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Default Risk Premium in the Equity Market

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Abstract

This paper explores the default risk premium within the equity market. To our knowledge, this is the first study that uses the commercially-available structural model, Moody's Analytics Public Firm Model, EDF9^{TM}, to explain the cross-section of stock returns. While distressed stocks have attracted attention in the past for their anomalously low returns, we also identify outperformance of "safe" stocks. The notions of safe and distressed are both defined in the context of Distance-to-Default within the Moody's Analytics Public Firm Model(also known as KMV). Our findings revisit the notion that value, size, and momentum price the financial distress risk. We find that safe stocks outperform the market, and risky stocks significantly underperform the market. Although our findings show similarities with the low volatility anomaly, our factor is not a proxy for the low volatility factor.

Contents

1. Introduction

A rich literature discusses using option pricing models to estimate the probability of default on single names. Merton pioneered structural credit risk models, and shortly after, they were further developed for more complicated capital structures;[1] see Merton (1974), Black and Cox (1976), Kealhofer (2003a), Kealhofer (2003b), and Leland (1994). This class of models looks at a firm's equity as a perpetual call option on the asset value of the firm. The model's goal is to quantify how close a firm is to financial distress. The majority of the literature assesses the performance of the calculated credit score, by benchmarking it against default events. In this study, however, we assess the performance of a Probability of Default (PD) model as a predictive signal to build portfolios in the public equity market.

Several studies focus on probability of default as an equity market risk factor. Campbell, Hilscher, and Szilagyi (2008) show the relationship between distress and cross-section of equity returns. They build a reduced-form model to calculate Distance-to-Default (DD). Vassalou and Xing (2004) show a relationship between default risk and equity returns using the Merton model. The results of these two papers are mostly consistent.

Our work focuses on the relationship between equity returns and distress for two reasons. First, most of the literature does not use commercially-available probability of default models, and the few who do, utilize older versions of the KMV model[2]. However, the most recent Moody's Analytics Public Firm Model has undergone notable improvements. Second, the past ten years have been an interesting economic period, where investors have experienced boom, bust, sluggish recovery, and low volatility. We are interested in assessing whether the anomaly documented by these studies has been arbitraged away or if it still persists.

Several studies examine the relationship between default risk and equity risk premium. A number of these studies try to establish whether default risk is systematic or idiosyncratic. These studies are important, because these two views suggest using different asset pricing models to price cross section of stock returns. Our work provides supporting evidence for systematic default risk. However, the literature has not yet arrived at consensus. Denis and Denis (1995) link default risk to macroeconomic factors and variability with the credit cycle. Opler and Titman (1994) and Asquith, Gertner, and Scharfstein (1994) provide evidence that default risk is related to idiosyncratic factors. Our study is perhaps most similar to those presented by Campbell, Hilscher, and Szilagyi (2008) and Vassalou and Xing (2004), which both present evidence for default risk as a systematic risk factor. While most of the studies have used accounting-based models to predict default, Campbell, Hilscher, and Szilagyi (2008) and Vassalou and Xing (2004) use market-based signals for predicting defaults. Studies by Dichev (1998) and Griffin and Lemmon (2002) fall in the class of accounting-based models. Both of these studies use Altman's Z-score or Olson's model to predict bankruptcy. Another relevant study is the relationship between financial distress and cross-section of equity returns by Garlappi and Yan (2011). They report a humped-shaped pattern between value premium and default probability, as well as stronger momentum profits for nearly distressed firms. In order to explain the relationship between shareholder recovery, the probability of default, and equity returns, Garlappi and Yan (2011) use a valuation model. Their study uses older generations of the Moody's Analytics Public Firm Model and the data spans 1969-2007.

Our work differs slightly from the aforementioned papers. First, we use market-based signals to predict default. While we do find valuable information in the financials released by companies, most of the data is irrelevant and backward-looking. Market-based signals are forward-looking, and when appropriately utilized, they provide more accurate estimates. Campbell, Hilscher, and Szilagyi (2008), Vassalou and Xing (2004), and Garlappi and Yan (2011) use market-based signals with slight variations. Campbell, Hilscher, and Szilagyi (2008) find that a DD-based on a structural model adds little explanatory power to their model. Vassalou and Xing (2004) implement Merton's structural model to predict default, and Garlappi and Yan (2011) use older generations of the EDF credit metric from Moody's Analytics Public Firm Model.[3] In this study, we use the DD values produced by the ninth generation of the KMV model, now under the Moody's Analytics brand. In its latest generation, the model has undergone significant changes, and we have seen improvements in accuracy ratios and levels. Therefore, it is worthwhile examining the relationship between default and equity risk premiums. Moreover, we are curious to examine this relationship within the context of latest credit cycle.

We begin our empirical work by looking at the Distance-to-Default/Expected Default Frequency (DD/EDF) values along with equity returns from January 2004 until December 2015. Since we are interested in the performance of the Moody's Analytics Public Firm Model, we take the EDF values as is. In the process of developing the public firm model, we use Moody's Analytics default database, a proprietary database with more than 11,000 single name defaults. While we have primarily used the DD values to rank firms, a

[1] For details regarding the KMV implementation of the model please refer to Corsbie and Bohn (2003), Dwyer and Qu (2007), Arora, Bohn, and Korablev (2005), Kealhofer03a, and Kealhofer (2003b). Nazeran and Dwyer (2015) report the latest implementation of the model along with validation of the model in the most recent financial crisis.

[2] Garlappi and Yan (2011) have looked at the Moody's KMV as a default indicator in their equity valuation model. The differences in modeling and performance between the version of the model they used and the latest version is significant. Moreover, our sample starts from 2004, spans 11 years.

[3] EDF^{TM} is Moody's trademark for Probability of Default produced by Moody's Analytics.

similar performance can be obtained by looking at the EDF values as there is a one-to-one mapping between DD and EDF values and the ranking is relative. Our findings confirm the results reported by Campbell, Hilscher, and Szilagyi (2008), Vassalou and Xing (2004) and Garlappi and Yan (2011). When it comes to default risk, the notion that high return demands high risk does not hold in our findings. However, while CAPM implies that higher risk implies higher return, we find the opposite with regard to credit risk and equity return. After estimating the DD, we look at the performance of the portfolios based on DD values benchmarked against well-known asset pricing models. Primarily, we are interested in the alphas, the significance of alphas, and the factor loadings.

One of the surprising take-aways of our study is that higher credit risk portfolios (according to the Moody's Analytics Public Firm model EDF's credit metric) show pronounced underperformance compared to the market. This finding is accompanied by elevated equity risk. Put differently, portfolios that show high EDF values underperform the market and also demonstrate elevated equity risk. The reverse is true for portfolios with low EDF values, considered "safe". We observe that extremely safe/risky portfolios show significant alphas that are not explained by conventional asset pricing models. It is beneficial to revisit the hump-shape reported by Garlappi and Yan (2011). While Campbell, Hilscher, and Szilagyi (2008), Vassalou and Xing (2004), and Garlappi and Yan (2011) report the same finding, we repeat the exercise with the low volatility factor. Although there seem to be non-trivial similarities between default risk factor and low-volatility, the returns in the "extremely risky" and the "safe" portfolios are left unexplained after adding low-volatility to the asset pricing model.

The remainder of this paper is organized as follows. Section 2 explains our back-test sample and various robustness filters we apply. It also provides summary statistics on the default database. Section 3 shows the results of the back-test as well as summary statistics on the portfolios. Section 4 concludes.

2. Data Description

Three sets of data are combined to form this study: equity returns, credit risk scores, and market risk factors. In the rest of this section, we will describe each of these datasets.

We use the CompuStat market price for equity returns. The data begins January 2004 and goes through December 2015. For credit risk, we use the ninth generation of the Moody's Analytics Public Firm EDF Model's Distance-to-Default, EDF9. This credit measure is, in turn, constructed by taking CompuStat market data and financial statements as input. The model's estimation and calibration benefits from a database of more than 11,000 public firm defaults. The Public Firm Model is an option-pricing model at heart, which considers the optionality in equity due to limited liability, and uses that optionality to estimate the market value of assets. The model then uses the liability term structure to arrive at a default-point, the conceptual equivalent to an option's strike price. Last, the model uses deleveraged equity returns to arrive at an asset volatility, as is used to properly price the optionality of the equity. All this information is then summarized in a single credit-risk factor known as Distance-to-Default (DD), which is not unlike Black Scholes' $d2$, in their option pricing model. For more details on the Public Firm EDF Model, refer to Nazeran and Dwyer (2015), and for more information on the option pricing refer to Black and Scholes (1973).

For market risk factors, we rely on two data sources, AQR and Professor Ken French's website.[4] In models with no low-volatility factor, we use data from Professor Ken French's website. In the model with a volatility factor (last row of Panel A of Table 2), we obtain data from AQR's website.[5] The default and bankruptcy data comes from Moody's Analytics default database. The sample accounts for bankruptcies (Chapter 11) and liquidations (Chapter 7).[6] In particular, this sourcing remains consistent with the framework in Campbell, Hilscher, and Szilagyi (2008), since the default database does not include delisting or acquisition. Table 1 shows the statistic on defaults and active firms per year.

Each observation's accounting and market data are aligned, such that, future information is never used. Our financial statement processing engine incorporates a timestamp on each newly available financial statement. This timestamp captures time of availability from the data vendor. We align the financial statement to the market data only when the timestamp on the financial statement comes before the timestamp on market data. This setup results in ex-ante measures of credit risk. Thus, we can see model performance in the equity market based on EDF credit metric's signals. Moreover, we are confident that we do not introduce forward-looking bias into the back-test, as financial statement arrival is accurately time-stamped and we are not merely relying on an effective date provided by the vendor.

Table 1: Shows the number of active firms, the number of observations, and the number of defaults in the United States. We define "Active Firm" as one that has been in the sample at least one month of the year.

Year	Active Firms	Observations	Defaults
2004	7,564	78,247	112
2005	7,315	82,370	98
2006	7,056	79,563	67
2007	6,904	77,092	91
2008	6,510	74,173	174
2009	6,231	71,167	269
2010	6,161	68,627	136
2011	5,965	65,444	122
2012	5,863	64,781	130
2013	5,815	64,319	71
2014	5,709	64,097	50
2015	5,816	62,634	77

In constructing the sample, we make a few assumptions to improve the robustness of the results. Since the study measures the return to distressed and safe stocks, it is critical to select an appropriate sample. First, we sort the stocks in the U.S. based on market capitalization, excluding the bottom 30%. Limiting the analysis to top 70$^{\text{th}}$ percentile helps us avoid trading microcap stocks. Second,

[4] Please refer to `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

[5] We used the data from 'Betting Against Beta' paper. For more details please refer to Frazzini and Pedersen (2014) and the library section in the AQR's website.

[6] For details regarding our definition of the default please refer to Nazeran and Dwyer (2015).

once the stock price becomes illiquid (if it is not traded during the 10 days prior to the month-end), we exclude it from the tradable universe for that particular month. Third, once a company files for bankruptcy, we calculate the return in that month and exclude the company from the sample going forward. This setup does not allow for multiple defaults, yet we are confident that multiple defaults will not change the results drastically, as they are infrequent. Fourth, if the stock price falls below $1, that observation is dropped from the sample for that particular month. This filter is very similar to the one employed by Campbell, Hilscher, and Szilagyi (2008), and it is intended to reduce turnover costs and the bid-ask bounce.

3. Default Risk Premium

This section investigates the asset pricing implications of the Moody's Analytics Public Firm Model. Previous studies use various accounting-based and structural models to predict default. Altman Z-score, Ohlson O-score, older versions of the KMV model, and custom models all appear in the literature. As mentioned in Section 1, recent advances in the Moody's Public Firm Model has substantially improved performance, thus, we can revisit the equity market default risk premium with more accuracy.

At the beginning of each month, we sort the tradable stocks in the universe according to their DD values. We calculate portfolio monthly returns, and, at the end of the month, we rebalance the portfolio. We then form nine value-weighted portfolios based on the percentiles of the DD distribution. In particular, the portfolios contain stocks in percentiles 0-5, 5-10, 10-20, 20-40, 40-60, 60-80, 80-90, 90-95, and 95-100. Although we sort the stocks based on their DD values, because of the monotonic mapping between DD and EDF values, results can be replicated using percentiles in the EDF space as well. Following Campbell, Hilscher, and Szilagyi (2008) and Vassalou and Xing (2004), we construct long-short market capitalization-weighted portfolios that go long 5% to 10% of safest stocks and short the 5% or 10% of riskiest stocks.

Figure 1 shows the annualized return and annualized volatility of the portfolios. Surprisingly, the portfolio with the highest (lowest) default risk, demonstrates lowest (highest) return and highest (lowest) volatility. The relationship is monotonic for both volatility and returns which makes the finding puzzling. This result contrasts with CAPM's risk-return notion.

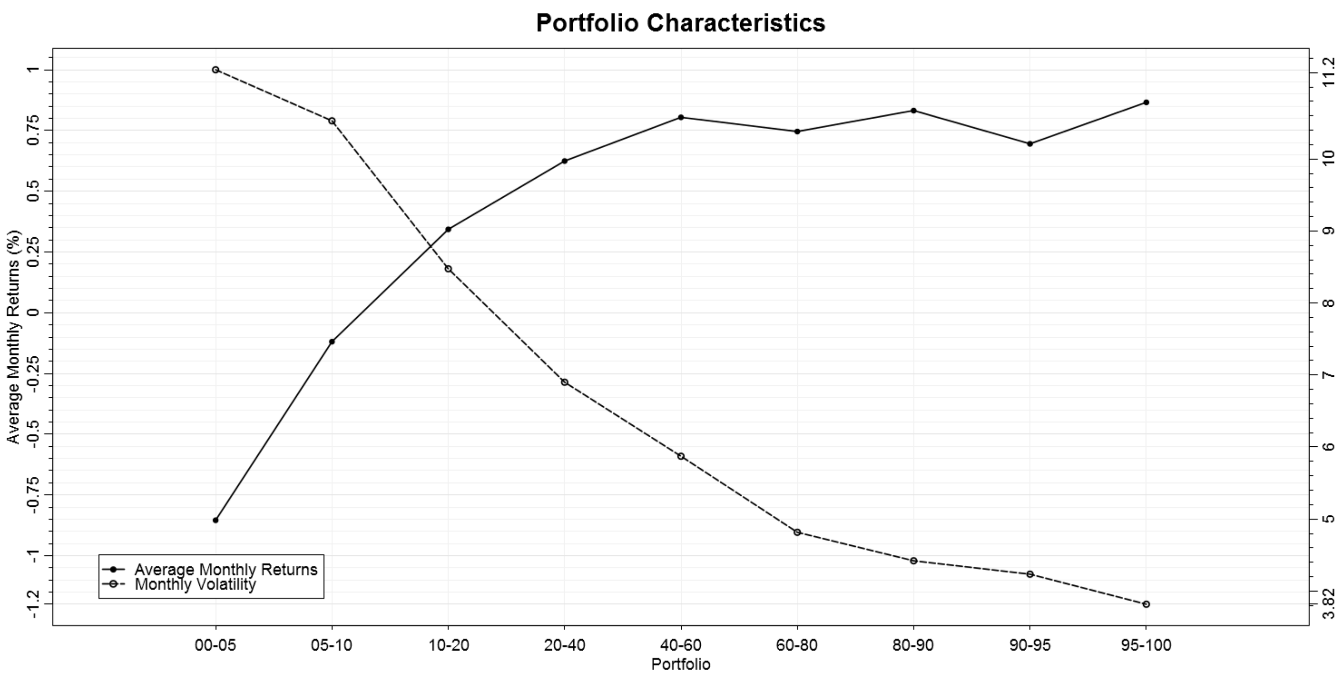

Figure 1: Monthly return versus monthly volatility of the portfolios based on DD buckets. The safe (risky) portfolios show positive (negative) returns as well as low (high) monthly volatility. The plot contrasts with CAPM's notion of risk and return.

Figure 1 indeed shows an intriguing result. Investors who hold portfolios with safe stocks not only experience higher returns, but they also observe lower volatility in their holdings. In order to assess the significance of these results, we look at the performance of annualized excess returns of holding portfolios formed based on DD against the well-known asset pricing models. Table 2 shows the results.

Panel A shows the annualized alphas and their significance with respect to various asset pricing models. We start from the CAPM and move to the seminal three-factor Fama and French model. Next, we consider the addition of the momentum factor reported by Carhart. The final asset pricing model we consider adds the low volatility factor to the four-factor model (please refer to Treynor (1961a), Treynor (1961b), Sharpe (1964), Lintner (1965), Fama and French (1993), Carhart (1997) and Frazzini and Pedersen (2014) for details regarding these asset pricing models). Panel B shows the factor loadings and their significance. Panel C shows the portfolio statistical characteristics. Portfolios that are extremely safe (risky) have experienced significant positive (negative) alpha. The result is robust with respect to various asset pricing models. In Figure 1 we see that high (low) volatility portfolios are associated with lower (higher) returns. This observation does seem to have similarities with low volatility anomaly, Frazzini and Pedersen (2014). Interestingly, results remain significant even after testing the returns against an asset pricing model that controls for low volatility factor.

Panel B shows factor loadings and their level of significance. Our findings are generally in-line with the loadings reported by Campbell, Hilscher, and Szilagyi (2008), with the exception of the market factor, which we report to have higher levels across the board. Campbell, Hilscher, and Szilagyi (2008) do not report momentum and low volatility factor loadings. Empirical results show low (high) market exposure, insignificant (positive) value and size loading, positive (negative) momentum exposure, and insignificant (positive) low volatility exposure in the portfolios that are safe (risky). If our null hypothesis is that credit risk proxies for low volatility factor, the data rejects our null.

Panel C provides portfolios characteristics. There are a few interesting observations in Panel C. First, we can see the Sharpe ratio is improving from the riskiest portfolio to the safest and, eventually, the long-short portfolios. Second, the portfolio volatilities falls as we move from riskier to safer portfolios, as we reported earlier. Third, the skewness of portfolios seems to be negative and increasing as we move to safer portfolios. Thus, the portfolios that outperform the market have a higher likelihood of large drawdowns. Fourth, portfolios that underperform the market have lower market capitalization compared to portfolios that outperform the market. This observation contrasts with the size factor reported by Fama and French (1993). Last, the mean EDF values demonstrate the average of EDF value in the risky and safe buckets.

In the last part of this section, we turn to the performance as well as the diversification benefits of long-short strategies based on the default factor. In Figure 2, we observe the equity curve of two unlevered value-weighted long-short portfolios compared to the S&P500. LS1090 and LS0595 represent the long-short portfolios based on 10^{th}-90^{th}, and 5^{th}-95^{th} DD percentiles respectively. Lo and Patel (2008) argue that leveraged portfolios cannot be benchmarked against the S&P500; in order to maintain a consistent comparison, we keep the portfolios unlevered. The long-short portfolios consistently outperform the market. In Figure 3, we see the drawdown curves of the long-short portfolios compared to the S&P500. In the midst of the global financial crisis, the S&P500 suffered a 70% drawdown, and it did not touch the high-water mark set in 2007 until 2013. However, the long-short portfolios experienced a 55% drawdown during the same time period and recovered their losses in early 2012.

Our empirical analysis thus far points to one conclusion, investors can construct better risk-adjusted portfolios ex-ante if they consider the default risk characteristics of the names in the portfolio. Our conclusion is not based solely on higher returns. The diversification benefits of long-short portfolios, and even long-only portfolios for that matter, can be quantified in terms of drawdowns, Sharpe ratio, and portfolio volatility.

Table 2: We define the universe of stocks in Section 2. We take all those stocks and sort them based on their DD values. We then construct nine value-weighted portfolios and calculate their returns. The top row shows the percentiles that define the cutoff. We also construct two long-short value-weighted portfolios that go long 5% or 10% of the safe stocks and short 5% or 10% of the risky stocks. We report the results of excess returns over the market on a constant, market return (CAPM), as well as three (MKT, HML, SMB), four (MKT, HML, SMB, UMD), and five (MKT, HML, SMB, UMD, BAB) factor model. The three and four-factor models are taken directly from professors Ken French's website, while the factors in the five-factor model are taken from AQR's website. The sample is from 2004-2016. Panel A shows the annualized alphas and their significance. Panel B shows the factor loadings and their significance. The factor loadings are from the regression of excess returns on the five-factor regression model. Panel C shows the characteristics of portfolios. All values in bold are significant at the 10% level. We use Newey-West kernel with three lags to calculate robust standard errors.

Portfolio (DD Percentile)	00-05	05-10	10-20	20-40	40-60	60-80	80-90	90-95	95-100	LS-05-95	LS-10-90
Panel A. Excess Returns											
Mean Excess Return	-16.63	-7.32	-1.98	1.38	3.59	2.89	**4.35**	1.70	**4.28**	**9.32**	**8.34**
	(1.90)	(0.95)	(0.36)	(0.36)	(1.38)	(1.75)	**(3.08)**	(1.17)	**(2.62)**	**(2.63)**	**(2.40)**
CAPM Alpha	**-24.54**	**-15.87**	**-8.30**	-3.20	0.11	0.62	**2.67**	0.62	**3.73**	**4.56**	**3.51**
	(3.49)	**(2.60)**	**(2.07)**	(1.10)	(0.06)	(0.51)	**(2.70)**	(0.50)	**(2.44)**	**(2.83)**	**(2.89)**
FF 3 Factor	**-23.33**	**-14.13**	**-7.02**	-2.35	0.52	0.74	**2.61**	0.41	**3.54**	**4.36**	**3.26**
	(3.81)	**(2.81)**	**(2.22)**	(0.99)	(0.31)	(0.62)	**(2.64)**	(0.35)	**(2.27)**	**(2.67)**	**(2.80)**
FF 3 + Carhart Mom	**-21.22**	**-12.53**	**-5.96**	-1.53	0.99	0.76	**2.52**	0.35	**3.22**	**3.99**	**2.97**
	(3.59)	**(2.76)**	**(2.19)**	(0.70)	(0.63)	(0.57)	**(2.46)**	(0.27)	**(2.30)**	**(2.74)**	**(2.72)**
FF 3 + Carhart Mom + BAB	**-25.85**	**-13.63**	-5.75	-1.45	1.70	2.00	**2.55**	0.16	**3.36**	**4.30**	**3.23**
	(4.29)	**(2.59)**	(1.80)	(0.59)	(1.04)	(1.98)	**(2.50)**	(0.13)	**(2.38)**	**(2.99)**	**(3.20)**
Panel B. Factor Loadings											
MKT	**1.44**	**1.54**	**1.36**	**1.20**	**1.15**	**1.05**	**0.99**	**0.99**	**0.89**	**0.82**	**0.83**
	(8.86)	**(15.80)**	**(13.72)**	**(33.62)**	**(30.16)**	**(38.11)**	**(34.81)**	**(44.43)**	**(30.75)**	**(23.36)**	**(27.61)**
HML	**0.90**	**0.97**	**0.65**	**0.53**	**0.35**	**0.14**	**0.09**	-0.09	-0.11	**-0.13**	**-0.15**
	(3.36)	**(5.25)**	**(3.87)**	**(6.27)**	**(4.67)**	**(2.75)**	**(2.18)**	(1.39)	(1.71)	**(2.01)**	**(2.82)**
SMB	0.42	**0.93**	**0.70**	**0.40**	0.11	0.02	-0.08	**-0.14**	-0.06	-0.06	**-0.12**
	(1.51)	**(4.81)**	**(4.23)**	**(4.78)**	(1.92)	(0.38)	(1.39)	**(2.77)**	(0.97)	(0.97)	**(2.72)**
MOM	**-0.84**	**-0.56**	**-0.34**	**-0.27**	**-0.13**	0.03	0.03	0.02	**0.11**	**0.13**	**0.10**
	(6.30)	**(4.37)**	**(4.82)**	**(6.17)**	**(4.26)**	(0.64)	(1.01)	(0.44)	**(2.89)**	**(3.36)**	**(2.49)**
BAB	**0.83**	0.20	-0.04	-0.01	**-0.13**	**-0.22**	-0.01	0.03	-0.03	-0.05	-0.05
	(2.17)	(0.80)	(-0.20)	(0.16)	**(2.46)**	**(5.67)**	(0.14)	(0.78)	(0.69)	(1.30)	(1.28)
Panel C. Portfolio Characteristics											
Portfolio Sharpe Ratio	-0.33	-0.13	0.07	0.25	0.42	0.46	0.59	0.46	0.67	0.80	0.69
Portfolio SD (%)	38	36	29	24	20	17	15	15	13	-	-
Portfolio Skewness	0.10	-0.77	-0.31	-0.45	-0.58	-0.47	-0.62	-1.08	-0.65	-	-
Mean Market Capitalization ($MM USD)	245	379	678	1113	1811	3346	5368	7790	9878	-	-
Mean Book-to-Market	1.55	1.21	0.95	0.75	0.61	0.52	0.46	0.41	0.40	-	-
Mean EDF (%)	12.13	5.95	3.31	1.47	0.59	0.25	0.13	0.09	0.07	-	-

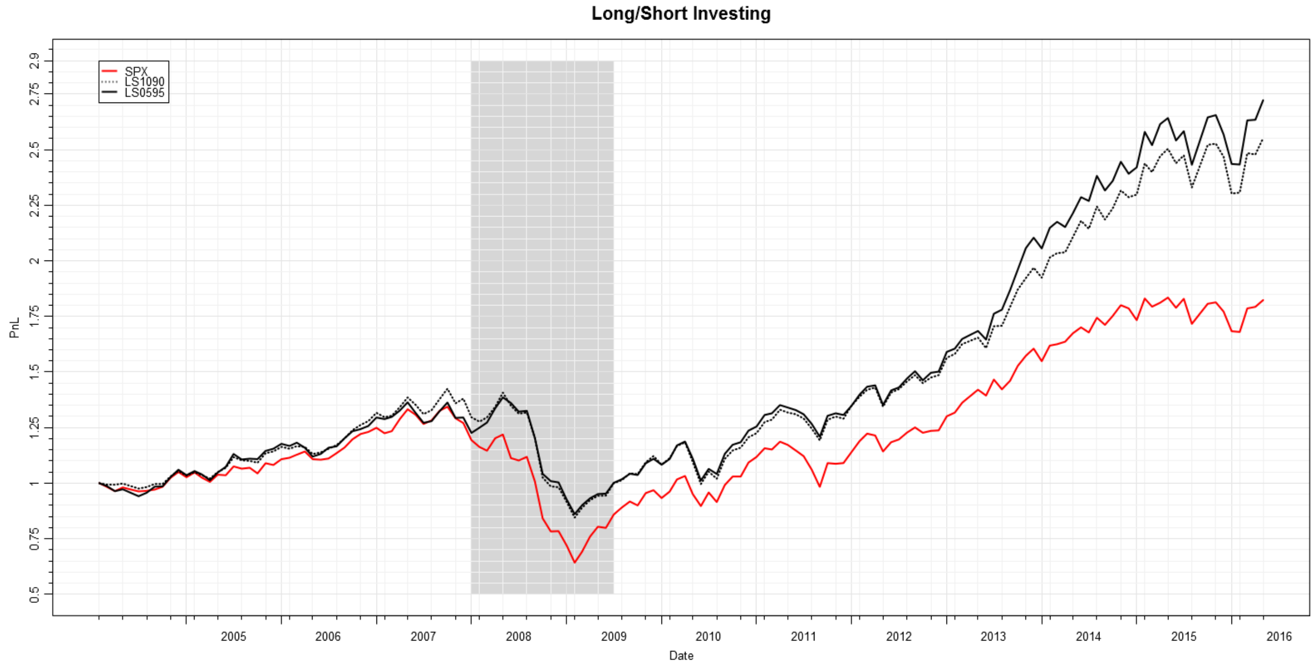

Figure 2: Equity curve of long-short portfolios with respect to the S&P500. The long-short portfolios go long 5% or 10% of the safest stocks and short 5% or 10% of the riskiest stocks.

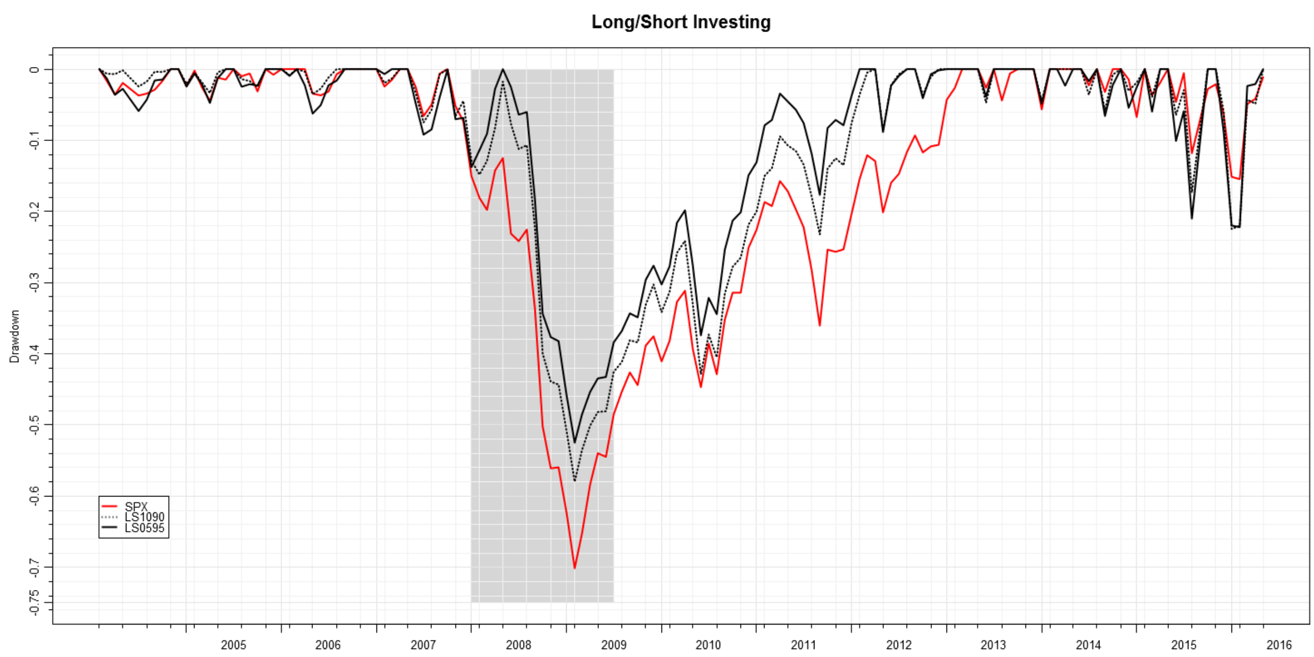

Figure 3: Long-short portfolio drawdown curves compared to the S&P500 drawdown. The S&P500 demonstrates a steeper and longer drawdown.

4. Conclusion

In this empirical study, we look at default risk premium in the equity market. Our findings extend the literature in a few new ways. First, we use the ninth generation of the Moody's Analytics Public Firm Model (EDF9) which shows significant improvement compared to its predecessors. Higher accuracy in estimating default risk results in better-constructed portfolios based on DD. Second, we test the excess returns of the portfolio constructed based on DD/EDF values using various asset pricing models, e.g. low volatility factor. We find that default risk is still a risk factor after controlling for market, value, size, momentum, and low-volatility. Third, we examine the performance of the anomaly after it was reported by Campbell, Hilscher, and Szilagyi (2008). Many papers have looked at various measures of default risk and reported similar results as Campbell, et al. In an efficient market, we would expect to find these opportunities arbitraged away, or at least less pronounced since their discovery. We do observe performance similar to that reported by Campbell, Hilscher, and Szilagyi (2008), and Vassalou and Xing (2004) in the portfolios for the U.S. equity market from 2004-2015. In fact, the performance of the long-only or long-short portfolios remains significant and robust against more recent anomalies and asset pricing models.

Contrary to the CAPM style risk and return notion, the portfolios with high (low) DD exhibit high (low) returns and low (high) volatilities. Garlappi and Yan (2011) report a hump-shaped relationship between risk and return of portfolios formed based on credit risk. We observe that high credit-risk portfolios show monotonicly increasing returns as credit risk drops. As for low credit-risk firm, the returns are somewhat insensitive to the credit risk. We find significant positive (negative) alpha in the safe (risky) portfolios as well as long-short portfolios. Results are robust with respect to various asset pricing models.

Last, we explore the diversification benefits of holding portfolios based on default risk compared to the S&P500. The unlevered long-short portfolios do outperform the S&P500 consistently. Moreover, they experience smaller and shorter drawdowns. Since the excess returns in the extremely safe and extremely risky portfolios are not explained by any of the asset pricing models, investors can construct better risk-adjusted portfolios by obtaining exposure to the default risk factor. Although our study constructs portfolios using percentiles of DD values, because of the monotonic mapping between DD and EDF values, we believe the results are reproducible in the EDF measure space.

In the final analysis, we find EDF9 of relevant ex-ante information for public equity market investors. Long-only, as well as, long-short portfolios demonstrate attractive risk-adjusted returns compared to the market.

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