The second robustness test ("Sample period 2000-2010") replicates the results in Table 7 for the period 2000-2010. The third robustness test ("Return of Defaulting Stocks=-100%") replicates the results in Table 6 setting the returns of filing firms to -100% in the filing month. The fourth robustness test ("Same Restrictions as Gao et al. (2012)") replicates the results in Table 6 excluding stocks with a zero price change from month *m-1* to *m* and stocks with incomplete data on the market and accounting variables used in the LOGIT model in the prior 12 months. The final robustness test replicates the results in Table 6 leaving no gap between the portfolio formation month (i.e., December of year *t-1*) and the beginning of the holding period, which now becomes January of year *t*. ** and * denote statistical significance at 5% and 10% levels, respectively.

		Value-weighted Portfolios			Equally-weighted Portfolios		
Modifications	Est	Decile 1	Decile 10	10-1	Decile 1	Decile 10	10-1
Panel A: C6 Countries							
Sample period 1998-2010	OOS	**1.30**	**11.03**	**9.73**	**6.87**	**15.58** *	**8.71**
		[0.19]	[1.11]	[1.49]	[0.95]	[1.76]	[1.62]
Sample period 2000-2010	IS	**-6.32**	**9.13**	**15.46** *	**2.45**	**14.72**	**12.27** *
		[-0.87]	[0.68]	[1.79]	[0.33]	[1.18]	[1.75]
Return of Defaulting Stocks = -100%	OOS	**-5.23**	**8.54**	**13.77** *	**4.43**	**14.89**	**10.46** *
		[-0.77]	[0.78]	[1.81]	[0.55]	[1.46]	[1.79]
Same Restrictions as Gao et al. (2012)	OOS	**0.00**	**9.46**	**9.47**	**6.96**	**19.48** *	**12.52** *
		[-0.00]	[0.78]	[1.32]	[0.85]	[1.65]	[1.83]
No Gap Between Formation & Holding Period	OOS	**-5.66**	**6.81**	**12.47**	**3.96**	**14.95**	**10.99** *
		[-0.81]	[0.63]	[1.61]	[0.49]	[1.49]	[1.81]
Panel B: C14 Countries							
Sample period 1998-2010	OOS	**1.19**	**12.29**	**11.11** *	**5.84**	**17.58** *	**11.74** **
		[0.18]	[1.25]	[1.77]	[0.87]	[1.93]	[2.35]
Sample period 2000-2010	IS	**-5.51**	**7.05**	**12.56**	**3.74**	**14.53**	**10.80** *
		[-0.73]	[0.55]	[1.58]	[0.53]	[1.18]	[1.72]
Return of Defaulting Stocks = -100%	OOS	**-4.70**	**9.51**	**14.21** **	**4.90**	**15.80**	**10.90** **
		[-0.68]	[0.88]	[2.02]	[0.64]	[1.55]	[1.96]
Same Restrictions as Gao et al. (2012)	OOS	**-0.30**	**11.35**	**11.66**	**7.34**	**21.29** *	**13.95** **
		[-0.05]	[0.94]	[1.56]	[0.93]	[1.82]	[2.07]
No Gap Between Formation & Holding Period	OOS	**-5.01**	**7.99**	**13.01** *	**4.63**	**16.17**	**11.54** **
		[-0.72]	[0.75]	[1.81]	[0.60]	[1.62]	[2.03]

Table 9
Out-of-Sample Default Risk Portfolios Across Bankruptcy-Law Regimes

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) default risk (CDR) measure. We construct these portfolios for stocks in each of the following 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 OOS CDR estimates are based on recursive LOGIT models run for each bankruptcy law regime. 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 CDR estimates and classify them to decile portfolios. We also form the spread strategy (P10-P1) that goes long the decile portfolio with the highest default risk stocks (P10) and goes 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. Returns are calculated for a U.S.-based investor and they are reported for both value-weighted (vw) and equally-weighted (ew) portfolios. Average excess portfolio returns and alphas are annualized and bolded; their associated t-statistics are reported in square brackets. The lower part of each panel reports the average number of firms per portfolio, stocks' average standard deviation of returns (SIGMA), their average log relative size (RSIZE) and their average OOS CDR estimate. The examined period is January 2000-December 2010. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

		Deciles							
		1	2	3-4	5-6	7-8	9	10	10-1
Panel A: Common Law									
Excess return	vw	**3.98**	**5.48**	**5.18**	**6.50**	**10.57**	**11.41**	**14.02**	**10.04**
		[0.46]	[0.69]	[0.64]	[0.66]	[0.92]	[0.92]	[1.09]	[1.38]
	ew	**12.58**	**10.43**	**10.92**	**14.67**	**17.39**	**21.06** *	**37.57** ***	**24.98** ***
		[1.12]	[1.00]	[1.00]	[1.28]	[1.53]	[1.74]	[2.93]	[2.73]
CAPM alpha	vw	**-5.48** ***	**-3.36**	**-3.03**	**-2.95**	**-0.15**	**0.11**	**2.71**	**8.19**
		[-2.56]	[-1.57]	[-1.01]	[-0.72]	[-0.03]	[0.02]	[0.45]	[1.25]
	ew	**0.89**	**-0.28**	**0.09**	**3.80**	**6.80**	**10.74** *	**29.00** ***	**28.11** ***
		[0.20]	[-0.07]	[0.02]	[0.80]	[1.50]	[1.81]	[2.75]	[2.86]
FFC alpha	vw	**-4.10** **	**-3.84** *	**-2.77**	**-3.63**	**-2.78**	**-3.54**	**-1.38**	**2.71**
		[-2.08]	[-1.90]	[-0.90]	[-0.98]	[-0.76]	[-0.99]	[-0.31]	[0.49]
	ew	**-0.96**	**-1.60**	**-1.66**	**1.10**	**3.11**	**5.18**	**24.23** ***	**25.20** ***
		[-0.27]	[-0.55]	[-0.63]	[0.35]	[1.24]	[1.56]	[2.70]	[2.75]
average # of firms		442	442	885	885	885	442	443	
average SIGMA		0.50	0.48	0.52	0.60	0.68	0.75	0.89	0.39
average RSIZE		-7.59	-8.09	-8.84	-9.73	-10.45	-10.98	-11.51	-3.93
average CDR		0.01%	0.02%	0.02%	0.03%	0.07%	0.13%	0.30%	0.29%

(continued on next page)

Table 9 (continued)
Out-of-Sample Default Risk Portfolios Across Bankruptcy-Law Regimes

		Deciles							
		1	2	3-4	5-6	7-8	9	10	10-1
Panel B: Napoleonic									
Excess return	vw	-3.15	0.39	0.61	4.79	8.31	4.31	2.74	5.89
		[-0.39]	[0.05]	[0.07]	[0.53]	[0.79]	[0.43]	[0.25]	[1.08]
	ew	6.25	4.02	7.22	7.95	9.43	8.79	28.06 **	21.80 **
		[0.87]	[0.52]	[0.93]	[1.05]	[1.17]	[1.07]	[2.02]	[2.30]
CAPM alpha	vw	-9.82 ***	-5.74 ***	-5.61 ***	-2.07	1.14	-3.42	-3.83	5.99
		[-3.15]	[-2.82]	[-2.95]	[-0.80]	[0.29]	[-0.93]	[-0.84]	[1.11]
	ew	0.62	-1.61	2.02	2.49	3.98	3.60	22.16 **	21.54 **
		[0.26]	[-0.68]	[0.77]	[1.03]	[1.34]	[0.90]	[2.17]	[2.33]
FFC alpha	vw	-8.10 ***	-6.00 **	-6.46 ***	-3.38	-0.92	-8.13 **	-9.23 *	-1.13
		[-3.58]	[-2.28]	[-3.23]	[-1.21]	[-0.26]	[-2.06]	[-1.88]	[-0.24]
	ew	-2.40	-4.95 **	-1.79	-1.32	-0.63	-1.05	15.06 *	17.46 **
		[-0.92]	[-2.19]	[-0.82]	[-0.85]	[-0.27]	[-0.27]	[1.76]	[2.23]
average # of firms		82	83	165	165	165	83	83	
average SIGMA		0.37	0.37	0.37	0.41	0.46	0.53	0.65	
average RSIZE		-6.91	-7.55	-8.26	-9.00	-9.90	-10.71	-11.35	
average CDR		0.00%	0.01%	0.01%	0.02%	0.04%	0.06%	0.15%	
Panel C: Roman-Germanic									
Excess return	vw	2.91	4.20	1.70	5.52	4.60	3.24	-0.28	-3.19
		[0.35]	[0.48]	[0.16]	[0.51]	[0.39]	[0.25]	[-0.02]	[-0.36]
	ew	7.61	7.56	5.65	4.08	4.22	7.16	10.18	2.57
		[0.87]	[0.83]	[0.64]	[0.45]	[0.43]	[0.68]	[0.73]	[0.28]
CAPM alpha	vw	-7.06 **	-6.20 ***	-9.95 ***	-6.27 **	-6.60	-6.78	-9.91	-2.85
		[-2.45]	[-2.81]	[-3.11]	[-1.99]	[-1.28]	[-0.89]	[-1.33]	[-0.33]
	ew	-1.98	-2.34	-4.03 *	-5.45 **	-4.90	-1.44	1.00	2.98
		[-0.81]	[-0.76]	[-1.74]	[-2.45]	[-1.17]	[-0.29]	[0.12]	[0.33]
FFC alpha	vw	-5.38 *	-8.15 ***	-7.40 **	-5.42	-7.95	-4.86	-7.58	-2.20
		[-1.79]	[-4.34]	[-2.23]	[-1.45]	[-1.43]	[-0.72]	[-1.14]	[-0.25]
	ew	-3.44 **	-3.85	-4.46 ***	-4.99 ***	-4.29	-0.46	4.56	8.00
		[-2.00]	[-1.54]	[-3.26]	[-3.06]	[-1.25]	[-0.11]	[0.61]	[0.97]
average # of firms		117	117	234	234	234	117	118	
average SIGMA		0.35	0.37	0.40	0.46	0.53	0.62	0.78	
average RSIZE		-5.44	-6.40	-7.48	-8.68	-9.61	-10.35	-10.97	
average CDR		0.08%	0.03%	0.05%	0.08%	0.14%	0.34%	1.88%	
Panel D: Mixed									
Excess return	vw	0.99	-3.56	-8.09	-6.60	3.16	7.52	6.20	5.21
		[0.16]	[-0.60]	[-0.88]	[-0.86]	[0.55]	[0.93]	[0.64]	[0.77]
	ew	7.38	3.08	0.41	1.03	4.52	7.52	9.86	2.49
		[0.99]	[0.43]	[0.05]	[0.14]	[0.66]	[1.00]	[1.10]	[0.74]
CAPM alpha	vw	1.18	-3.37 **	-7.83 ***	-6.38 ***	3.36	7.79 *	6.52	5.34
		[0.51]	[-2.03]	[-3.33]	[-3.67]	[1.57]	[1.83]	[1.17]	[0.83]
	ew	7.57 **	3.28	0.63	1.24	4.73	7.76 **	10.13 **	2.56
		[2.03]	[1.04]	[0.20]	[0.41]	[1.50]	[2.21]	[2.19]	[0.80]
FFC alpha	vw	2.82	-2.24	-3.47 ***	-5.95 ***	-0.03	2.13	-5.08	-7.89
		[1.22]	[-1.55]	[-2.61]	[-3.84]	[-0.02]	[0.60]	[-1.45]	[-1.58]
	ew	3.30	0.02	-3.42	-4.14 **	-2.50	-1.45	-1.93	-5.23
		[0.95]	[0.01]	[-1.25]	[-2.05]	[-1.48]	[-0.79]	[-0.80]	[-1.39]
average # of firms		351	352	704	704	704	352	352	
average SIGMA		0.36	0.38	0.41	0.41	0.40	0.43	0.50	
average RSIZE		-9.22	-9.08	-9.23	-9.58	-9.89	-10.24	-10.55	
average CDR		0.00%	0.00%	0.00%	0.01%	0.02%	0.05%	0.13%	

Table 10
Out-of-Sample Comparison of CDR and MDD-Sorted Portfolios

This table reports average excess returns for portfolios sorted on the basis of out-of-sample (OOS) estimates of the Campbell et al. (2008) default risk (CDR) 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 CDR measures are recursively estimated as described in Section 3 and the caption of Table 6. Moreover, we follow the methodology of Vassalou and Xing (2004) to estimate MDD for each firm in our sample. At the end of December of year *t-1*, we sort stocks in ascending order on the basis of their OOS CDR or, alternatively, MDD estimates and classify them to decile portfolios. We also form the spread strategy (P10-P1) that goes long the decile portfolio with the highest default risk stocks (P10) and goes 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. Returns are calculated for a U.S.-based investor and they are reported for both value-weighted (vw) and equally-weighted (ew) portfolios. Average excess portfolio returns and alphas are annualized and bolded; their associated t-statistics are reported in square brackets. The lower part of each panel reports the average number of firms per portfolio. 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 CDR estimate. The examined period is January 2000-December 2010. ** and * denote statistical significance at 5% and 10% levels, respectively.

		Deciles							
		1	2	3-4	5-6	7-8	9	10	10-1
Panel A: C6 Countries									
CDR	vw	**-5.13**	**-5.61**	**-0.01**	**4.62**	**5.67**	**5.90**	**9.26**	**14.39** *
		[-0.77]	[-0.70]	[-0.00]	[0.58]	[0.65]	[0.60]	[0.86]	[1.92]
	ew	**4.17**	**3.95**	**7.15**	**11.86**	**13.06**	**10.81**	**17.32** *	**13.15** **
		[0.54]	[0.49]	[0.84]	[1.20]	[1.31]	[1.15]	[1.71]	[2.13]
MDD	vw	**6.94**	**1.00**	**-0.78**	**-0.67**	**0.31**	**3.71**	**2.48**	**-4.46**
		[0.83]	[0.14]	[-0.11]	[-0.09]	[0.04]	[0.34]	[0.22]	[-0.86]
	ew	**22.39** **	**14.97**	**5.63**	**4.77**	**7.21**	**9.49**	**18.31**	**-4.07**
		[2.05]	[1.45]	[0.74]	[0.61]	[0.85]	[0.93]	[1.50]	[-0.63]
average # of firms		743	716	1,445	1,453	1,441	719	723	
MDD average SIGMA		0.64	0.55	0.39	0.42	0.49	0.58	0.73	
MDD average RSIZE		-10.27	-9.74	-8.92	-9.20	-9.91	-10.45	-10.85	
MDD average CDR		0.06%	0.03%	0.03%	0.03%	0.07%	0.14%	0.26%	
Panel B: C14 Countries									
CDR	vw	**-4.58**	**-5.18**	**0.53**	**5.00**	**5.89**	**6.03**	**9.89**	**14.48** **
		[-0.67]	[-0.64]	[0.07]	[0.63]	[0.66]	[0.62]	[0.92]	[2.06]
	ew	**4.70**	**4.46**	**7.72**	**11.34**	**13.29**	**11.92**	**18.00** *	**13.30** **
		[0.64]	[0.58]	[0.91]	[1.16]	[1.34]	[1.24]	[1.77]	[2.27]
MDD	vw	**3.73**	**2.66**	**-0.17**	**-0.29**	**1.26**	**3.11**	**2.39**	**-1.33**
		[0.48]	[0.36]	[-0.02]	[-0.04]	[0.15]	[0.28]	[0.21]	[-0.27]
	ew	**20.16** *	**14.38**	**5.70**	**5.63**	**8.09**	**11.21**	**19.34**	**-0.82**
		[1.94]	[1.40]	[0.78]	[0.71]	[0.93]	[1.10]	[1.62]	[-0.14]
average # of firms		921	886	1,800	1,806	1,783	889	892	
MDD average SIGMA		0.62	0.52	0.38	0.42	0.49	0.57	0.72	
MDD average RSIZE		-10.02	-9.40	-8.50	-8.85	-9.55	-10.11	-10.54	
MDD average CDR		0.06%	0.03%	0.03%	0.03%	0.07%	0.14%	0.26%	

Table 11
Double-Sorted Default Risk Portfolios

This table reports average excess returns for double-sorted portfolios on the basis of out-of-sample (OOS) estimates of the Campbell et al. (2008) default risk (CDR) measure and each of the following firm characteristics: *(i)* SIZE (dollar market capitalization), *(ii)* VALUE (book-to-market value ratio), *(iii)* PRICE (log stock price expressed in U.S. dollars), *(iv)* TANGIBILITY (ratio of property, plant and equipment to total assets), *(v)* TLTA (ratio of total liabilities to total assets), *(vi)* ANALYST COVERAGE (dummy variable indicating whether a company is followed by at least one analyst or none) and *(vii)* SIGMA (the annualized standard deviation of a firm's daily log stock returns in the prior three months). Panels A and B report the results for the C6 countries, while Panels C and D report the corresponding results for the C14 countries. The OOS CDR measures are recursively estimated as described in Section 3 and the caption of Table 6. We sort stocks into ascending order according to their OOS CDR estimated values in December of year $t-1$ and classify them into quintile portfolios (Q1 to Q5), while we also independently sort stocks into ascending order according to the value of each firm characteristic in December of year $t-1$ and classify them into tercile portfolios (Low, Medium, High). The only exception is analyst coverage, where we assign firms to two portfolios depending on whether there is at least one analyst following the firm or none. The intersection of these two classifications yields the double-sorted portfolios. Portfolios are held from February of year t to January of year $t+1$, at which point they are rebalanced. Results are reported only for the highest and the lowest default risk quintile portfolios (Q5 and Q1, respectively) within the High or the Low classification for each firm characteristic, respectively. Moreover, we report the average excess return for the spread strategy Q5-Q1 within the H or L classification. For comparison, column ALL reports the returns for single-sorted quintile portfolios according to OOS CDR estimates. Returns are calculated for a U.S.-based investor and they are reported for both value-weighted (vw) and equally-weighted (ew) portfolios. Average excess portfolio returns and alphas are annualized and bolded; their associated t-statistics are reported in square brackets. The examined period is January 2000-December 2010. ***, ** and * in the column "Diff" indicate that the difference between the High and Low classification returns in each case is statistical significant at 1%, 5% and 10% levels, respectively.

		SIZE			BOOK-TO-MARKET			PRICE			TANGIBILITY			TLTA			ANALYST			SIGMA		
CDR	ALL	High	Low	Diff	High	Low	Diff	High	Low	Diff	High	Low	Diff	High	Low	Diff	0	> 0	Diff	High	Low	Diff
Panel A: Value-weighted Global Portfolios Based on C6 Countries																						
Quintile 5	**5.34**	**5.21**	**11.10**	*	**11.93**	**3.22**	**	**2.10**	**15.89**	**	**8.81**	**2.46**		**5.09**	**3.98**		**-4.13**	**8.84**		**3.48**	**5.79**	
	[0.57]	[0.55]	[1.14]		[1.17]	[0.36]		[0.24]	[1.36]		[0.93]	[0.22]		[0.57]	[0.32]		[-1.83]	[0.93]		[0.27]	[0.66]	
Quintile 1	**-4.35**	**-4.52**	**15.86**	***	**7.83**	**-8.58**	***	**-5.65**	**28.77**	***	**-5.94**	**-7.19**		**-2.63**	**-5.79**		**-8.22**	**2.64**		**-6.01**	**-1.80**	
	[-0.59]	[-0.61]	[1.47]		[1.04]	[-1.07]		[-0.77]	[2.46]		[-0.79]	[-0.78]		[-0.39]	[-0.73]		[-2.24]	[0.34]		[-0.40]	[-0.29]	
Spread (Q5-Q1)	**9.69**	**9.73**	**-4.77**	**	**4.11**	**11.80**	*	**7.74**	**-12.87**	***	**14.75**	**9.65**		**7.72**	**9.77**		**4.09**	**6.20**		**9.49**	**7.59**	
	[1.96]	[1.83]	[-0.86]		[0.76]	[2.60]		[1.69]	[-1.89]		[2.34]	[1.88]		[2.48]	[1.39]		[1.24]	[1.47]		[1.17]	[1.64]	
Panel B: Equally-weighted Global Portfolios Based on C6 Countries																						
Quintile 5	**13.35**	**7.15**	**24.30**	***	**20.08**	**9.83**		**1.89**	**24.38**	***	**20.69**	**7.63**	**	**10.81**	**21.96**	*	**-11.85**	**17.92**	***	**24.66**	**6.63**	***
	[1.37]	[0.67]	[2.41]		[1.99]	[0.91]		[0.23]	[2.08]		[2.21]	[0.67]		[1.18]	[1.84]		[-3.50]	[1.83]		[2.00]	[0.84]	
Quintile 1	**4.76**	**-0.13**	**26.74**	***	**11.73**	**-1.87**	***	**-2.38**	**35.85**	***	**8.55**	**3.69**		**4.66**	**5.77**		**-7.23**	**9.10**	*	**11.54**	**3.78**	
	[0.58]	[-0.02]	[2.32]		[1.49]	[-0.18]		[-0.29]	[2.78]		[1.08]	[0.34]		[0.56]	[0.60]		[-1.99]	[0.97]		[0.78]	[0.68]	
Spread (Q5-Q1)	**8.59**	**7.27**	**-2.44**		**8.35**	**11.70**		**4.28**	**-11.47**	***	**12.14**	**3.95**	*	**6.14**	**16.20**	*	**-4.62**	**8.83**	**	**13.11**	**2.85**	
	[1.99]	[1.27]	[-0.47]		[1.61]	[2.06]		[0.81]	[-2.87]		[2.74]	[0.72]		[1.54]	[2.77]		[-1.45]	[2.49]		[1.98]	[0.65]	

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Table 11 (continued)
Double-Sorted Sorted Default Risk Portfolios

		SIZE			BOOK-TO-MARKET			PRICE			TANGIBILITY			TLTA			ANALYST			SIGMA		
CDR	ALL	High	Low	Diff	High	Low	Diff	High	Low	Diff	High	Low	Diff	High	Low	Diff	0	> 0	Diff	High	Low	Diff
Panel C: Value-weighted Global Portfolios Based on C14 Countries																						
Quintile 5	**5.99**	**6.00**	**10.20**		**13.16**	**2.64**	**	**3.18**	**14.87**	*	**8.69**	**3.55**		**5.78**	**3.83**		**-4.90**	**9.98**		**3.97**	**7.01**	
	[0.64]	[0.64]	[0.99]		[1.28]	[0.29]		[0.36]	[1.20]		[0.93]	[0.32]		[0.64]	[0.32]		[-2.11]	[1.06]		[0.34]	[0.80]	
Quintile 1	**-4.05**	**-4.25**	**15.04**	***	**8.19**	**-6.74**	***	**-5.54**	**5.05**	*	**-4.98**	**-7.09**		**-2.58**	**-4.55**		**-8.42**	**2.96**		**-7.48**	**0.29**	
	[-0.53]	[-0.56]	[1.51]		[1.11]	[-0.81]		[-0.73]	[0.52]		[-0.65]	[-0.77]		[-0.37]	[-0.54]		[-2.65]	[0.37]		[-0.51]	[0.05]	
Spread (Q5-Q1)	**10.04**	**10.25**	**-4.84**	**	**4.97**	**9.38**		**8.72**	**9.82**		**13.67**	**10.64**		**8.36**	**8.38**		**3.52**	**7.03**	*	**11.45**	**6.71**	
	[2.17]	[2.06]	[-0.86]		[0.92]	[2.06]		[1.90]	[1.73]		[2.35]	[2.05]		[2.55]	[1.33]		[1.15]	[1.75]		[1.48]	[1.50]	
Panel D: Equally-weighted Global Portfolios Based on C14 Countries																						
Quintile 5	**13.97**	**8.66**	**22.99**	***	**21.16**	**8.83**	**	**2.02**	**25.12**	***	**20.07**	**8.62**	**	**11.51**	**20.74**	*	**-11.06**	**17.90**	***	**22.63**	**7.87**	**
	[1.42]	[0.84]	[2.29]		[2.08]	[0.82]		[0.23]	[2.13]		[2.12]	[0.76]		[1.25]	[1.78]		[-3.36]	[1.80]		[1.88]	[1.00]	
Quintile 1	**5.07**	**0.44**	**23.57**	***	**12.42**	**-1.93**	***	**-1.43**	**24.02**	***	**8.59**	**3.19**		**5.62**	**5.85**		**-6.98**	**9.14**	*	**10.41**	**5.57**	
	[0.65]	[0.06]	[2.21]		[1.62]	[-0.20]		[-0.18]	[2.37]		[1.15]	[0.30]		[0.71]	[0.65]		[-2.05]	[1.05]		[0.72]	[1.05]	
Spread (Q5-Q1)	**8.90**	**8.21**	**-0.58**		**8.75**	**10.75**		**3.45**	**1.10**		**11.48**	**5.43**		**5.89**	**14.89**	**	**-4.08**	**8.76**	**	**12.21**	**2.30**	
	[2.20]	[1.73]	[-0.12]		[1.76]	[2.15]		[0.69]	[0.28]		[2.99]	[1.05]		[1.45]	[3.00]		[-1.56]	[2.63]		[1.83]	[0.56]	

Figure 1
Default Risk Portfolio Factor Loadings

This figure presents the market, size (SMB), value (HML) and momentum (MOM) factor loadings (betas) of decile portfolios sorted on the basis of the out-of-sample (OOS) Campbell et al. (2008) default risk (CDR) measure. 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 January 2000-December 2010. Factor loadings are presented for portfolios of stocks from the C6 countries (Australia, Canada, France, Germany, Japan and the U.K.), the C14 countries (the C6 countries plus Denmark, Finland, Hong Kong, New Zealand, Portugal, Spain, Sweden and Taiwan) and for each of the 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). Factor returns are calculated for each asset universe described. To estimate OOS CDR values, a LOGIT model is recursively run for each of the C6 countries; see section 3 and the caption of Table 6. For the rest countries that feature too few bankruptcies, we run recursively a LOGIT model for each bankruptcy law regime.

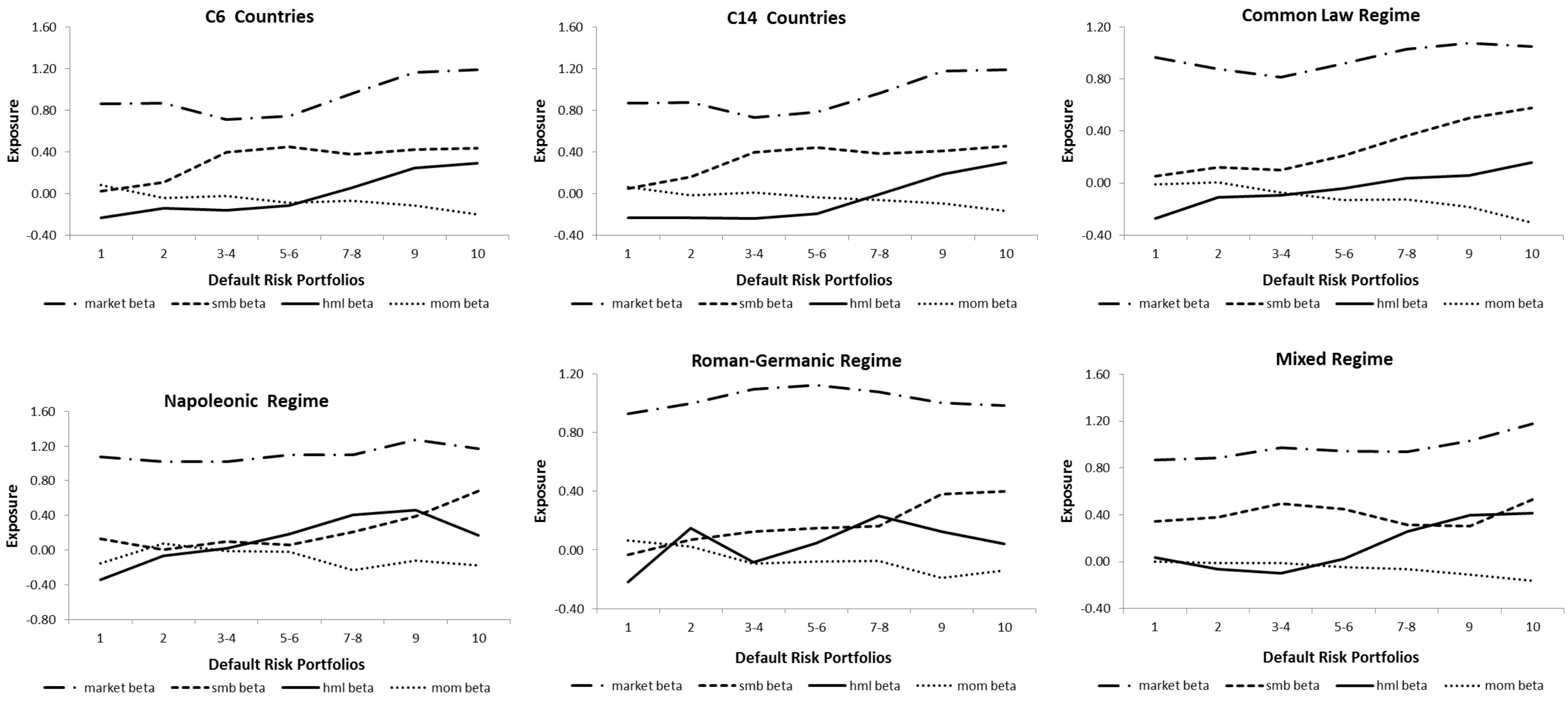

Figure 2
Profitability of Distress Risk Spread Strategies

This figure shows the profitability of distress risk spread strategies that go long the decile portfolio with the highest default risk stocks (P10) and go short the decile portfolio with the lowest default risk stocks (P1), as classified on the basis of the Campbell et al. (2008) default risk (CDR) measure. The upper panel uses as a portfolio sorting variable out-of-sample (OOS) CDR values, estimated recursively using LOGIT models, as described in the caption of Table 6, and the examined period is January 2000-December 2010. The lower panel uses as a portfolio sorting variable in-sample (IS) CDR values, estimated from full sample LOGIT models, as described in the caption of Table 7, and the examined period is January 1992-December 2010. Portfolios P10 and P1 are formed at the end of each December of year *t-1* and they are held from February of year *t* to January of year *t+1*, at which point they are rebalanced. Returns are calculated for a U.S.-based investor and they are reported for both value-weighted (vw) and equally-weighted (ew) portfolios. The investment universe are the C6 countries (Australia, Canada, France, Germany, Japan and the U.K.) or 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 bear market periods characterized with respect to the dollar-denominated price level of the MSCI World ex US index.