Essays on Equity Duration and Default Risk

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Abstract

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This dissertation investigates the cross-sectional implications of equity duration, the weighted average time for shareholders to receive cash-flows from a firm in which weights are the ratio of the firm's discounted future cash-flows to the firm's price. The first chapter investigates techniques to more accurately measure equity duration. The second chapter examines the pervasiveness of the default risk puzzle that high default risk (HDR) firms earn lower abnormal returns under existing asset pricing models than low default risk (LDR) firms. The third chapter examines whether firms that differ in default risk also differ in equity duration.

In the first chapter, I examine whether cross-sectional variation in firm characteristics affects equity duration of firms. Compared to the existing estimation method, a duration measurement technique that accounts for cross-sectional variation in growth opportunities reduces firm cash-flow forecasting error scaled by the firm market-value throughout the cash-flow projection horizon (ten years). The spread in average scaled forecasting error between the two techniques is 24.16% at the end of the ten years. This less noisy cash-flow prediction translates into a longer duration differential (11.98 years) and a larger return spread (-1.83% per month) between the top and bottom decile of firms differing in equity duration than the

previously thought duration differential (8.71 years) and return spread (-1.08% per month). Existing risk factors span only 43% of the new return spread. The new technique also implies a steeper sloped term structure of equity risk premium, a 1.83% decrease as opposed to 1.48% decrease in monthly mean excess returns over the risk-free rate for a one-year increase in equity duration. This chapter suggests that accounting for cross-sectional variation in firm characteristics results in a less noisy measure of equity duration.

In the second chapter, I examine whether the default risk puzzle is pervasive across firms. The top 40th percentile of default risk firms can either delist, recover, or possess elevated default risk at the end of the sample. Irrespective of the paths, these firms earn lower abnormal returns under Fama and French (1993) three-factor model than the bottom 40th percentile of default risk firms. Further, firms that recover from elevated default risk levels earn significant positive Fama and French (1993) three-factor alphas. The alphas persist despite allowing six months for the market to assimilate earnings information before rebalancing default risk portfolios, suggesting the possibility of a missed pricing factor.

In the third chapter, I investigate whether firms with elevated default risk also have elevated equity duration and earn lower returns than LDR firms due to the downward-sloping term structure of equity risk premium. In expectation, HDR firms take longer than LDR firms to generate cash-flows for shareholders because HDR firms may use most of their short-term cash-flows to ensure their survival. Consequently, equity duration for HDR firms is 4.03 years longer than that for LDR firms. An arbitrage portfolio that buys the top decile and sells the bottom decile of firms differing in equity duration based on the new technique (chapter 1) reduces the default risk puzzle by 57% on the value-weighted arbitrage portfolio that buys the top quintile and sells the bottom quintile of default risk firms. This chapter suggests that equity duration has implications for the cross-section of returns.

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DEDICATION

To my parents, Professor Saraladevi Desabandhu and Alagarsamy Sundarraj, and my husband, Shashank, for their continuous support and encouragement.

In memory of my grandfathers.

Chapter 1

EQUITY DURATION

1.1 Introduction

Recent research in finance focuses on the timing of cash-flows from stocks to their shareholders (e.g., Van Binsbergen, Brandt, and Koijen (2012); Van Binsbergen, Wouter, Koijen, and Vrugt (2013); Van Binsbergen and Koijen (2017); Weber (2018)). Analogous to bonds, duration proxies for the timing of cash-flows from stocks to shareholders. Like Macaulay (1938)'s bond duration, equity duration of a firm is the weighted average time for shareholders to receive cash-flows from the firm with weights are the ratio of discounted future cash-flows to the firm's price (e.g., Dechow, Sloan, and Soliman (2004); Weber (2018)). Several studies suggest that long-duration stocks earn lower returns than short-duration stocks, resulting in a downward-sloping term structure of equity returns (e.g., Lettau and Wachter (2007); Van Binsbergen et al. (2012); Giglio, Maggiori, and Stroebel (2014); Van Binsbergen and Koijen (2017)).

However, no universally accepted approach exists to estimate inputs, such as projected cash-flows and discount rates. The finance literature has thus far measured equity duration indirectly. For example, Cornell (1999), Campbell and Vuolteenaho (2004), and Lettau and Wachter (2007) suggest that long-duration equities have higher exposure to discount rate shocks than short-duration equities. Lettau and Wachter (2007) develop a theoretical model with long-duration growth and short-duration value stocks that is sufficient to explain the value premium from Fama and French (1996). Van Binsbergen et al. (2012, 2013) study dividend strips and dividend futures with durations up to ten years to document the downward-sloping term structure of equity risk premium.[1] Chen (2017) proxies for duration with long-run dividend growth rates and empirically show that growth and value stocks do not differ significantly in duration. Overall, indirect proxies for equity duration present confounding implications for the cross-section of equities, thereby decreasing the credibility of indirect proxies.

In contrast, the accounting literature has developed a direct method of measuring equity duration by borrowing from fixed-income research (e.g., Dechow et al. (2004)). Weber (2018) employs the technique in Dechow et al. (2004) to verify the downward-sloping term structure of equity risk premium initially documented in Van Binsbergen et al. (2012). Although Dechow et al. (2004) acknowledge that their methodology is likely to vary with firm characteristics, they do not address the impact of such differences on equity duration. This research gap raises the following questions. How to estimate equity duration more accurately? How do measures of equity duration impact the term structure of equity risk premium? In this chapter, I answer these questions by investigating techniques to enhance the measures of equity duration.

I begin by explaining the basic measurement framework of Dechow, Sloan, and Soliman (2004) (henceforth called DSS) that adapts the traditional bond duration method to account for equities' uncertain and perpetual cash-flows. Secondly, I develop firm characteristic-specific methodologies (henceforth called modified DSS models) to project cash-flows and compare them to realized cash-flows. I suggest two firm characteristics - book-to-market (BM) ratio that proxies for growth opportunities, and industry that is independent of market information. Thirdly, I compute various discount rates that can discount cash-flows such as a constant rate, return-on-equity, and implied cost of capital (ICC), which are likely to vary with BM

[1]Dividend strips are similar to zero-coupon bonds that pay a particular dividend at maturity. Owing to their short maturities, dividend strips cannot capture the returns on the term structure of equity risk premium beyond ten years.

ratio and industries. Fourthly, I investigate the effects of DSS and modified DSS methods on firm-level equity duration. Fifthly, I examine the effects of DSS and modified DSS methods on the return spread due to equity duration and on the term structure of equity risk premium. Finally, I test the hypothesis that return spread due to duration is confounded by other risk factors by performing a spanning test of the return spread due to duration from DSS and modified DSS methods with recent asset pricing factors.

Results from the above analysis suggests that parameters that predict cash-flows differ with firm characteristics. The modified DSS that accounts for differences in firm characteristics predicts cash-flows that more accurately match realized cash-flows than the DSS model. Precisely, the spread between DSS and modified DSS methods for an average error term (expressed in percentage) that represents the market value-scaled absolute difference between expected and realized cash-flows of firms is 24.16% at the end of the projection horizon of ten years. Secondly, discount rates indeed vary with firm characteristics. Thirdly, equity duration from the modified DSS model yields a longer duration differential between the top and bottom decile of firms differing in equity duration than the DSS model. Precisely, the industry modified DSS method yields the longest duration differential under industry characteristic-specific ROE discount rate (13.73 years) whereas the BM modified DSS presents a longer duration differential (11.98 years) than the DSS method (8.71 years). Finally, all models result in a downward-sloping term structure of equity risk premium. The BM modified DSS model results in the largest return spread (1.83% monthly return) between the top and bottom duration deciles, and the steepest sloped yield curve with a 1.83% decrease in annual excess return over the risk-free rate for a one-year increase in equity duration. Finally, the spanning tests reveal that recent asset pricing factors partially confound equity duration (43% for BM modified DSS model).

Interestingly, the industry modified DSS method that has the largest duration differential does not result in the largest return spread between the top and bottom duration deciles. One potential reason is that the number of varying parameters in the industry modified DSS method introduces more noise than information about equity duration. The cash-flows projection results support this hypothesis because the industry modified DSS method presents a larger dispersion in the cash-flow error term than the BM modified DSS method that has less number of varying parameters for the same set of firms.

This chapter contributes to the literature surrounding the downward-sloping term structure of equity risk premium. My results extend evidence in Van Binsbergen et al. (2012) and Van Binsbergen et al. (2013) that investors require a premium to hold short-duration equities. An alternate interpretation, consistent with Lakonishok, Shleifer, and Vishny (1994) and Daniel, Hirshleifer, and Subrahmanyam (1998, 2001), is that investors are irrationally optimistic about the prospects of long-duration equities resulting in high market valuations relative to their existing fundamentals. However, comparing predicted cash-flows across growth and value stocks, it appears that both the DSS and BM modified DSS models predict cash-flows for long-duration growth stocks more accurately than for short-duration value stocks (See Sub-section 1.5.3). Specifically, both models over-predict cash-flows for value stocks than for growth stocks within the projection horizon suggesting that investors are optimistic about short-duration value firms, not long-duration growth firms, atleast within the projection horizon.

Additionally, my results imply that the term structure of equity risk premium is steeper than previously thought. Specifically, parameters related to growth opportunities (BM ratio) yield a -1.83% annual return for a one-year increase in equity duration whereas Weber (2018) implies a -0.83% annual return for a one-year increase in equity duration. Growth opportunities specific parameters also yield a higher Sharpe ratio of -0.43 for a zero-investment strategy that buys the top decile and sells the bottom decile of firms differing in equity duration in comparison to a Sharpe ratio of -0.22 under Weber (2018)), both for a one-year horizon. The downward-sloping term structure of equity risk premium (e.g., Van Binsbergen et al. (2012, 2013); Weber (2018)) implies that a longer duration differential should result in a larger return spread. Hence, the larger Sharpe ratio from the BM modified DSS method suggests that the longer duration differential between the top and bottom duration deciles is informative about duration and is not a result by chance.

Finally, this chapter offers a method for institutional investors like pension funds and endowments to directly compute the duration of their equity assets. Institutional investors have been concerned with matching the duration of their equity-based assets to that of their liabilities (e.g., Leibowitz (1986); Leibowitz, Sorensen, Arnott, and Hanson (1989); Siegel and Waring (2004); Cooper, André, Gabovich, and Pomerantz (2010); Gilbert (2016)).[2] Computing duration addresses the primary challenge of pension funds, i.e., to match the timing of cash-flows from assets with that of liabilities as opposed to existing methods that focus on a different problem and may mitigate the primary challenge as a side-effect (e.g., modified duration, surplus optimization). Further, my method does not require assumptions about the distribution of firm-level monthly returns or about investors risk preferences, that are characteristic of mean-variance optimizations sometimes adopted for asset-liability management. The independence from these assumptions is advantageous because I establish that duration has implications for the cross-section of returns in this dissertation.

[2] A separate literature exists in asset-liability management for institutional investors that largely covers modified duration (price sensitivity to interest rates (Leibowitz (1986); Leibowitz et al. (1989))), surplus optimization (Sharpe and Tint (1990)), and strategic asset allocation based on mean-variance optimization (Leibowitz and Henriksson (1988, 1989)) Optimization problems restate assets and liabilities in each period in terms of cumulative return on assets and cumulative growth in liabilities, and solve the problems with historical data, thereby circumventing the need to project cash-flows for assets and liabilities. In the finance industry, duration matching employing Macaulay (1938) duration is adopted exclusively for fixed-income based assets. Refer to the CFA Level III curriculum on asset-liability management for a comprehensive overview of this literature.

1.2 Related Literature

In this section, I review research that has implications for estimating equity duration. Fixed-income literature pioneered the concept of duration as a proxy for the timing of cash-flows from bonds. Recently, the equity literature adopted a modified form of duration to suit the underlying characteristics of cash-flows from equities (uncertain and perpetual cash-flows). I first review the fixed-income literature followed by the equity literature on duration.

1.2.1 Modeling Duration in Fixed Income

Macaulay (1938) suggested duration as a proxy for the time that elapsed before debtholders received the average dollar of present value (PV) from a bond's stream of cash-flows. Suggesting examples and counter-examples, Macaulay (1938) derived a formula for duration - the weighted average time for debtholders to receive cash-flows from a bond with weights are the ratio of discounted future cash-flows from the bond to the bond's price. In general, Macaulay (1938) duration increases with an increase in time to maturity of the bond, a decrease in coupon rate, and a decrease in the bond's yield to maturity (YTM) used to compute the PV of cash-flows.

Features such as default risk, or call options, or both can introduce uncertainty in a bond's cash-flows that are otherwise known in advance. Chance (1990) replicates a default-prone bond with a default-free bond and a put option on the assets of the firm to theoretically show that default risk reduces the Macaulay (1938) duration of the default-prone bond compared to a default-free bond. Similarly, Acharya and Carpenter (2002) show through numerical simulations of an option-based valuation model of coupon-bearing callable and defaultable bonds that default risk reduces the Macaulay (1938) duration of such bonds. In contrast, Nawalkha (1996) find that when a firm's asset values depend on interest rates, the duration of a defaultable bond issued by the firm may be shorter, equal to, or longer than an identical but default-free bond. Conclusively, Xie, Liu, Wu, and Bing (2009) empirically show that default risk, proxied by wide differences in yield spreads across bonds, reduces the duration of a bond except when the bonds' default probability and interest rates are positively related.

Additionally, Acharya and Carpenter (2002) show that the duration of a callable bond is shorter than that of a non-callable bond. Finally, Xie et al. (2009) show that the duration of a callable, defaultable bond is always shorter than that of an identical but non-callable, non-defaultable or defaultable bond. However, Xie et al. (2009) compute modified duration for callable, defaultable bonds rather than Macaulay (1938) duration.[3]

In conclusion, the fixed-income literature computes Macaulay (1938) duration for default-free vanilla coupon-paying bonds and does not provide an empirical equivalent of Macaulay (1938) duration under uncertainty in cash-flows or time to maturity.

1.2.2 Modeling Duration in Equities

Duration in the equities context has been examined from the perspective of modified duration (e.g., Lanstein and Sharpe (1978); Leibowitz (1986); Leibowitz et al. (1989); Leibowitz and Kogelman (1993)). Dechow et al. (2004) pioneered to measure equity duration from the perspective of timing of cash-flows to shareholders. The authors address the key challenges of uncertain and perpetual cash-flows from equities in measuring equity duration.[4] The authors forecast cash-flows for an assumed period, T, and impute the sum of PV of cash-flows beyond T from the observed price and forecasted cash-flows until T. The authors acknowledge that their method of forecasting cash-flows is likely to vary with industry and firm characteristics. This chapter addresses the implications of such characteristics on equity duration.

[3]Modified duration of a security is computed and interpreted as the sensitivity of the security's price to interest rates.

[4]Dechow et al. (2004) calculate Macaulay (1938) duration, a direct measure of the timing of cash-flow from firms to shareholders.

Valuation models do not model default when forecasting cash-flows by the assumption that firms live forever (going-concern). However, firms can default in reality. Gilson, Hotchkiss, and Ruback (2000) compare the market value of firms under Chapter 11 (reorganization under bankruptcy) with estimates from management's published estimated cash-flows that are based on existing valuation models. They show that projected cash-flows provide unbiased estimates of firm value with a wide dispersion in valuation errors.

Weber (2018) implements Dechow et al. (2004) with recent cross-sectional data to verify the downward-sloping term-structure of returns for the market documented by Van Binsbergen et al. (2013) and Van Binsbergen and Koijen (2017). In doing so, the paper updates the Dechow et al. (2004) parameters but does not examine cross-sectional differences despite the paper's focus on the cross-section of returns.

In conclusion, the duration literature within equities provides a crude time-based measure of duration in the presence of uncertain and perpetual cash-flows. In this chapter, I focus on investigating the effects of variation in firm characteristics on equity duration with the intent of providing a more accurate duration measure for equities.

1.3 Equity Duration - Definition

Macaulay (1938) duration is defined as the weighted average time to receive cash-flows from a security. The weights are the ratio of discounted future cash-flows from the security to the security's price. It can mathematically be expressed as follows.

$$Duration_0 = \frac{\sum_{t=1}^{T} t \times CF_t/(1+r)^t}{P_0} \tag{1.1}$$

where $Duration_0$ is the duration at time $t = 0$, CF_t is the cash-flows at time $t \in [1, T]$, r is the yield to maturity of the security, T is the security's time to maturity, and P_0 is the observed price of the security at time $t = 0$.

For vanilla bonds, cash-flows and time to maturity are known in advance. However, equities are characterized by uncertain and perpetual cash-flows. Dechow et al. (2004) propose the following workarounds. The authors project expected cash-flows based on firm fundamentals for a fixed period, T, and then apply a transversality condition. Their proposed equity duration can be mathematically expressed as follows.

$$\text{Equity Duration}_0 = \underbrace{\frac{\sum_{t=1}^{T} t \times E_0[CF_t]/(1+r)^t}{P_0}}_{\substack{\text{Duration of expected cash-flows, } E_0[CF_t], \\ \text{maturing in T periods (Term A)}}} + \underbrace{(T + \frac{1+r}{r})}_{\substack{\text{Duration of perpetuity} \\ \text{starting T periods from now (Term B)}}} \times \underbrace{\frac{P_0 - \sum_{t=1}^{T} E_0[CF_t]/(1+r)^t}{P_0}}_{\substack{\text{Difference between price and} \\ \text{sum of PV of expected cash-flows (Term C)}}} \tag{1.2}$$

where $E_0[CF_t]$ is the expected cash-flows to shareholders as of $t = 0$ and paid at time t, T is the number of projection years, P_0 is the firm's observed price at $t = 0$, and r is the discount rate at which cash-flows are discounted.

Term A in Equation 1.2 is similar to the duration of a bond with periodic cash-flows equal to expected cash-flows, $E_0[CF_t]$, and yield to maturity, r. Term B is similar to the duration of a perpetual bond at time T with a yield to maturity, r, that provides cash-flows from $T + 1$. Term C adjusts term B to reflect the difference between equity's price today and the sum of PV of expected cash-flows. Term B and term C together eliminate the need for terminal value assumptions typical of valuation models.

1.4 Data

I measure equity duration of US non-financial firms in CRSP/COMPUSTAT with listed common shares (share codes 10 and 11 in CRSP) between 1963 and 2017. Annual balance sheet data come from the COMPUSTAT database. I obtain monthly stock return data from

CRSP. Monthly risk-free rate comes from Kenneth French's website and annual risk-free rate comes from the 10-year treasury bond rate on FRED St. Louis.

Unlike Dechow et al. (2004) and Weber (2018), I do not remove firms with negative book equity. Firms with negative book equity are likely to have an elevated probability of bankruptcy (e.g., Ohlson (1980) and Dichev (1998)). Their expected duration might either be longer or shorter than the market depending on the firms' prospects. I include these firms in my sample because of their duration implications.

Several terms enter into computing the equity duration of a firm. Book value of equity is computed as the sum of total stockholders equity (CEQ), deferred taxes (TXDB) and investment tax credit (ITCB), when available. Net income is the earnings before extra-ordinary items (IB). Sales is the total sales (sale). Book-to-market ratio is computed as the book value of equity for the fiscal year ending in calendar year $t-1$ over the market equity at the end of June t. Return-on-equity is computed as the income before extra-ordinary items (IB) over the previous year's book value of equity. All variables are winsorized at the 1st and 99th percentile annually.

1.5 Predicting Expected Cash-Flows

Valuation models such as the Gordon growth model (i.e., Gordon (1962)) employ expected dividends to proxy for expected cash-flows to shareholders. However, cash-flows to shareholders include both dividends and repurchases. Moreover, Penman (2018) documents that the valuation models based on only dividends are inconsistent with the Modigliani-Miller dividend irrelevance proposition that dividends do not represent the generation of firm value but only the distribution of firm value. However, in the Gordon growth model, an increase in dividends paid results in an increase in firm value. In contrast, firm earnings represent a direct proxy for generated value. Accurately, the residual income valuation model employs firm earnings to forecast firm-level cash-flows. In this section, I first introduce the Dechow et al. (2004) method that employs a residual income model. Later, I show how extending the Dechow et al. (2004) model to account for variation in firm characteristics can help predict firm cash-flows more accurately.

1.5.1 Dechow, Sloan, and Soliman (2004) - DSS Method

This section explains the Dechow et al. (2004) method of estimating firm cash-flows.

Under the residual income model, cash-flows to shareholders from firm i at time t, $CF_{i,t}$, equals its earnings at t, $Earn_{i,t}$, plus the change in its book value of equity between $t-1$ and t, $(BV_{i,t} - BV_{i,t-1})$.[5] Cash-flows to shareholders can be represented as,

$$
\begin{aligned}
CF_{i,t} &= Earn_{i,t} - (BV_{i,t} - BV_{i,t-1}) && (1.3)\\
&= BV_{i,t-1} \times (\frac{Earn_{i,t}}{BV_{i,t-1}} - \frac{BV_{i,t} - BV_{i,t-1}}{BV_{i,t-1}}) && (1.4)
\end{aligned}
$$

Taking expectation on either side as of $t-1$

$$
\begin{aligned}
E_{t-1}[CF_{i,t}] &= BV_{i,t-1} \times (E_{t-1}[\frac{Earn_{i,t}}{BV_{i,t-1}}] - E_{t-1}[\frac{BV_{i,t} - BV_{i,t-1}}{BV_{i,t-1}}]) && (1.5)\\
&\approx BV_{i,t-1} \times (E_{t-1}[ROE_{i,t}] - E_{t-1}[SalesGrowth_{i,t}]) && (1.6)
\end{aligned}
$$

where $E[CF_{i,t}]$ is the expected cash-flows to shareholders from firm i at time t, $BV_{i,t-1}$ is the book value of equity from firm i at $t-1$, $E[ROE_{i,t}]$ is the expected return-on-equity of firm i at t, and $E[SalesGrowth_{i,t}]$ is the expected sales growth of firm i at t, and t ranges from one to ten, the length of the projection horizon. Nissim and Penman (2001) show that expected

[5] This statement is an accounting identity under the clean-surplus assumption which states that the current book value of equity is only a function of the beginning book value of equity, earnings, and cash-flows to shareholders, $(BV_{i,t} = BV_{i,t-1} + Earn_{i,t} - CF_{i,t})$.

sales growth proxies for expected growth in book value of equity accurately.

Stigler (1963) and Penman (1991) argue that profitability (ROE) is mean-reverting because competition in product markets would force profitability towards the cost of equity. Similarly, Fama and French (2000) show with a simple cross-sectional partial adjustment regression based on Fama and MacBeth (1973) that profitability (earnings before interest and extraordinary items to book value of total assets) is mean-reverting to a firm-specific value at an average rate of 0.38. Nissim and Penman (2001) empirically show that return-on-equity (ROE) and sales growth of all firms mean-revert to 12% and 6%, respectively. Dechow et al. (2004) follow Nissim and Penman (2001), and model ROE and sales growth as first-order autoregressive processes.

Equation 1.7 summarizes the model specification under Dechow et al. (2004). Specifically, Dechow et al. (2004) assume that ROE and sales growth mean-revert to long-run means of 12% and 6% at certain rates, respectively. The rates of mean-reversion for ROE (0.57) and sales growth (0.24) equal the AR(1) coefficients computed from regressing current values on past values and averaged across all firm-years, respectively.[6] Dechow et al. (2004) project firm cash-flows for ten years under the assumption that mean-reversion in ROE and sales growth is complete within this period.

$$\begin{bmatrix} ROE_t \\ BV_t \end{bmatrix} = \begin{bmatrix} 0.12 \times (1 - 0.57) \\ 0.06 \times (1 - 0.24) \end{bmatrix} + \begin{bmatrix} 0.57 & 0 \\ 0 & 0.24 \end{bmatrix} \begin{bmatrix} ROE_{t-1} \\ BV_{t-1} \end{bmatrix} \tag{1.7}$$

I implement the Dechow et al. (2004) model in my sample and refer to it as the DSS method. Under the DSS method, I estimate the long-run means and the average AR(1) coefficients

[6] Long-run averages can be computed as the ratio of intercept from AR(1) regression to (1-AR(1) coefficient). However, the intercept term in an AR(1) regression is primarily used to satisfy the OLS assumption that the error terms have mean 0. Hence, computing the long-run averages distinct from the AR(1) coefficient estimation process will reduce errors associated with the intercept term.

for ROE and sales growth as follows. Each year (t), I follow firms 15 years into the future and compute firm ROE at the end of 15 years (future ROE). The median of the future ROE computed across all firm-years (t) is the long-run ROE. Similarly, I compute the long-run sales growth. I compute average AR(1) coefficients for ROE and sales growth identical to Dechow et al. (2004). Table 1.1, column A summarizes the DSS implied long-run ROE, long-run sales growth, and average AR(1) coefficients for ROE and sales growth over the sample period from 1963 to 2017 under this procedure. Columns B and C of table 1.1 show the parameters under Dechow et al. (2004) and Weber (2018), respectively. Column A implies a long-run ROE of 10.03%, a long-run sales growth of 6.28%, and average AR(1) coefficients for ROE and sales growth of 0.42 and 0.19, respectively. The average AR(1) coefficients for ROE and sales growth are approximately consistent with Weber (2018). The long-run ROE in my sample is less than while the long-run sales growth is marginally greater than those in Dechow et al. (2004) and Weber (2018). One reason for the lower long-run ROE could be that my sample includes two additional recessions than the Dechow et al. (2004) sample (See figure A.1 in Appendix A.).

Summarizing, the DSS method projects firm cash-flows employing parameters related to ROE and sales growth that are common across all firms. Any differences in expected cash-flows across firms occur only due to differences in the book value of equity at the beginning of the projection horizon. In the next section, I present evidence that cross-sectional differences in parameters are prevalent beyond ten years, and suggest a method to project cash-flows that accounts for these differences.

1.5.2 Modified DSS Method

Dechow et al. (2004) provide a parsimonious estimation procedure for expected cash-flows by assuming that parameters that forecast cash-flows are invariant in the cross-section. However, the cost of equity to which ROE reverts to in the DSS method may not be common across all firms. Risk differences across firms or systematic differences in the noisiness of a noisy proxy like ROE can lead to persistent differences in expected profitability (e.g., Fama and French (2000)). In this section, I show that such differences exist beyond the projection horizon. Hence, it is important to account for these differences while forecasting firm cash-flows. Accordingly, I extend the DSS method to forecast cash-flows that accounts for these cross-sectional differences. I choose to focus on cross-sectional differences along two dimensions - book-to-market (BM) ratio which is a proxy for growth opportunities that is time-varying, and industry which is a proxy for cross-sectional differences independent of the market and is less time-varying than the BM ratio.

One way to account for cross-sectional differences is to model an out-of-sample mean-reverting process for profitability and sales growth for every firm-year as a function of BM ratio (e.g., Fama and French (2000)) and industry. However, firm profitability is also affected by other variables. Hence, this model setup would introduce omitted variable bias that would lead to biased regression coefficients. Hence, I follow a portfolio approach.

At the end of every June, I sort firms based on their BM ratios into decile portfolios or their Fama-French industry classifications into 48 portfolios, respectively. Each year, I follow firms in each portfolio 15 years into the future and compute ROE for each firm at the end of 15 years (future ROE). The median of the future ROE computed across all firm-years within each portfolio is the portfolio's long-run ROE. Similarly, I compute the long-run sales growth for each portfolio. I compute average AR(1) coefficients for ROE and sales growth similar to the DSS method, but average over firm-years in each portfolio. Hence, each portfolio has a long-run ROE, a long-run sales growth, and average AR(1) coefficients for ROE and sales growth. I refer to this method of estimating parameters to compute cash-flows as the modified DSS method, in general, and BM modified DSS method for BM deciles specific parameters, or industry modified DSS method for industry portfolios specific parameters, in particular.

Table 1.2 presents the model parameters for the BM modified DSS (Panel A) and industry modified DSS methods (Panel B). Panel A shows that the median long-run ROE and long-run sales growth for growth firms are 59% and 54% higher than that for value firms, respectively. Similarly, ROE and sales growth for growth firms are 125% and 63% more persistent than that for value firms on average, respectively. Additionally, the dispersion in parameter values across all BM sorted deciles is greater than zero. Similarly, Panel B shows that these parameters also vary by industry. Further, the dispersion in parameter values across industry portfolios is greater than that across BM portfolios partly because there are a greater number of industry portfolios than BM deciles. These results collectively suggest that all firms neither revert to the same long-run parameters nor at the same rate.

It is essential to reconcile any seeming inconsistencies in the parameter values with literature. The long-run ROE for value firms is lower than that of growth firms, which is inconsistent with the value premium documented in Fama and French (1996). However, this result is consistent with Fama and French (1995) who document that growth firms have a higher return on book equity than value firms for five years before and five years after firms are sorted into portfolios. Further, Chen (2017) document that the real dividend growth rate for growth firms is 2.76% higher than that for value firms at the end of ten years of portfolio formation.[7] One interpretation of these confounding results is that the ROE is an accounting number that represents cash-flows to shareholders (similar to dividend growth rate) rather than a measure of market returns. The observed pattern in the long-run ROEs is consistent with Lettau and Wachter (2007) that long-duration growth firms deliver cash-flows to shareholders later than short-duration value firms.

[7]However, Chen (2017) document that growth firms have lower long-run cash-flows growth rate than value firms.

It is important to consider alternate methods of accounting for cross-sectional variation in firms that affect duration estimates. In the DSS and modified DSS methods, the long-run parameters are forward-looking and hence, introduce look-ahead bias. One solution is to estimate long-run parameters based on the past 15 years rather than the future 15 years. Table 1.3 shows that the patterns in parameters estimated based on the past 15 years are similar in pattern to that of the modified DSS method. Alternatively, I could proxy for long-run profitability with long-run analyst earnings estimates. However, these estimates are available only for reasonably sized firms, thereby introducing selection bias.

Several other methods to estimate parameters also exist. A concurrent paper, Chen and Li (2018), employs a VAR framework with additional accounting variables (gross profitability, O-score, and investment) to predict firm cash-flows, which I can modify to account for cross-sectional variation in parameters. These methods will have to be compared against the DSS and modified DSS methods to evaluate accuracy differences in forecasting cash-flows (see the next section). However, by allowing for variation in parameters in the existing DSS method, I focus on examining the implications of cross-sectional variation in parameters on equity duration in a straight-forward manner.[8]

In conclusion, parameters in the DSS method that predict firm cash-flows differ significantly with firm characteristics such as BM ratio and industry classification. Further, these differences feed into the cash-flow projection methodology. Hence, differences in expected cash-flows occur due to cross-sectional variation in firm characteristics in addition to variation in book value of equity across firms observed at the beginning of the projection horizon.

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[8] It is possible that cross-sectional variation in parameters confounds with differences in estimation methodologies such as including additional variables (e.g., Chen and Li (2018)) with the intent to predict accurate cash-flows. This methodological research question can be addressed more thoroughly in a separate paper (e.g., Nissim and Penman (2001)).

1.5.3 Comparison of Cash-Flow Prediction Models

Having documented that parameters that predict firm cash-flows vary in the cross-section, I turn to evaluate how predicted cash-flows from the DSS and modified DSS methods match with realized cash-flows.

Expected cash-flows are the primary input to duration. Ceteris-paribus, if the modified DSS models predict cash-flows that match realized cash-flows throughout the projection horizon more accurately than the DSS model, then the equity duration based on modified DSS methods will likely match the true expected duration more accurately than that based on the DSS method.[9] I calculate realized cash-flows at $t+1$ as realized earnings at $t+1$ minus the difference between realized BV at t and $t+1$ (equation 1.4). To compare models, I compute an error term for each firm-year-projection year. The error term is the ratio (expressed in percentage) of the absolute difference between projected and realized firm cash-flows to the market value of the firm observed at the beginning of the projection horizon.

Figure 1.1 plots the above error term averaged across all firm-years for each projection year on the vertical axis, and the projection year from one to ten on the horizontal axis. The red, green, and black lines represent the DSS, BM modified DSS, and industry modified DSS methods, respectively. The figure shows that the modified DSS methods predict cash-flows more accurately than the DSS method throughout the projection horizon, except for the industry modified DSS method in projection year one. This improved performance amplifies as we move from projection year one to ten. At the end of the projection horizon, the spread between the error terms of the DSS and BM modified DSS method rises to 24.16% that is significant at the 5% level under a paired t-test of firm-year observations. The industry modified DSS method performs similar to the BM modified DSS method on average but

[9] A more accurate match to realized cash-flows implies a more accurate match to duration with realized cash-flows. Rational expectation implies that the true expected duration should match duration computed with realized cash-flows on average.

the dispersion in the error term is higher for the former (176%) than the latter (117%). Nevertheless, the dispersion in error term for the DSS method is the highest amongst the three methods (180%). Hence, the modified DSS methods predict cash-flows more accurately than the DSS method, on average.

The error term can be examined from different perspectives such as value-weighted average across all firm-years, portfolio-level for BM deciles or industry portfolios, or the market. Figures A.4, A.5, and A.6 in Appendix A show that the modified DSS methods predict cash-flows more accurately than the DSS method under all these perspectives.

In conclusion, expected cash-flows from the modified DSS methods match realized cash-flows across firms, portfolios, and the market more accurately than the DSS method. This result implies that cross-sectional variation in parameters within the duration estimation model is critical to predicting cash-flows accurately. The improved performance of modified DSS models is because the modified DSS models acknowledge the systematic differences in how future looks for different firms in addition to providing an evolution process for firm cash-flows like the DSS model. Equity duration is a function of projected cash-flows, observed price and the rate at which the cash-flows are discounted. In the next section, I study various discount rates.

1.6 Discount Rates

Similar to the previous section, discount rates can vary with firm characteristics. In this section, I discuss reasonable rates to discount expected cash-flows.

1.6.1 Constant Discount Rate

Dechow et al. (2004) and Weber (2018) discount cash-flows at a constant discount rate, the market-wide long-run ROE that equals 10.03% in my sample. The intuition behind this discount rate is that in the long-run competition should drive firms to earn their cost of equity capital. By assumption, firms have a constant long-run ROE. However, this assumption is inconsistent with the modified DSS models' implication that firms do not revert to the same long-run profitability (ROE) measure. Nevertheless, a constant discount rate provides a framework to observe differences in firm duration between the DSS and modified DSS methods due to differences in predicted cash-flows.

1.6.2 Long-Run Return-on-Equity

As discussed in section 1.5.2, modified DSS methods imply that the dispersion in long-run ROE across all BM and industry portfolios is substantial. If firms earn their cost of equity capital in the long-run as per Dechow et al. (2004), then the modified DSS methods imply a wide dispersion in the cost of equity capital across BM and industry portfolios. Hence, each BM or industry portfolio should have a portfolio-specific discount rate equal to the portfolio-specific long-run ROE.

1.6.3 Implied Cost of Capital

Duration studies in the fixed-income literature discount cash-flows at the bond's yield to maturity (YTM). The equity-equivalent of a bond's YTM is the firm's implied cost of capital (ICC). In this section, I discuss how to calculate ICC for firms.

The ICC of a stock j, similar to bond YTM, is the discount rate that equates current stock price, $Price_{j,0}$, to the sum of PV of expected future cash-flows. It can be mathematically represented as,

$$Price_{j,0} = \sum_{t=1}^{\infty} \frac{E_0[CF_{j,t}]}{(1 + ICC_{j,0})^t} \tag{1.8}$$

The DSS and modified DSS methods do not model how cash-flows evolve beyond the projection horizon of ten years. Instead, the PV of cash-flows beyond the projection horizon (terminal value) is implied to be the difference between the observed price at the beginning of the projection horizon and the sum of PV of cash-flows predicted within the projection horizon. This assumption implies infinitely many solutions for the ICC.

$$Price_{j,0} = \sum_{t=1}^{T} \frac{E_0[CF_{j,t}]}{(1+ICC_{j,0})^t} + (Price_{j,0} - \sum_{t=0}^{T} \frac{E_0[CF_{j,t}]}{(1+ICC_{j,0})^t}) \tag{1.9}$$

Hence, I require a distinct terminal value of cash-flows to overcome this issue. Consistent with other valuation models (e.g., Gordon growth model), I assume that firms pay out a 100% of their earnings beyond the projection horizon and that these earnings perpetually grow at some rate, e.g., the rate of inflation observed at the beginning of the projection horizon. The ICC is then computed from the following formula for each firm-year.

$$Price_{j,0} = \sum_{t=1}^{T} \frac{E_0[CF_{j,t}]}{(1+ICC_{j,0})^t} + \frac{E[Earnings_{j,T+1}]}{(1+ICC_{j,0})^T * (ICC_{j,0} - inflation_0)} \tag{1.10}$$

The discount rate for the DSS method is the median of firm ICCs computed across all firm-years, and that for the modified DSS methods is the median of firm ICCs computed across all firm-years within each portfolio. Table 1.4 presents the ICC summary statistics for the DSS (Panel A), BM modified DSS (Panel B), and industry modified DSS (Panel C) methods. The average ICC across all firm-years weighted equally (EW ICC) is 14.23%, 13.82%, and 14.33% for DSS, BM modified DSS, and industry modified DSS methods, respectively.[10] One reason for the similar values across methods could be that the similarity in assumptions regarding the evolution of terminal cash-flows over-powers the cross-sectional differences across DSS and modified DSS methods in the projection horizon. This reasoning is consistent with accounting studies documenting that the terminal value contributes a significant portion to

[10]The ICCs imply an equal-weighted equity risk premium of 7.89%, 7.48%, and 7.99% for DSS, BM modified DSS, and industry modified DSS methods, respectively.

the PV of firm cash-flows (e.g., Penman (1998)). Nevertheless, we can observe cross-sectional variation in ICC across portfolios. Table 1.5, Panel A shows that growth firms have a lower ICC than value firms consistent with the value premium. Similarly, Panel B shows that industry portfolios have a wide dispersion in ICC. Overall, observed prices imply that firms differ in ICCs based on characteristics like BM and industry. Further, discounting cash-flows at the median portfolio ICC shows consistency with Macaulay (1938) duration and accounts for variations in cost of equity capital.

One caveat in computing ICC is that the timing of cash-flows can influence it. This influence is one of the reasons why long-run ROE is inconsistent with ICC for BM portfolios. Consider a two-period model in which two firms, 1 and 2, the same cash-flows to shareholders, x, and the same sum of PV of cash-flows. Firm 1 provides cash-flows, x, only in period 1, while firm 2 provides cash-flows, x, only in period 2. That is, firm 1 has shorter duration than firm 2. No arbitrage condition implies that the sum of PV of cash-flows should equal the price. Then, the observed prices would imply that the short duration firm has a higher ICC than the long duration firm. Hence, given firms that differ in equity duration, their ICC can be endogenous to their equity durations.

In conclusion, cross-sectional variation in discount rates exists similar to cross-sectional variation in parameters that determine firm-level cash-flows. Further, differences across discount rates for the same characteristic such as the ROE and ICC for BM portfolios suggest that discount rates can drive equity duration in opposing ways. In the next section, I examine whether these effects are large enough to alter firm-level durations quantitatively.

1.7 Measuring Equity Duration

In this section, I compute equity duration for each firm-year by employing cash-flows computed in section 1.5 and discount rates computed in section 1.6. The choice of discount rate presents a trade-off between differences in equity duration being driven through cross-sectional differences in discount rates rather than in the timing of cash-flows and computing equity duration accurately by accounting for cross-sectional differences in the cost of equity capital. Therefore, the three different methods of projecting cash-flows namely, DSS, BM modified DSS, and industry modified DSS, and the three different discount rates namely, constant, long-run ROE (2 versions), and ICC (3 versions) suggest that there are 20 methods of computing firm equity duration.[11] I discuss eight of the 20 combinations that are informative and sufficient to examine the influence of cross-sectional variation in parameters and discount rates on equity duration.

Table 1.6 summarizes the different parameters for the eight methods that I discuss. In order to compare equity duration across the eight methods, I sort firms at the end of June every year into deciles based on equity duration. For each decile, I compute the average equity duration across all firm-years. This methodology allows to observe differences across a broad spectrum of equity duration. Table 1.7 presents the average equity duration for the deciles and the arbitrage portfolio that buys the long-duration decile and sells the short-duration decile. Vertical panels A, B, and C present the results under the DSS, BM modified DSS, and industry modified DSS methods, respectively. Within each panel, I present average duration under constant discount rate (const), ROE discount rate (ROE), and ICC discount rate (ICC). Panel A contains only two columns because the long-run ROE equals the constant discount rate under the DSS method. The following paragraphs explain the baseline result (DSS) and comparisons with the modified DSS results.

Under the DSS method (Panel A), the average duration differential between the high and low duration decile is 8.71 years under a constant discount rate and 7.38 years under

[11]Seven types of discount rates (2 long-run ROE, 3 ICCs, and one constant rate) and three methods of cash-flows yield ${}_6C_3 = \frac{6!}{3!(6-3)!} = 20$ combinations.

ICC discount rate with a standard deviation of 2.47 and 2.01, respectively. The correlation between the duration implied by the two discount rates is high at 0.63. [12]

Under the BM modified DSS method (Panel B), the average duration differential between the long and short duration deciles rises to 10.73 years under a constant discount rate, 11.98 years under long-run ROE, and 10.08 years under ICC discount rates. Additionally, the dispersion across the numbers increases to 2.75, 3.13, and 2.76 years, respectively, in comparison to dispersion across deciles under the DSS method. Further, the correlation amongst the duration measures is high at 0.94 (const vs ROE), 0.77 (const vs ICC), and 0.65 (ROE vs ICC).

Similarly, under the industry modified DSS method (Panel C), the duration differential between long and short duration deciles rises to 10.59, 13.73, and 12.59 years for a constant, long-run ROE, and ICC discount rates. Further, the dispersion across the numbers is larger than that under the DSS and BM modified DSS methods. The correlations across durations under different discount rates are 0.93 (const vs ROE), 0.72 (const vs ICC), and 0.61 (ROE vs ICC).[13]

The results collectively imply that the modified DSS methods produce larger dispersions in duration and longer duration differentials between the top and bottom duration deciles than the DSS method. Specifically, the industry modified DSS method implies the largest dispersion (4.07 years) and the longest duration differential (13.73 years) under long-run ROE discount rate. The ability of the modified DSS methods to predict cash-flows more accurately than the DSS method suggest that the durations from modified DSS methods are likely to be more accurate than those from the DSS method. Further, the high correlations across

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[12] Refer to table A.1 in Appendix A for the correlation matrix.

[13] Correlations across DSS, BM modified DSS, and industry modified DSS durations are low indicating that cross-sectional differences alter the ordering of firms based on duration. Refer to Table A.1 in Appendix A for the correlation matrix.

durations based on different discount rates within the same method suggest that discount rate differences do not drive duration numbers significantly.

One inconsistency between expected cash-flows and duration numbers is that the industry modified DSS method, on average, performs as good or slightly worse than the BM modified DSS method in matching expected and realized cash-flows (see Sub-section 1.5.3) but it implies a longer duration differential than the BM modified DSS method. One potential reason could be that the increased number of varying parameters (48 sets) under the industry modified DSS method adds more noise than information related to duration compared to the BM modified DSS method (10 sets of varying parameters). This hypothesis is partly supported by the higher dispersion in the error term regarding predicted cash-flows for the industry modified DSS (176%) than for the BM modified DSS (117%) methods. In the next section, I further test this hypothesis by examining mean excess returns over the risk-free rate to the duration deciles.

Overall, cross-sectional variation in parameters that predict firm cash-flows has implications for the cross-section of equity duration. Specifically, the variation in parameters implies a larger dispersion in equity duration and a longer duration differential between long and short duration firms than previously thought. This result finds credibility in the modified DSS methods predicting more accurate cash-flows than the DSS method.[14]

1.8 Impact on the Term Structure of Equity Risk Premium

In this section, I seek to answer the second research question of this chapter which is to examine the implications of the modified DSS methods on the term structure of equity risk premium. Several studies document a downward-sloping term structure of equity risk

[14]In the context of rational expectation, the true expected equity duration should equal the realized duration on average. Hence, another way to check whether the duration numbers reflect reality is to compare them with duration computed based on realized cash-flows. See table A.2 in Appendix A for details.

premium (e.g., Van Binsbergen et al. (2012, 2013); Weber (2018)). That is, monthly returns for firms decrease with an increase in equity duration. By this argument, the higher duration differential documented in the cross-section in the previous section should imply a greater return spread in the cross-section.

I employ the annual duration deciles constructed previously to examine whether the above statement holds in the data. For each duration decile, I calculate equal-weighted (EW) monthly mean excess returns over the risk-free rate. This technique allows examining how average excess returns vary over the spectrum of equity duration, instead of imposing a linear relationship between excess returns and equity duration in a Fama and MacBeth (1973) cross-sectional regression.

First, consider the baseline DSS method. Figure 1.2 presents the downward-sloping term-structure of equity returns under the DSS constant DR method. The horizontal axis plots the average equity duration for deciles of firms sorted on equity duration computed under the DSS method with a constant discount rate of 10.03%, and the vertical axis plots the average monthly excess returns over the risk-free rate for each duration decile. The average duration (market duration) of 17.82 years well-approximates the equity duration of 18.77 years and the average age of a firm of 17.59 years, both under Weber (2018). Finally, the term structure of equity risk premium implies an annual equity risk premium (ERP) of 8.88% for the market that is close to the annual ERP of 7.10% from Kenneth French's website for the same sample period. Hence, the summary statistics from the DSS method are approximately consistent with previous literature and empirical data.

Now, I compare the term structure of equity risk premium produced by the DSS and modified DSS methods. Table 1.8 presents the average monthly excess returns between 1963 and 2017 across duration deciles under the eight equity duration computation methods. Panels A, B, and C in both tables represent the Dechow, BM modified DSS, and Industry modified DSS methods, respectively. In panel A, I present the returns for duration computed under constant and ICC discount rates since the long-run ROE and constant discount rates are the same under the DSS method. Within panels B and C, I present returns calculated under constant, long-run ROE, and ICC discount rates in that order. Panels A, B, and C in tables 1.7 and 1.8 taken together show that all methods produce a negatively sloped term structure of equity risk premium but differences driven by returns to the higher duration deciles exist across the panels. Specifically, the BM modified DSS method produces the largest monthly spread between the top and bottom deciles of -1.83% and the steepest sloped term structure of equity risk premium of -1.83% annual return for a one-year increase in equity duration, both under long-run ROE discount rate. The BM modified DSS method also yields the largest Sharpe ratio under all discount rates, i.e., it yields the greatest return for a unit total risk measured as the standard deviation of returns. This result, consistent with the downward-sloping term structure of equity risk premium, suggests that equity duration constructed with parameters specific to growth opportunities contains information about equity duration.

The industry modified DSS method does not produce the largest return spread between the top and bottom duration deciles even though it produces the longest duration differential between the deciles. The baseline results suggest a downward-sloping term structure of equity risk premium. That is, monthly mean excess returns for firms over the risk-free rate decrease with an increase in equity duration. By this argument, a longer duration differential between the top and bottom duration deciles should produce a higher spread between these deciles, provided the duration differential contains information about equity duration rather than noise. This reasoning suggests that the longest duration differential under the industry modified DSS method may be due to more noise than information about duration introduced by the 48 sets of varying parameters. Another potential reason could be that sorts on common risk factors such as size or profitability may have confounded duration sorts under industry-specific parameters. Indeed, this hypothesis could hold for other duration measures too. Hence, I explore this hypothesis next.

If sorts on common risk factors confound duration sorts then the duration-implied return spread should be correlated with the return spread from these common risk factors. Table 1.9 illustrates the correlation between the BM modified DSS duration factor (ROE discount rate) and other asset pricing factors. The new duration factor is positively related to the market, default, and size factor. Additionally, the new duration factor is negatively related to value factor, profitability, and investment. The correlations are similar for other duration factors. This result suggests that existing risk factors may indeed confound duration sorts. It is then possible that some of these highly correlated variables may subsume the return spread due to equity duration. I explore this hypothesis next.

I perform spanning tests by regressing the return spread due to duration on common risk factors to strip the component of return spread in duration attributed to other factors. Table 1.10 shows that existing asset pricing factors do not span the BM modified DSS ROE duration factor completely in a linear regression model, suggesting that the duration factor represents something additional to a linear combination of these risk factors. However, factors in the Barillas model subsume the industry modified DSS implied return-spread under constant and ICC discount rates. This result implies that the sorting on duration based on industry-specific parameters is no more than sorting on variables in the Barillas model. Further research in explaining why the industry modified DSS method yields a lower return spread than the DSS method and which characteristics contain information about equity duration is delegated to future work.

Overall, the cross-sectional variation in parameters that determine duration impact the downward-sloping term structure of equity risk premium. Specifically, parameters specific to growth opportunities (BM ratio) contain information about equity duration and produce a larger return spread with a higher Sharpe ratio between the top and bottom duration deciles than the DSS method. Moreover, they yield a steeper sloped term structure of equity risk premium than previously thought. However, the industry specific parameters introduce more noise than information about duration, are confounded by common risk factors, and result in a lower return spread and Sharpe ratio than the BM modified DSS method.

1.9 Conclusion

In this chapter, I enhance the existing equity duration measurement technique by investigating the impact of cross-sectional differences in firm characteristics and discount rates on firm equity duration. I show that these differences result in a larger dispersion in duration and longer duration differential between the top and bottom duration deciles.

Further, the cross-sectional variation in firm characteristics impacts the term structure of equity risk premium. Parameters specific to growth opportunities yield the largest return spread between top and bottom duration deciles and result in the steepest sloped term structure of equity risk premium. This result suggests that any cross-sectional return effects that equity duration might have is higher than previously thought.

However, all cross-sectional differences in characteristics do not result in a steeper sloped term structure of equity risk premium. For instance, the industry modified DSS method yields a term structure of equity risk premium similar to that of the DSS method because common risk factors confound the return spread due to duration under the former method. Further, industry modified DSS method results in a higher variance for the cash-flow forecasting error than the BM modified DSS method suggesting that the 48 sets of industry-specific parameters may have introduced more noise than information about duration in comparison to the BM modified DSS method. Identifying characteristics that contain information about duration and examining why the industry modified DSS method performs equivalent to the DSS method is delegated to future research.

Table 1.1: Parameters under the DSS Method

	1963-2017 (A)	Dechow et al. (2004) (B)	Weber (2018) (C)
Average AR(1) ROE	0.42***	0.57	0.41
Long-run ROE	10.03%***	12.00%	12.00%
Average AR(1) Sales Growth	0.19***	0.24	0.24
Long-run Sales Growth	6.28%***	6.00%	6.00%

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

This table lists the parameters that predict cash-flows and their values under the Dechow et al. (2004) (DSS) method. Columns A, B, and C present the parameter values for US non-financial firms in CRSP/COMPUSTAT with common shares (share codes 10 and 11) listed between 1963 and 2017, for the sample from Dechow et al. (2004), and for the sample from Weber (2018), respectively. I compute parameter values under column A as follows. Each year, I follow firms 15 years into the future and compute ROE for each firm at the end of 15 years (future ROE). The median of the future ROE computed across all firm-years is the portfolio's long-run ROE. Similarly, I compute the long-run sales growth. ROE AR(1) and SG AR(1) are computed from regressing current values on past values and averaging the regression coefficients across all firm-years. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively. Dechow et al. (2004) and Weber (2018) do not provide information on statistical significance.

Table 1.2: Cross-sectional Differences in Parameters that Predict Cash-Flows

Panel A: Book-to-Market Deciles

BM Decile	LR ROE(%)	LR SG(%)	ROE AR(1)	SG AR(1)
Growth	12.47	7.83	0.60	0.18
2	12.02	7.09	0.41	0.15
3	11.81	6.43	0.38	0.17
4	10.83	6.45	0.34	0.15
5	10.44	5.85	0.33	0.15
6	9.92	5.86	0.34	0.12
7	9.71	5.75	0.30	0.14
8	9.26	5.79	0.23	0.13
9	8.75	5.41	0.15	0.16
Value	7.84	5.07	0.27	0.11
Growth-Value	4.63	2.76	0.34	0.07
Std. Dev.	1.50	0.82	0.12	0.02

Panel B: Fama-French 48 Industries - Top and Bottom Two Industries

Industry Portfolio	LR ROE(%)	LR SG(%)	ROE AR(1)	SG AR(1)
Beer & Liquor	16.42	6.15	0.61	0.18
Tobacco Products	19.83	6.48	0.66	0.27
Pharmaceutical Products	9.25	8.79	0.47	0.04
Construction	9.72	9.53	0.60	0.20
Retail	12.35	6.13	0.37	0.32
Apparel	11.01	4.6	0.41	0.36
Precious Metals	1.33	5.03	0.5	0.15
Real Estate	3.05	4.71	0.44	0.12
Agriculture	7.42	2.72	0.57	0.17
Steel Works	7.76	3.16	0.4	0.17
Entertainment	6.48	5.20	0.23	0.12
Defense	14.95	5.66	0.24	0.02
Pharmaceutical Products	9.25	8.79	0.47	0.04
Std. Dev.	3.12	1.38	0.10	0.07

This table presents the cross-sectional differences in parameters that predict cash-flows. Panels A and B present differences across book-to-market (BM) deciles and industry portfolios, respectively. At the end of June every year, firms are sorted into BM deciles or 48 industry portfolios based on their BM ratio or Fama-French industry classification, respectively. The BM ratio is computed as the book value of equity for the fiscal year ending in calendar year $t-1$ over the market equity at the end of June t. Return-on-equity (ROE) is computed as the income before extra-ordinary items (IB) over the previous year's book value of equity. Sales growth (SG) is computed as current sales divided by previous year's sales. LR refers to long-run. Each year, I follow firms in each portfolio 15 years into the future and compute ROE for each firm at the end of 15 years (future ROE). The median of the future ROE computed across all firm-years within each portfolio is the portfolio's long-run ROE (LR ROE). Similarly, I compute the long-run sales growth (LR SG) for each portfolio. ROE AR(1) and SG AR(1) are computed from regressing current values on past values averaged across all firm-years within each portfolio. Growth - Value refers to the average difference in parameters between the bottom decile of BM firms (growth firms) and the top decile of BM firms (value firms). Std. Dev. is the standard deviation of the parameter values across the BM or industry portfolios. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed (10 and 11) between 1963 and 2017. Refer to figures A.2 and A.3 for parameters for all 48 industries.

Table 1.3: Cross-sectional Differences in Parameters that Predict Cash-Flows based on Past 15 Years

Variable	Dechow (A)	Modified Dechow - Book-to-Market Portfolios (B)				Modified Dechow-Industry Portfolios (C)
		Growth	Value	Growth - Value	Std. Dev.	Std. Dev.
Long-run ROE (%)	11.21	20.23	3.11	17.12	6.04	7.67
Long-run Sales Growth (%)	11.09	25.05	3.04	22.02	7.77	9.26
Average ROE AR(1)	0.42	0.60	0.27	0.34	0.12	0.10
Average Sales Growth AR(1)	0.19	0.18	0.11	0.07	0.02	0.07

This table presents the cross-sectional differences in parameters that predict cash-flows based on past data. At the end of June every year, firms are sorted into book-to-market (BM) deciles based on their BM ratio. The BM ratio is computed as the book value of equity for the fiscal year ending in calendar year $t-1$ over the market equity at the end of June t. Return-on-equity (ROE) is computed as the income before extra-ordinary items (IB) over the previous year's book value of equity. Sales growth (SG) is computed as current sales divided by previous year's sales. LR refers to long-run. Each year, I follow firms in each portfolio 15 years into the past and compute ROE for each firm at the end of 15 years (past ROE). The median of the past ROE computed across all firms for each year and average across the years within each portfolio is the portfolio's long-run ROE (LR ROE). Similarly, I compute the long-run sales growth (LR SG) for each portfolio. ROE AR(1) and SG AR(1) are computed from regressing current values on past values averaged across all firm-years within each portfolio. Growth - Value refers to the average difference in parameters between the bottom decile of BM firms (growth firms) and the top decile of BM firms (value firms). Std. Dev. is the standard deviation of the parameter values across the BM or industry portfolios. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed (10 and 11) between 1963 and 2017.

Table 1.4: Summary Statistics - Implied Cost of Equity Capital and Implied Risk Premia

Variable	Mean	Median	Std.Dev.	Min	Max
Panel A: Dechow et. al. (2004)					
EW ICC	14.23	13.03	3.38	10.83	25.65
EW IRP	7.89	7.77	2.93	1.70	18.11
VW ICC	12.17	11.15	3.13	7.77	19.93
VW IRP	5.83	5.71	2.34	1.62	12.39
Panel B: Modified DSS - Book-to-Market Portfolios					
EW ICC	13.82	12.64	3.34	10.49	25.20
EW IRP	7.48	7.40	2.92	1.26	17.66
VW ICC	12.33	11.11	3.17	8.37	21.09
VW IRP	5.99	5.61	2.48	0.98	13.55
Panel C: Modified DSS - Industry Portfolios					
EW ICC	14.33	13.08	3.38	10.96	26.06
EW IRP	7.99	7.98	2.99	1.56	18.52
VW ICC	12.38	11.39	3.10	8.15	20.15
VW IRP	6.04	5.88	2.32	1.63	12.61

This table presents the summary statistics for the annual time-series of the equal-weighted and value-weighted implied cost of capital (ICC) and implied risk premia (IRP) for cash-flows projected using the DSS (panel A), BM modified DSS (panel B), and industry modified DSS (panel C)models. The IRP equals the implied cost of equity capital for the market minus the yield on 10-year constant maturity treasury bond. Mean and median refer to the average and median implied values computed across all years, respectively. Std. Dev., Min, and Max refer to the standard deviation, minimum, and maximum of the implied values across all years, respectively. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed (10 and 11) between 1963 and 2017.

Table 1.5: Implied Cost of Capital - Modified DSS Portfolios

Portfolio/ Industry	Modified DSS (%)	DSS(%)
Panel A: Book-to-Market Deciles		
Growth	9.31	6.58
2	10.93	8.54
3	11.85	9.84
4	12.63	11.00
5	12.99	12.12
6	13.71	13.27
7	14.57	14.44
8	15.34	15.58
9	16.13	17.30
Value	19.83	21.00
Growth - Value	-8.79	-18.42
Std. Dev.	2.60	4.31
Panel B: Select Industries		
Beer & Liquor	17.69	12.83
Tobacco Products	22.28	14.50
Pharmaceutical Products	11.00	9.10
Construction	19.42	15.08
Retail	16.31	13.61
Apparel	15.46	14.86
Precious Metals	4.93	12.53
Real Estate	9.03	12.55
Agriculture	9.88	13.35
Steel Works	12.40	16.08
Entertainment	11.08	13.33
Defense	17.15	13.42
Std. Dev.	2.55	1.66

This table presents the median firm-level implied cost of capital (ICC) computed based on cash-flows predicted from modified DSS (column 1) or DSS (column 2) methods. Panels A and B present statistics for the book-to-market deciles and select industry portfolios, respectively. At the end of June every year, firms are sorted into BM deciles or 48 industry portfolios based on their BM ratio or Fama-French industry classification, respectively. The BM ratio is computed as the book value of equity for the fiscal year ending in calendar year $t-1$ over the market equity at the end of June t. Growth - Value refers to the average difference in parameters between the bottom decile of BM firms (growth firms) and the top decile of BM firms (value firms). Std. Dev. is the standard deviation of the parameter values across the BM or industry portfolios. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed (10 and 11) between 1963 and 2017.

Table 1.6: Summary of Equity Duration Methods

Variables	Dechow (A)		BM Mod (B)			Ind Mod (C)		
	Const	ICC	Const	ROE	ICC	Const	ROE	ICC
Discount Rate	10.03	13.26	10.03	Long-run ROE	Median ICC per BM portfolio	10.03	Long-run ROE	Median ICC per industry portfolio
Long-run ROE	10.03	10.03	Specific to each BM decile			Specific to each industry portfolio		
Long-run Sales Growth	6.28	6.28	Specific to each BM decile			Specific to each industry portfolio		
ROE AR(1)	0.42	0.42	Specific to each BM decile			Specific to each industry portfolio		
Sales Growth AR(1)	0.19	0.19	Specific to each BM decile			Specific to each industry portfolio		

This table illustrates the parameters that enter the eight combinations of constructing equity duration. Dechow, BM Mod, and Ind Mod refer to the DSS, BM modified DSS, and Industry modified DSS methods, respectively. Const, ROE, and ICC refer to the equity duration computed with discount rates equal to a constant, portfolio long-run return-on-equity, and portfolio implied cost of capital, respectively. Portfolio refers to the market, BM decile, or industry 48 portfolios for the DSS, BM modified DSS, or industry modified DSS methods, respectively. At the end of June every year, firms are sorted into book-to-market (BM) deciles based on their BM ratio. The BM ratio is computed as the book value of equity for the fiscal year ending in calendar year $t-1$ over the market equity at the end of June t. Return-on-equity (ROE) is computed as the income before extraordinary items (IB) over the previous year's book value of equity. Sales growth (SG) is computed as current sales divided by previous year's sales. LR refers to long-run. Each year, I follow firms in each portfolio 15 years into the past and compute ROE for each firm at the end of 15 years (past ROE). The median of the past ROE computed across all firms for each year and average across the years within each portfolio is the portfolio's long-run ROE (LR ROE). Similarly, I compute the long-run sales growth (LR SG) for each portfolio. ROE AR(1) and SG AR(1) are computed from regressing current values on past values averaged across all firm-years within each portfolio. ICC for each firm-year is computed assuming that cash-flows beyond the projection horizon grow at the rate of inflation and are paid out to shareholders completely. The median ICC per portfolio refers to the median computed across firm-years in either BM or industry portfolio. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed (10 and 11) between 1963 and 2017.

Table 1.7: Average Equity Duration of Deciles sorted on Equity Duration

Duration Deciles	Dechow (A)		BM Mod (B)			Ind Mod (C)		
	Const	ICC	Const	ROE	ICC	Const	ROE	ICC
Low	13.15	12.55	14.41	14.28	13.39	12.68	12.56	11.36
2	15.19	14.82	16.98	17.16	15.32	15.26	14.95	14.15
3	16.28	15.59	17.61	17.67	15.97	16.71	16.42	15.18
4	17.01	16.15	17.96	18.10	16.41	17.68	17.53	15.95
5	17.60	16.58	18.25	18.62	16.79	18.45	18.51	16.67
6	18.12	16.95	18.52	19.20	17.20	19.15	19.53	17.45
7	18.62	17.28	18.85	19.76	17.71	19.72	20.54	18.25
8	19.17	17.66	19.36	20.31	18.49	20.26	21.78	19.06
9	19.99	18.23	20.47	21.36	20.03	21.00	23.35	20.12
High	21.86	19.93	25.13	26.26	23.47	23.27	26.30	23.95
High-Low	8.71***	7.38***	10.73***	11.98***	10.08***	10.59***	13.73***	12.59***
Std. Dev.	2.47	2.01	2.75	3.13	2.76	3.02	4.07	3.46

This table illustrates the average equity duration of deciles constructed on firms differing in equity duration computed using different methods. Dechow, BM Mod, and Ind Mod refer to the DSS, BM modified DSS, and Industry modified DSS methods, respectively. Const, ROE, and ICC refer to the equity duration computed with discount rates equal to a constant, portfolio long-run return-on-equity, and portfolio implied cost of capital, respectively. Portfolio refers to the market, BM decile, or industry 48 portfolios for the DSS, BM modified DSS, or industry modified DSS methods, respectively. Low and high refer to duration deciles with the bottom and top 10 percentile of firms differing in equity duration, respectively. High-Low represents an arbitrage portfolio that buys the top and sells the bottom duration deciles. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed (10 and 11) between 1963 and 2017. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Table 1.8: Monthly Expected Returns of Deciles sorted on Equity Duration

Duration Deciles	Dechow (A)		BM Mod (B)			Ind Mod (C)		
	Const	ICC	Const	ROE	ICC	Const	ROE	ICC
Low	0.96	0.95	0.81	1.10	0.68	0.95	0.96	0.95
2	0.95	0.94	0.86	1.05	0.63	0.89	0.89	0.91
3	0.83	0.85	0.90	0.79	0.73	0.85	0.79	0.79
4	0.81	0.82	0.73	0.59	0.60	0.72	0.68	0.75
5	0.78	0.77	0.60	0.62	0.41	0.64	0.69	0.56
6	0.66	0.67	0.40	0.41	0.40	0.61	0.67	0.59
7	0.63	0.63	0.23	0.29	0.31	0.67	0.54	0.59
8	0.55	0.58	0.06	0.10	0.26	0.60	0.57	0.56
9	0.38	0.44	-0.07	-0.18	0.11	0.41	0.53	0.52
High	-0.12	-0.02	-0.50	-0.73	-0.63	0.06	0.12	0.00
High-Low (%)	-1.08***	-0.97***	-1.31***	-1.83***	-1.31	-0.89***	-0.83***	-0.95***
Std. Dev.	4.24	4.19	4.25	4.27	4.20	4.21	3.81	4.24
Sharpe Ratio	-0.25	-0.23	-0.31	-0.43	-0.31	-0.21	-0.22	-0.22
Slope (Annual return%)	-1.48	-1.59	-1.47	-1.83	-1.56	-1.00	-0.74	-0.91

This table illustrates the average monthly excess returns over the risk-free rate (%) for deciles sorted on firms differing in equity duration computed using different methods. Dechow, BM Mod, and Ind Mod refer to the Dechow et al. (2004) method, BM modified DSS, and Industry modified DSS methods, respectively. Const, ROE, and ICC refer to the equity duration computed with discount rates equal to a constant, portfolio long-run return-on-equity, and portfolio implied cost of capital, respectively. Portfolio refers to the market, BM decile, or industry 48 portfolios for the DSS, BM modified DSS, or industry modified DSS methods, respectively. Low and high refer to duration deciles with the bottom and top 10 percentile of firms differing in equity duration, respectively. High-Low represents an arbitrage portfolio that buys the top and sells the bottom duration deciles. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed (10 and 11) between 1963 and 2017. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Table 1.9: Correlation Matrix: Recent Asset Pricing Factors

Variables	$Duration_{BMROE}$	Weber	QMJ	HML DEVIL	IA	ROE	Market	SMB	HML	RMW	CMA	MOM
$Duration_{BMROE}$	1.00											
Weber	0.71	1.00										
	(0.00)											
QMJ	-0.50	-0.44	1.00									
	(0.00)	(0.00)										
HML DEVIL	-0.20	-0.30	-0.21	1.00								
	(0.00)	(0.00)	(0.00)									
IA	-0.39	-0.48	0.14	0.50	1.00							
	(0.00)	(0.00)	(0.00)	(0.00)								
ROE	-0.58	-0.46	0.62	-0.35	0.11	1.00						
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)							
Market	0.35	0.36	-0.50	-0.11	-0.38	-0.25	1.00					
	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)						
SMB	0.48	0.42	-0.50	-0.21	-0.25	-0.39	0.20	1.00				
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					
HML	-0.47	-0.59	0.01	0.77	0.69	0.01	-0.29	-0.30	1.00			
	(0.00)	(0.00)	(0.80)	(0.00)	(0.00)	(0.79)	(0.00)	(0.00)				
RMW	-0.67	-0.62	0.68	0.07	0.24	0.72	-0.32	-0.51	0.27	1.00		
	(0.00)	(0.00)	(0.00)	(0.16)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
CMA	-0.30	-0.43	0.10	0.48	0.91	-0.01	-0.41	-0.14	0.69	0.13	1.00	
	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.87)	(0.00)	(0.00)	(0.00)	(0.01)		
MOM	-0.15	-0.12	0.28	-0.69	0.02	0.50	-0.14	0.07	-0.21	0.12	0.01	1.00
	(0.00)	(0.02)	(0.00)	(0.00)	(0.75)	(0.00)	(0.00)	(0.18)	(0.00)	(0.01)	(0.82)	

This table illustrates the correlations between the duration return spread and recent asset pricing factors or puzzles. The duration return spread is computed as the difference in monthly returns between the top and bottom decile of firms differing in equity duration constructed using the BM modified DSS method with a discount rate equal to the BM decile specific long-run ROE. Refer to section 1.5.2 for details on constructing BM deciles and long-run ROE. Weber refers to the Weber (2018) duration factor. QMJ is the quality-minus-junk portfolio from Asness et. al., (2018). HML DEVIL is the HML factor from Asness and Frazzini, 2013. IA and ROE are investment and profitability factors from Zhang (2014). Market, SMB, HML, RMW, and CMA are excess market, small , value , profitability, and investment factors based on Fama and French (2015). MOM is the momentum factor from Carhart (1997). All correlations are significant at the 5% level.

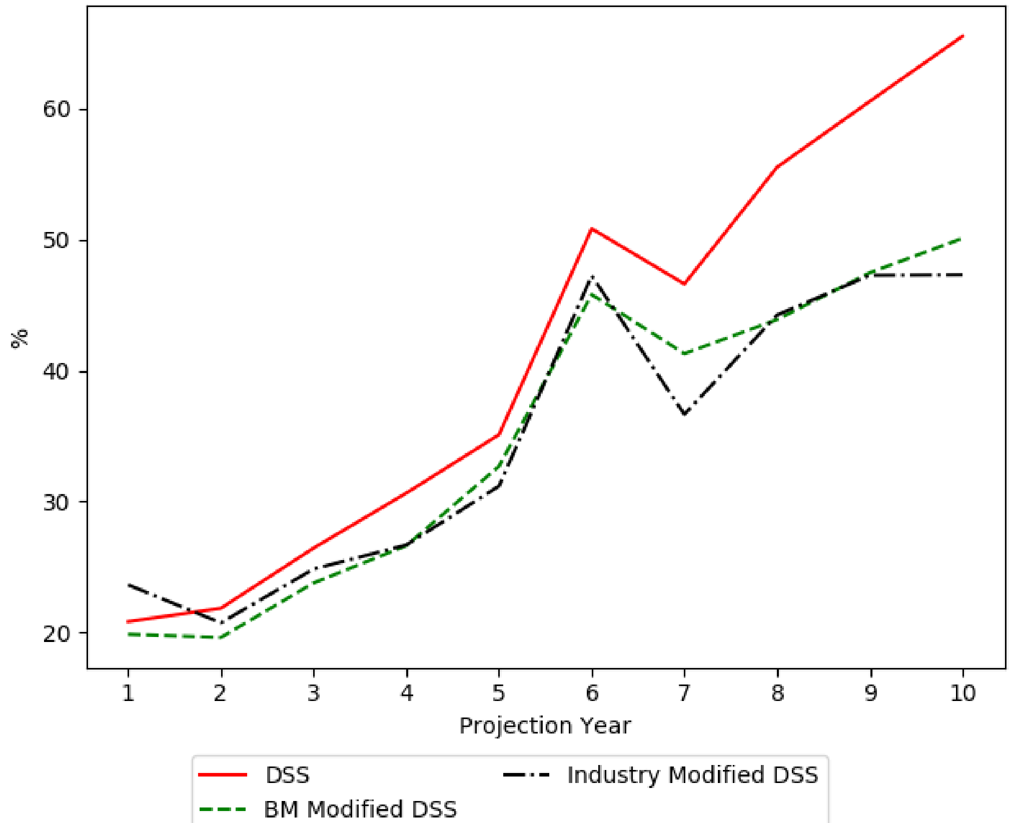
Table 1.10: Spanning of Duration Factor with Recent Asset Pricing Factors

	Excess Returns	Market	FF3	Carhart	FF5	FF5-Devil	Q-Factor	Q-Factor+Mom	Barillas
Mkt-rf		0.21***	0.08**	0.04	-0.02	-0.02	-0.00	0.00	0.00
		(5.58)	(2.18)	(1.17)	(-0.59)	(-0.65)	(-0.08)	(0.10)	(0.14)
SMB			0.51***	0.52***	0.26***	0.27***	0.22***	0.20***	0.21***
			(9.80)	(10.08)	(5.50)	(5.64)	(4.55)	(4.09)	(4.08)
HML			-0.13**	-0.20***	-0.17**		-0.38***	-0.35***	
			(-2.30)	(-3.51)	(-2.56)		(-5.79)	(-5.38)	
MOM				-0.20***	-0.15***	-0.13***		0.07*	-0.02
				(-5.35)	(-4.59)	(-2.74)		(1.87)	(-0.48)
CMA					-0.08	-0.25***			
					(-0.86)	(-2.67)			
RMW					-0.94***	-0.97***			
					(-14.36)	(-14.75)			
HML DEVIL						-0.00			-0.29***
						(-0.07)			(-3.99)
ROE							-0.95***	-1.01***	-1.05***
							(-16.00)	(-14.92)	(-14.69)
IA							0.03	0.01	-0.08
							(0.31)	(0.06)	(-0.82)
Alpha	-1.83***	-1.93***	-1.95***	-1.77***	-1.46***	-1.48***	-1.28***	-1.29***	-1.20***
	(-10.72)	(-11.53)	(-12.39)	(-11.30)	(-10.55)	(-10.43)	(-8.76)	(-8.83)	(-7.98)
R2(not %)	0.00	0.05	0.19	0.23	0.42	0.42	0.44	0.44	0.43
Alpha (Constant DR)	-1.31***	-1.44***	-1.14***	-1.15***	-0.88***	-0.68***	-0.90***	-0.92***	-0.62***
	(-7.70)	(-8.78)	(-8.26)	(-8.13)	(-6.94)	(-5.23)	(-6.23)	(-6.49)	(-4.26)
Alpha (IND ROE)	-0.85***	-0.97***	-0.71***	-0.66***	-0.49***	-0.36***	-0.46***	-0.47***	-0.27**
	(-6.16)	(-7.37)	(-6.25)	(-5.68)	(-4.46)	(-3.13)	(-4.01)	(-4.09)	(-2.24)
Alpha (IND Constant DR)	-0.89***	-1.03***	-0.74***	-0.73***	-0.45***	-0.28**	-0.42***	-0.44***	-0.17
	(-5.29)	(-6.42)	(-5.38)	(-5.15)	(-3.66)	(-2.13)	(-2.90)	(-3.11)	(-1.14)
Alpha (Dechow)	-1.08***	-1.26***	-0.89***	-0.81***	-0.57***	-0.34***	-0.60***	-0.61***	-0.27**
	(-6.38)	(-7.96)	(-7.36)	(-6.62)	(-5.30)	(-2.95)	(-4.87)	(-4.94)	(-2.07)

* p<0.10, ** p<0.05, *** p<0.01

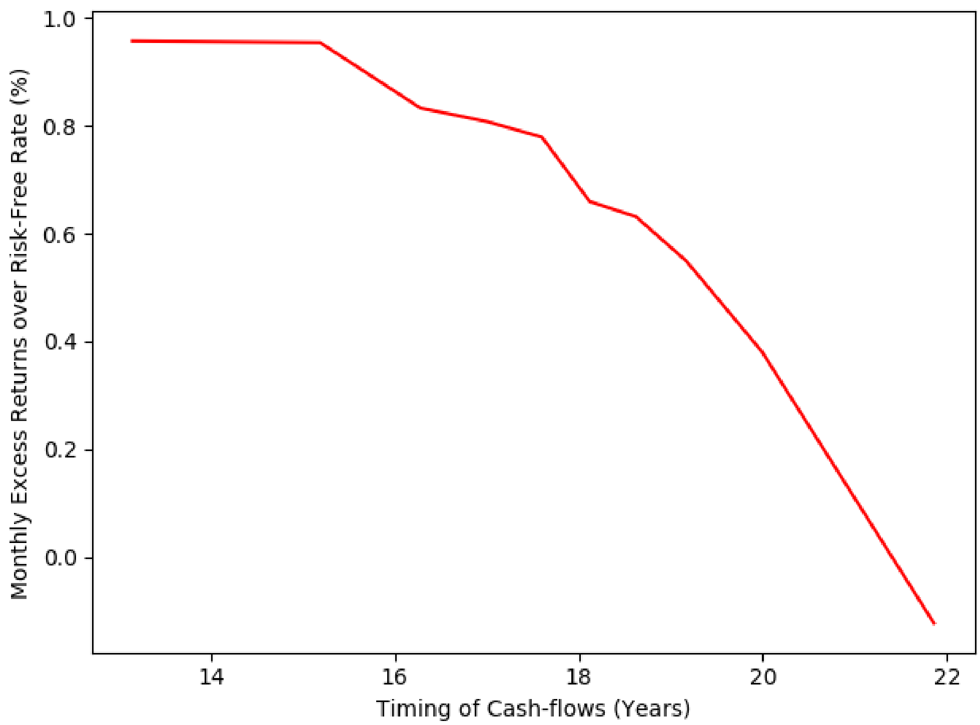
This table illustrates how well recent asset pricing factors span the duration return spread. The duration return spread is computed as the difference in monthly returns between the top and bottom decile of firms differing in equity duration constructed using the BM modified DSS method with a discount rate equal to the BM decile specific long-run ROE. Refer to section 1.5.2 for details on constructing BM deciles and long-run ROE. HML DEVIL is the HML factor from Asness and Frazzini, 2013. IA and ROE are investment and profitability factors from Zhang (2014). Mkt-rf, SMB, HML, RMW, and CMA are excess market, small , value , profitability, and investment factors based on Fama and French (2015). MOM is the momentum factor from Carhart (1997).T-statistics are reported in parenthesis. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Figure 1.1: Cash-Flow Comparison - Firm-Level



This figure plots the average error term computed across all firm-years. The error term is the absolute difference between expected cash-flows and realized cash-flows for each firm-year scaled by the market value observed at the beginning of the projection horizon of ten years. Firm-level expected cash-flows are projected employing one of DSS, BM modified DSS, or industry modified DSS methods. Refer to sections 1.5.1 and 1.5.2 for details on DSS, BM modified DSS, and industry modified DSS methods. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1963 and 2017.

Figure 1.2: Term Structure of Equity Risk Premium - DSS Method



This figure plots the downward-sloping term structure of equity risk premium under the DSS method. The horizontal axis plots the average equity duration for deciles of firms sorted on equity duration computed under the DSS method with a constant discount rate of 10.03%. The vertical axis plots the monthly average excess returns over the risk-free rate for each duration decile. Refer to section 1.5.1 for a detailed explanation of the DSS method. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1963 and 2017.

Chapter 2

DEFAULT RISK

2.1 Introduction

Corporate firms face the risk of bankruptcy. Extant research has investigated the relationship between the ex-ante probability that a firm will file for bankruptcy within the next one-year (default risk) and its equity returns. For instance, Dichev (1998) documents that high default risk firms have higher systematic market risk but earn lower excess returns over the risk-free rate than low default risk firms. Similarly, Griffin and Lemmon (2002), Ferguson and Shockley (2003), and Agarwal and Taffler (2008) document the above default risk puzzle in the United Kingdom under various models that predict default. Similarly, Avramov, Chordia, Jostova, and Philipov (2009) proxy for default risk with variation in firm long-term credit ratings, and Campbell, Hilscher, and Szilagyi (2008) extend the Shumway (2001) default prediction model to document the default puzzle in the United States.

This robust puzzle leaves certain empirical questions unanswered. Do all high default risk firms, irrespective of their future states such as delisting, recovering, or remaining high default risk, earn lower returns than low default risk firms? Turning the puzzle around, why do low default risk firms earn higher returns than high default risk firms? I address these questions in two steps. First, I verify the default risk puzzle and document its characteristics in the United States and in the United Kingdom with different proxies for default risk. Second, I classify firms into different categories based on their future states, i.e., delisting, recovering, and remaining high default risk, and examine average monthly abnormal returns based on Fama and French (1993) three-factor (henceforth FF3) asset pricing model under these categories.

I begin by discussing different default prediction models to answer the first research question. Secondly, to understand the data, I examine the joint distribution of default risk and firm-level monthly excess returns over the risk-free rate, and to what extent firm characteristics drive default risk in a Fama and MacBeth (1973) cross-sectional regression. Thirdly, I replicate the default risk puzzle employing time-series regressions. Finally, I examine average monthly abnormal returns of the highest 40 percentile default risk firms based on the FF3 model depending on their future paths. Similarly, I examine average monthly abnormal returns of the least 60th percentile default risk firms conditional on whether they enter one of the future paths of firms with elevated default risk within my sample period, to answer the second research question.

The above analysis suggests that the Shumway (2001) model predicts firm-level default more accurately than the Campbell et al. (2008) model in my sample. Secondly, although firms are distributed across all default probabilities, the majority of firms (94.86%) lie within 0-10% default probability based on the Shumway (2001) model. Thirdly, a Fama-Macbeth (1973) regression of firm-level monthly excess returns over the risk-free rate on Shumway (2001) default probability suggests a 12 bps decrease in monthly excess returns for a 1% increase in default probability after controlling for variables that enter default prediction, and characteristics such as book-to-market (BM) ratio and exposure to the market. Fourthly, an arbitrage portfolio that buys the top 20th percentile and sells the bottom 20th percentile default risk firms earns an equal-(value-) weighted monthly FF3 alpha of -3.36% (-1.95%). Finally, the top 40th percentile default risk firms earn lower returns than the bottom 40th percentile default risk firms irrespective of whether the former firms delist, recover, or remain high default risk firms in the future. To answer the follow-up research question, positive skewness in firm-level monthly excess returns and firms that recover from default risk contribute to low default risk firms earning higher returns than high default risk firms.

This chapter contributes to the default risk literature in understanding the implications of the distributive properties of default-risk. Campbell et al. (2008) build default portfolios that pay attention to the tails of default risk but do not explain their hypothesis that default risk is more relevant at the tails of the default risk distribution. The univariate distribution of default-risk, explored in this chapter, shows that 94.86% of firms have less than 10% default probability but a few significant number of firms have huge default probability. This finding suggests that studying default risk at the tails of the default risk distribution offers economically meaningful variation in default risk with high variance whereas the left tail offers low variance but economically less meaningful variation in default risk.

Hou, Xue, and Zhang (2017) suggest that the top decile of default risk firms do not earn statistically significant lower value-weighted returns than bottom decile of default risk firms under NYSE breakpoints for default risk (measured under various models). This result is consistent with the univariate distribution of default probability, and the inverse relation between default probability and size (e.g., Dichev (1998); Campbell et al. (2008)). NYSE breakpoints for default risk, and value-weighted returns pay greater attention to big firms which also tend to be low default risk firms. By forming equally-spaced deciles, the authors mechanically capture only the low end of the default risk in all of the deciles. Hence, the deciles may not offer meaningful variation in default risk.

Secondly, this chapter adds external validity to the default risk puzzle. I show that the default risk puzzle is prevalent both in the US and the UK using the two well-known discrete-hazard models, Shumway (2001) and Campbell et al. (2008). Further, adjusting returns to default risk for exposure to common risk factors exacerbates the puzzle. This result is directly related to Hou et al. (2017) who document the default risk puzzle only as portfolio excess returns over the risk-free rate. Therefore, the default risk puzzle is crucially about how the puzzle amplifies under various asset pricing models.

Thirdly, this chapter pioneers in documenting that delisting cannot proxy for default. In the US, firms that default (file for Chapter 7 or Chapter 11) delist under default-related, merger-related, and unexplained codes. I show that a default prediction model based on delisting is equivalent to a model based on chance implying that delisting is a poor proxy for default. This result is consistent with almost all default-risk related studies in the US choosing to employ proprietary databases (e.g., Altman default database, Capital Changes Reporter, LoPucki bankruptcy database from UCLA law school) to identify default. Additionally, studies that document a positive relation between default risk and returns (e.g., Chan and Chen (1991); Fama and French (1992); Vassalou and Xing (2004)) do not model default based on bankruptcy databases. It is then possible that a positive default risk premium is due to poor default risk modeling that does not capture default risk.

Fourthly, this chapter also pioneers in examining the returns for the different paths a default-prone firm potentially takes. As mentioned, irrespective of the path, the top 20 percentile earn lower monthly excess returns over the risk-free rate than the bottom 20 percentile of default risk firms. This result implies the possibility of a missing pricing factor for default risk firms. An alternate implication is that investors are consistently surprised by the poor performance of firms with elevated default risk. However, the Shumway (2001) model predicts default with a high accuracy casting doubts on the investor surprise hypothesis.

2.2 Related Literature

In this section, I discuss research relevant to the default risk puzzle. Early studies indirectly document a positive default risk premium while recent research that study default risk directly document a negative default risk premium.

2.2.1 Positive Risk Premium

Chan and Chen (1991) show that firms in the bottom 20 percentile of size are distressed firms (high leverage firms) and are riskier than the top 20th percentile of size when exposed to macroeconomic news. Hence, investors require a premium to hold the bottom 20 percentile of size firms.

Similarly, Fama and French (1992) show that their size and value factors explain several firm characteristics that are typical of default risk firms. Fama and French (1996) state that their value factor may capture distress risk because companies with high probability of failure may fail to meet their financial obligations in bad times and their stock prices may move together, making their risk non-diversifiable or systematic.

Vassalou and Xing (2004) show that default risk, measured with Merton (1974) model, is rewarded positively only in small value portfolio of Fama and French (1996) six portfolios. Chava and Purnanandam (2010) show that default risk is positively related to expected returns measured as the implied cost of capital (ICC).

Anginer and Yildizhan (2010) adjust corporate bond credit spreads for expected losses, taxes, and liquidity and claim that the resultant spread captures credit risk premia. Under this measure, the paper documents a positive distress risk premium. However, Elton, Gruber, Agrawal, and Mann (2001) and Vassalou and Xing (2004) document that corporate credit spreads contain little information (15%) about a firm's default risk.

2.2.2 Negative Risk Premium

Dichev (1998) employ accounting variables to measure default risk (e.g., Altman (1968); Ohlson (1980)) for US non-financial firms between 1981 and 1995 and documents a negative relation between default risk and mean excess returns over the risk-free rate. Similarly, Griffin and Lemmon (2002); Ferguson and Shockley (2003) document the negative relation between default risk and abnormal returns based on the FF3 model, and that firms with elevated default risk are more exposed to the value (HML) factor. Campbell et al. (2008) enhance the Shumway (2001) model, and document the negative default risk-return relationship. In the UK market, Agarwal and Poshakwale (2010) confirm the default puzzle as documented in Ferguson and Shockley (2003).

Avramov et al. (2009) document the default risk puzzle with credit ratings proxying for relative default probability between firms. They document that high credit risk (low credit rating) firms earn lower returns than low credit risk (high credit rating) firms. Specifically, low credit rated firms earn negative returns around rating downgrades. Similarly, Avramov, Chordia, Jostova, and Philipov (2013) document the negative distress risk premium using credit ratings and that momentum, investments, and idiosyncratic volatility puzzles are driven by short positions in low credit rating firms.

Garlappi and Yan (2011) document a hump-shaped relationship between default risk and firm returns under the Merton (1974) default model. Further, the authors build a model in which shareholders strategically default, thereby reducing the systematic risk of default and hence expected returns for the top decile of default risk firms.

In this chapter, I test the null hypothesis that there is no relation between default risk and firm monthly returns under different asset pricing models, and that the default risk-return pattern does not differ across different paths that default-prone firms may take.

2.3 Overview of Bankruptcy

This section provides an overview of the bankruptcy procedures in the United States and the United Kingdom to set the context for this chapter.

2.3.1 The United States

The United States Constitution reserves the governance of bankruptcy solely to federal courts. The federal courts deal with bankruptcy according to the Bankruptcy Code of 1978 that replaced the Chandler Act of 1938. Chapter 7 (Liquidation) and chapter 11 (Reorganization) of this code describe the bankruptcy process for corporate firms.

A firm can choose to file for bankruptcy under chapter 7 or chapter 11. Chapter 7 is designed to liquidate a firm. Once a firm files for Chapter 7, its assets are placed in the hands of a court-appointed trustee who liquidates the assets for the best price available, distributes the net proceeds to the creditors in the order of priority, and administers the firm as the liquidation process proceeds. In general, no equity remains. The trustee is paid a fee from the liquidation proceeds.

Chapter 11 is designed to reorganize a failing firm. Under chapter 11, shareholders retain control of firm assets while various stakeholders draft a reorganization plan. Such a firm is formally called debtor-in-possession. In contrast to Chapter 7, a debtor-in-possession firm can acquire financing by promising new lenders seniority over existing lenders. The reorganization plan is approved through a majority (two-thirds in claim amount) vote in each class of creditors. If no plan is approved, the firm continues to operate while a buyer is sought for all or part of the firm ("cramdown" reorganization). Further discussion on the US Bankruptcy Code and its effect on shareholder bargaining power can be found in White (1983) and Hackbarth, Haselmann, and Schoenherr (2015).

2.3.2 The United Kingdom

In the United Kingdom, corporate bankruptcy is commonly termed as insolvency, and is primarily governed by the Insolvency Act of 1986.

Insolvency proceeds primarily through administration or liquidation, although there are different forms under each category. Unlike the US, creditors or shareholders can file for insolvency in the UK. Under administration, a court/creditor appointed administrator negotiates the sale of business and assets to a new firm owned by a buy-out team or competitor. Hence, administration is similar to chapter 11 in the US.

Under liquidation, assets of the firm are sold for cash and distributed amongst creditors. A firm can also voluntarily file for liquidation when it can fulfill all debt obligations, and shareholders intend to realize their investments. Hence, liquidation is identical to chapter 7 in the US. Further discussion of the UK Insolvency Act 1986 can be found in PricewaterhouseCoopers (2009).

2.4 Data

This section describes the data in the United States and the United Kingdom used in this chapter.

2.4.1 The United States

The sample consists of US non-financial firms in CRSP/COMPUSTAT with common shares listed (share codes 10 and 11) between July 1980 and June 2015. Firm-level market data come from CRSP, and accounting data come from COMPUSTAT. I account for delisting returns while calculating returns. The average delisting return is -52%, but the most frequent delisting return is -100%. Following Fama and French (1993), I lag accounting data by six months to ensure that data is available when I construct portfolios. The portfolio formation date (PFD) in the US is the end of June because most US firms have December as the fiscal year-end. Within six months, accounting data is made public as per listing requirements. I winsorize all firm-specific variables at the 1st and 99th percentile every portfolio year to mitigate the effects of outliers.

In the US, a firm is default if it enters chapter 7 or chapter 11. Data on default US firms are not readily available. The UCLA - LoPucki Bankruptcy Research Database (BRD) contains data on US large public default since October 1979. A company is public if it filed a form 10-K or form 10 with the Securities and Exchange Commission (SEC) within the last three years of filing for bankruptcy. A company is large if the filed annual report states assets worth 100 million USD or greater, measured in 1980 USD (about 305 million in 2018 USD).

In order to match the gvkey from LoPucki BRD to CRSP permno, I follow a two-stage approach. I match gvkey from LoPucki BRD to gvkey in COMPUSTAT. Following this step, I match the gvkey to permno using the link table in Wharton Research Data Service (WRDS) accounting for the dates during which the link remains valid. A firm can delist or move exchanges before bankruptcy. Hence, the gvkey-permno link may have expired before the date of bankruptcy. So, I compare the firm name in both the LoPucki database and the link table, and use the link if the gvkey-permno expired less than or equal to 2 years before bankruptcy. If a valid permno cannot be found, I manually search the company name in the link table to identify a corresponding permno that exists after June 1980. Table B.1 in appendix B details the results of this procedure. The final sample consists of 495 failed firms amongst 132,953 firm-year observations (refer to Table 2.1). 458 of 495 firms have accounting and market information available to compute annual ex-ante default probability.

2.4.2 The United Kingdom

The sample consists of all UK non-financial firms listed on the main segment of the London Stock Exchange (LSE) between October 1990 and September 2012. Specifically, I remove firms with ICB codes in the 8000 series (financial firms) except for 8986, Real Estate Investment Trusts (REITs) because firms under the real estate industry own most REITs.

In the UK, a firm is default if it enters administration or receivership (liquidation). I start with dead firms in DATASTREAM. Following this step, I gather firms from London Share Price Database (LSPD) with codes 7, 16, 20, and 21. I also manually gather firms from Capital Gains Tax (CGT) capital losses book, February 2012 that are of negligible value or in administration/ receivership. Then, if a firm appears in any one of these databases, I manually cross-check for its administration/receivership placement date in FACTIVA-Regulatory News Service (RNS). I cross-check manually with RNS those firms that have Members Voluntary Liquidation (MVL) as the reason for entering administration to ensure that MVL is not because of operating losses. If so, I consider such firms to have defaulted. Otherwise, the firm is not considered default when modeling default risk. First three years of data (1990 to 1992) is used to calibrate of the default prediction models (e.g., Shumway (2001); Campbell et al. (2008)). The final sample consists of 2,929 unique firms of which 306 failed with 24,309 firm-year observations (refer to Table 2.2).

2.5 Modeling Default

In order to test my central null hypothesis, I require a measure of default risk. This section provides an overview of default risk models employed in various studies, including this chapter.

2.5.1 Default Models

Default models fall into one of accounting, market, or hazard models.

Accounting Models

Accounting based models employ financial statements' data to measure firm default risk. Despite a long history in bankruptcy prediction (e.g., Beaver (1966); Altman (1968); Ohlson (1980); Taffler (1983); Zmijewski (1984)), these models have been criticized for their backward-looking perspective and possibility of being subject to managements manipulation. Also, accounting ratios change with time elucidating that coefficients in accounting models need to be updated often. Further, accounting-based models are static and hence, cannot account for asset/liability volatility (e.g., Hillegeist, Keating, Cram, and Lundstedt (2004)). This observation implies firms with the same accounting ratios can have different default probabilities (e.g., Vassalou and Xing (2004)).

Market and Hybrid Models

Market-based models employ firm market data to measure firm default risk. Hybrid models take advantage of both accounting and market variables for firms (e.g., Beaver (1966)).

Market models are mostly contingent-claims based models and hence, depend on the option-pricing model developed by Black, Scholes, and Merton (BSM) (i.e., Black and Scholes (1973); Merton (1974)). The BSM model assumes that equity is a call option on the underlying assets of the firm with a strike price equal to the face value of the firm's liabilities. The option expires worthless if the value of the assets falls below the value of the liabilities. Crosbie and Bohn (2003), Vassalou and Xing (2004), and the KMV corporation adopt various enhanced versions of the BSM model.

Bharath and Shumway (2008) examine the accuracy of the Merton (1974) Distance to Default (DD) model (naive model) in predicting default for US non-financial firms listed on NYSE, AMEX, and NASDAQ between 1980 and 2003. They propose a naive model by approximating a firm's market value of debt with its face value and the volatility of debt with a fraction of the equity's volatility. The naive model predicts firm default as good as the Shumway (2001) model in-sample (see next section for details on how to compare models).

Credit-rating based models also fall under market/hybrid models as credit-rating agencies employ versions of the Merton (1974) model to predict firm default.

Hazard Models

Shumway (2001) is the pioneer hazard model for default probability in the finance literature. Shumway (2001) applies a hazard model to US non-financial firms trading on NYSE and AMEX between 1962 and 1992. The model is a multi-period logit estimation program that calculates maximum likelihood estimates for the likelihood that a firm will default within the next one-year. The logit model can be expressed as

$$P_{i,t} = \frac{e^{\alpha+\beta X_{i,t}}}{1+e^{\alpha+\beta X_{i,t}}} = \frac{1}{1+e^{-\alpha-\beta X_{i,t}}} \tag{2.1}$$

where $P_{i,t}$ is the one-year ex-ante probability of default for firm i at time t, α and β are regression coefficients in the logit regression, $X_{i,t}$ is a vector of independent variables used in the logit model. Shumway (2001) applies net income to total assets (NITA), total liabilities to total assets (TLTA), market capitalization to total size of CRSP NYSE/AMEX index (RSIZE), excess rate of return in comparison to the market (EXRET), and annualized standard deviation of monthly residual returns (obtained from regressing firm monthly returns on CRSP NYSE/AMEX index) over the past 12 months (SIGMA) as independent variables. The dependent variable is an indicator variable, $Indicator_{it}$, that takes the value 1 if the firm i defaults in year t and takes the value 0 if the firm i survives in year t. No observations exist for firms beyond the year in which they default.

Shumway (2001) documents that his model predicts default more accurately than accounting or market models owing to time-varying independent variables and accounting for the time-frame in which a firm remains at the risk of default.

Campbell et al. (2008) extend Shumway (2001) model by including lagged information on profitability and excess stock returns over the S&P 500 index. Within the sample, the authors show that their model has higher predictive power than Shumway (2001) model. Campbell et al. (2008) logit model can be expressed as

$$P_{i,t} = \frac{e^{\alpha+\beta X_{i,t}}}{1+e^{\alpha+\beta X_{i,t}}} = \frac{1}{1+e^{-\alpha-\beta X_{i,t}}} \tag{2.2}$$

where $P_{i,t}$ is the one-year ex-ante probability of default for firm i at time t, α and β are regression coefficients in the logit regression, $X_{i,t}$ is a vector of independent variables used in the logit model. The independent variables include past 12 months moving-average net income to total assets (NIMTAAVG), total liabilities to total assets (TLTA), market capitalization to total size of the S&P 500 index (RSIZE), past 12 months moving-average excess rate of return in comparison to the S&P 500 index (EXRETAVG), 12-month moving average of cash and short-term investments to the market value of total assets (CASHMTA), and standard deviation of residual returns. The 12 months moving-average assigns geometrically declining weights on past lags to indicate that the distant past matters less.

I estimate firm default probability with the Shumway (2001) and Campbell et al. (2008) models in the US and the UK. With hand-collected data on firms that default in the UK, I estimate the parameters of the models under the UK data. Each year, default probability is calculated out-of-sample using coefficients estimated with data from 1990 up to but not including the year of prediction. I start estimating firms' default probability from 1993. This expanding window ensures that every estimate is out-of-sample and avoids look-ahead bias. I use the authors calibrated model for the US because the UCLA BRD contains only large firms (total assets) but small firms are more likely to default (e.g., Campbell et al. (2008)).[1] Table 2.3 summarizes the logit model estimates for a logit regression on the entire sample

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[1]Nevertheless, a logit model based on LoPucki BRD performs worse than the pre-calibrated Shumway (2001) model. Specifically, the model calibrated with the LoPucki BRD suggests that flipping the indicator variable (firms that default as non-default firms) predicts default as good as the pre-calibrated Shumway (2001) model.

in the UK. Overall, the estimates are consistent with Shumway (2001) and Campbell et al. (2008) qualitatively. Specifically, profitability (NITA, NIMTAAVG) and return volatility (SIGMA) are positively related to default while leverage (TLTA, TLMTA), size relative to the market (RSIZE), cash relative to total assets (CASHMTA), return over the market (EXRET, EXRETAVG) are negatively related to default. The dependent variable is an indicator variable, $Indicator_{it}$, that takes the value 1 if the firm i defaults in year-month t and takes the value 0 if the firm i survives in year-month t. No observations exist for firms beyond the year in which they default.

2.5.2 Comparison of Default Prediction Models

The purpose of default risk models is to predict firm default in the next one-year accurately without assigning a default probability of 100% to all firms. Hence, a default model must be able to differentiate between default and non-default firms accurately by assigning a higher default probability to the former firms. The goal of the default model, therefore, is to minimize the overlapping area of the distribution of non-default and default firms.

Commonly used measures to evaluate the ability of default models to distinguish between default and non-default firms include receiver operating characteristic, accuracy ratio, and Kolmogorov-Smirnov test (e.g., Bauer and Agarwal (2014)). While default risk models provide default probability for a firm, the mentioned measures compare binary outcomes for a firm - default and non-default. Each measure deals with this issue differently, which I discuss next.

Statistical software that compute receiver operating characteristic (ROC) generates scenarios under which a probability cut-off values segregate firms into expected default and expected non-default categories. Then, the software computes how well predicted default matches realized default. A default prediction models ROC, expressed in percentage terms, represents the average degree of non-overlap between the distributions of expected default and expected non-default firms accounting for the accuracy of default prediction, averaged over the scenarios with different cut-off values. Statistical software that compute accuracy ratio (AR), expressed in percentage, compute how well, on average, the model can predict default accurately in comparison to a perfect model, within a top x-percentile of firms reverse sorted on predicted default probability. The averaging happens over different top x-percentiles. In contrast, the KS test is the maximum percentage of non-overlap offered by a cut-off value that best distinguishes between default and non-default firms.

A model with a higher ROC, AR, or KS than another model implies that the former model has a higher degree of non-overlap between the expected default and expected non-default distributions after accounting for the accuracy of default prediction. In this context, the Shumway (2001) model distinguishes between default and non-default models more accurately than the Campbell et al. (2008) model in terms of ROC (91% vs 85%), AR (83% vs 71%), and KS (69% vs 60%) in the UK data.[2] Hence, the Shumway (2001) model is preferred over the Campbell et al. (2008) model to predict default in the UK sample.

Now, I evaluate the Shumway (2001) model as calibrated in the paper in comparison to one calibrated with delisting data in the US. The Shumway (2001) pre-calibrated model distinguishes default and non-default risk firms with an ROC of 65%. I calibrate the Shumway (2001) model with delisting data though a logit program as follows. Table 2.11 shows that 88% of default firms in the LoPucki BRD delist either under "default" or "dropped" related codes. Hence, a firm that delists under one of these codes contributes a default observation ($Indicator_{it} = 1$) to the logit model. Each year a firm survives, it contributes a non-default observation ($Indicator_{it} = 1$) to the logit model. I estimate the logit model with the indicator variable, $Indicator_{it}$, and each firm's annual variables based on the Shumway (2001) independent variables as dependent and independent variables, respectively. Then, I

[2]The appendix (section B.1) contains further technical details on the comparative statistics.

evaluate how well the estimated model distinguishes between default and non-default firms as categorized in the LoPucki BRD. Such a model has an ROC of 49% suggesting that the model is based on chance. Hence, delisting is not a good proxy for default in the US. Henceforth, I employ the Shumway (2001) model as calibrated in the Shumway (2001) paper to compute ex-ante one-year default probability for firms in the US.

2.6 Properties of Default Risk Firms

Before answering the main research question of this chapter, I document several characteristics of default risk firms in this section. First, I examine the distribution of default probability and monthly excess returns over the risk-free rate on a univariate and bivariate basis to understand the data. Second, I examine to what extent firm-characteristics drive default risk.

2.6.1 Distributive Properties

In this section, I plot the univariate and bivariate density functions for default probability and monthly excess returns over the risk-free rate ($R_{it} - Rf_t$) to understand the distribution of default probability and returns.

Figure 2.1 plots the univariate distribution of default probability. I find that the majority of firms possess a low default probability. Precisely, 94.86% of firms lie within 0-10% default probability. Figure 2.2 plots the bivariate probability density function for default probability (x-axis) and firm $R_{it} - Rf_t$ (y-axis). The figure shows that $R_{it} - Rf_t$ are approximately normally distributed within 0-10% default probability but are right-skewed, i.e., few firm-months have huge positive $R_{it} - Rf_t$. No distributional deductions can be made about returns beyond 10% default probability due to few, wide-spread observations.

The figure reiterates that although firms have a wide range of default probability, most firms (94.86%) lie within 10% default probability. This observation implies a trade-off between variation in default risk and statistical significance due to small number of observations. The right tail of default risk offers meaningful variation in default risk at the cost of few observations while the left tail offers numerous observations (and hence, estimates likely have a low standard deviation) at the cost of less meaningful variation in default risk.

This evidence suggests that different perspectives of the data affect the economic and statistical significance of default risk studies. Hence, I present results from various perspectives of the data in the US and check for robustness in the UK.

2.6.2 Do Firm Characteristics Drive Default Risk?

Several firm-characteristics enter the Shumway (2001) default prediction model, such as leverage, profitability, idiosyncratic volatility, and firm size in relation to the market size. In this section, I document to what extent a linear combination of these, and other firm characteristics drive default risk.

To explore this possibility, I perform a Fama and MacBeth (1973) cross-sectional regression of monthly firm excess returns over the risk-free rate on variables that determine firm default probability. Tables 2.6 and 2.7 present the results. Comparing model 1 and model 10 of both tables shows that the effect of default probability increases in magnitude and becomes statistically significant after controlling for firm characteristics in the UK and the US. This result suggests that the Shumway (2001) model predicted default probability represents information over and above a linear combination of the variables that determine default probability. Additionally, the negative sign on default probability suggests that firm monthly excess returns over the risk-free rate are negatively related to firm default probability across all models. Further, models 1 to 8 suggest that the significant negative loading on default probability is not due to the presence of any single variable in the US (see Table 2.6) while it is due to relative size in the UK (see Table 2.7). Further, the direction of coefficients are consistent with the sign of predictor variables in the logit model (see Table 2.3).

This cross-sectional evidence suggests that a one-percentage increase in firm default risk reduces the firm excess returns by 12 bps and 100 bps in the US and UK, respectively, after controlling for exposure to systematic market risk (market beta) and several other firm characteristics. As already mentioned, default probability for firms is concentrated within 10% default probability and empirically observing a one-percentage increase in default probability is unlikely. Moreover, the cross-sectional regression imposes a linear relationship between default risk and returns. Hence, in the next section, I quantify the default risk-return relationship through portfolios of firms sorted on default risk.

2.7 The Default Risk Puzzle

This section verifies the presence of the default risk puzzle. I examine the asset pricing implications of default risk through portfolios of firms sorted on default probability. First, I describe the construction of portfolios and their summary statistics. Second, I detail the return characteristics and risk exposures of the default sorted portfolios. Finally, I examine whether the return and risk exposure characteristics are robust to recent asset pricing models.

As previously mentioned, I document results from different perspectives of the data in the US, and check for robustness in the UK. At the end of June each year from 1980 through 2014, I sort US non-financial firms with listed common shares into equally-spaced and right-skewed quintiles based on Shumway (2001) model's default probability. Similarly, at the end of September every year between 1993 and 2012, I classify UK non-financial firms into equally-spaced deciles based on Shumway (2001) model's default probability. I choose different portfolio cuts for the countries to further show that results are not dependent on unique cuts of the data. Panels A and B of table 2.4, and 2.5 illustrate summary statistics for equally-spaced and right-skewed quintiles, and for deciles in the UK, respectively. Consistent with the Fama and MacBeth (1973) regressions discussed in the previous section, high default risk firms are small, less profitable, and are highly levered. Further, high default risk firms are more likely to have negative book-equity.

Now, I examine the return characteristics of default risk portfolios. Tables 2.8 and 2.9 present returns and risk exposures under the US data for equally-spaced and right-skewed quintiles, respectively. Table 2.10 presents returns and risk exposures under the UK data for equally-spaced deciles. Panels A and B of the three tables present equal-weighted and value-weighted returns for each default portfolio, respectively. In each panel, the first row presents mean excess returns over the risk-free rate, $E[R_p - Rf]$, the second row presents abnormal returns from FF3 model, α, and the last three rows present the exposure to systematic risk factors namely, the market (β_{Mkt}), size (β_{SMB}), and value (β_{HML}). In each panel, the arbitrage portfolio that buys the "High" default risk portfolio and sells the "Low" default risk portfolio summarizes the spread in returns and risk exposures between firms that fall under the bottom and top default risk portfolios.

For equally-spaced quintiles, both $E[R_p - Rf]$ and α monotonically decrease from low to high default risk portfolios in equal- and value-weighted terms. The arbitrage portfolio earns a monthly EW (VW) $E[R_p - Rf]$ of -3.12% (-1.43%) and an α of -3.36% (-1.95%). For right-skewed default quintiles, both $E[R_p - Rf]$ and α monotonically decrease from low to high default risk portfolios for equal-weighted portfolios. In contrast to equally-spaced quintiles, the value-weighted high default risk right-skewed quintile earns higher returns than the previous quintile suggesting that size interacts with default risk in the right tail of default risk. Nevertheless, the arbitrage portfolio earns a monthly EW (VW) $E[R_p - Rf]$ of -2.62% (-0.96%) and an α of -2.76% (-1.34%).

For equally-spaced quintiles, β_{Mkt}, β_{SMB}, and β_{HML} monotonically increase from low to high default risk portfolios under equal- and value-weighted terms. The arbitrage portfolio summarizes the spread in exposure to market, size, and value factors to be 0.08, 0.70, and 0.33, respectively. For right-skewed default quintiles, β_{HML} increases monotonically for equal- and value-weighted portfolios from low to high default risk portfolio. In contrast to equally-spaced quintiles, high default risk portfolio has lower exposures, β_{Mkt} and β_{HML}, than the previous portfolio suggesting that risk exposures contain non-linearities in the right tail of default risk. Nevertheless, the arbitrage portfolio summarizes a positive spread in exposure to market and size factors for both equal- and value-weighted portfolios.

For the UK market, return and risk exposure patterns in the US hold. Specifically, the arbitrage portfolio earns a monthly EW (VW) $E[R_p - Rf]$ of -2.42% (-1.79%) and an α of -2.40% (-1.80%) with a positive and significant exposure to value factor under equal-weighted terms and to size factor under value-weighted terms.

Hence, high default risk firms earn lower returns but have higher exposure to systematic risk factors than low default risk firms. Additionally, low default risk firms earn positive significant alphas. These two empirical results are a puzzle. Specifically, the first result is inconsistent with Chan and Chen (1991) and Fama and French (1996) conjectures that the size and value factors proxy for default risk, respectively.

One potential reason for the puzzle could be that the return pattern arises from only a subset of stocks with a specific future path. For instance, only firms with elevated default risk that delist may earn lower returns than firms in the bottom default risk portfolio. If the proportion of firms that delist increases from "Low" to "High" default risk portfolios then these firms may drive the significant low returns to the top two default risk portfolios (e.g., see Table 2.8, Panel A). Hence, I explore whether the default risk puzzle is pervasive across potential future paths for firms with elevated default risk in the next section.

2.8 Pervasiveness of the Default Risk Puzzle

The previous section documented that the default risk puzzle is robust across different perspectives of the data and countries. This section investigates the main research question of this chapter, i.e., I investigate the pervasiveness of the default risk puzzle across potential future paths for firms differing in default risk from Shumway (2001). I choose the US equally-spaced quintiles as the main data perspective. The qualitative results in this section hold under right-skewed quintiles in the US.

Firms with elevated default risk may delist, recover, or remain high default risk at the end of my sample period. If only one of these category of firms earn lower returns than others and occupy a majority proportion of the high default risk portfolio then such firms may drive the observed default risk puzzle. Table 2.12 presents the monthly FF3 alphas to the potential paths for firms with greater than 60th percentile default risk. Panel A presents the puzzle, Panel B presents the FF3 alphas to firms that eventually recover into the first three default risk quintiles, Panel C presents the FF3 alphas to firms that eventually delist, and Panel D presents the FF3 alphas to firms that remain in the highest two default risk portfolios at the end of my sample period. In addition to FF3 EW and VW alphas in the first two rows, respectively, each panel presents the proportion of firm-months in the third row. Panel C also presents the delisting returns in the fourth row.

The results indicate that firms with elevated default risk earn significantly lower returns than "Low" default risk firms across all potential paths. However, firms that delist, which also occupy the majority of firm-months for the top two default risk portfolios, earn significantly more negative returns including delisting returns than other categories. The delisting returns themselves are highly negative but do not influence monthly returns heavily because they contribute only one observation. Hence, high default risk firms earn lower returns than low default risk firms pervasively across future paths of high default risk firms.

The default risk puzzle is as much about the low default risk firms earning positive significant FF3 alphas as it is about high default risk firms earning negative FF3 alphas. One reason for the greater over-performance of the low default risk stocks may be that firms that emerge from the highest default risk portfolios earn significantly positive returns as investors are surprised. Therefore, I examine returns to the first three default quintiles under various categories. Specifically, I look at firms that never entered the highest two default risk portfolios within my sample period, firms before they entered the highest two default risk portfolios ("before default risk"), and firms after they emerged from the highest two default risk portfolios ("after default risk").

I define certain rules for firm-months within the first three default risk quintiles to be classified under "before default risk" and "after default risk" categories. I classify firms in the initial months they enter my sample within the first three default risk quintiles as "before default risk". At any point in time, 40 percentile of firms fall in the highest two default risk quintiles by construction. In order to mitigate this bias, I offer firms that enter my sample in the top two default risk portfolios a chance to feature in the "before default risk" category. So, firms that enter the sample in the top two default risk portfolios and recover to the first three portfolios within two years of entering the sample will feature in the "before default risk" category during the months of their first recovery into the first three default risk portfolios. Similarly, firms that move from the top two default portfolios to the first three default portfolios and stay there for more than a year, except for firm-months in which they have been classified under "before default risk", occupy the "after default risk" category.

Table 2.13 presents the monthly FF3 alphas to the different categories of firms with the least 60th percentile default risk. Panel A presents the puzzle, Panel B presents the FF3 alphas to firms that never enter the highest two default risk portfolios in my sample period, Panel C presents the FF3 alphas to firms under "before default risk" category, Panel D presents the FF3 alphas to firms under "after default risk" category, and Panel E presents FF3 alphas to firms that recover for only one year. Each panel also presents the proportion of total firm-months under the first three default risk portfolios.

The results indicate that for firms with the least 20th percentile default risk, all categories earn significant positive FF3 alphas. However, for firms between 20th and 40th percentile default risk, only firms that recovered from default risk (Panel D) earn significant positive alphas. Within the least 20th percentile default risk firms, the least 5 percentile default risk firms earn significant FF3 alphas (result not shown). This result is similar to Bessembinder (2018) who documents that the net gain for the entire US stock market since 1926 comes from 4% of listed companies owing to the positive skewness in the distribution of monthly stock returns. Hence, low default risk firms earn positive monthly FF3 alphas partly due to positive skewness in monthly returns and due to firms that recover from high default risk.

In conclusion, the default risk puzzle is pervasive across potential paths for high default risk firms namely, delisting, recovering, or remaining high default risk, and across different categories of low default risk firms. One reason for the pervasive default risk puzzle is valuation errors leading to mispricing. For instance, investors may not have realized that the independent variables in the Shumway (2001) or Campbell et al. (2008) model predict default risk firms and may have not discounted the prices of high default risk firms enough. In this case, negative returns around earnings announcements should largely resolve such mispricing. However, Campbell et al. (2008) find that high default risk firms earn positive, not negative returns, around earnings announcements because investors perceive the ability to announce earnings to be positive. This result indicates that the alphas to firms after recovery may be due to the positive surprise of recovery. However, markets would largely reflect these positive surprises before portfolio rebalancing which allows six months time for accounting information to become available. This collective evidence suggests the presence of a missed pricing factor, a hypothesis that I investigate in the next chapter.

2.9 Conclusion

In this chapter, I verify the presence of the default risk puzzle under various perspectives of the data and countries. Additionally, I document that the default risk puzzle is pervasive across different paths of high default risk firms namely, delisting, recovering, or remaining high default risk. Further, firms that recover from elevated default risk levels earn positive and significant Fama and French (1993) three-factor alphas. These alphas persist despite allowing six months for the market to assimilate earnings information before rebalancing default risk portfolios. This pervasive and robust puzzle suggests that there may exist a missed pricing factor for default risk. In the next chapter, I explore this hypothesis.

Table 2.1: Sample Observations - USA

Year (1)	No. of Firms (2)	No. of Firms with assets >100 MIL (3)	No. of Failures (4)	Failure Rate (4/2)(%)	Failure Rate (4/3)(%)
1980	3,324	1,364	2	0.06	0.15
1981	3,512	1,359	3	0.09	0.22
1982	3,633	1,307	9	0.25	0.69
1983	3,777	1,326	4	0.11	0.30
1984	3,903	1,314	5	0.13	0.38
1985	3,843	1,263	3	0.08	0.24
1986	3,975	1,295	9	0.23	0.69
1987	4,108	1,323	5	0.12	0.38
1988	4,072	1,322	5	0.12	0.38
1989	3,998	1,344	5	0.13	0.37
1990	3,959	1,358	17	0.43	1.25
1991	4,003	1,364	15	0.37	1.10
1992	4,189	1,438	16	0.38	1.11
1993	4,534	1,528	11	0.24	0.72
1994	4,730	1,634	6	0.13	0.37
1995	4,977	1,762	7	0.14	0.40
1996	5,229	1,851	7	0.13	0.38
1997	5,145	1,928	8	0.16	0.41
1998	4,787	1,943	18	0.38	0.93
1999	4,552	1,959	28	0.62	1.43
2000	4,327	2,032	47	1.09	2.31
2001	4,003	1,919	62	1.55	3.23
2002	3,694	1,846	47	1.27	2.55
2003	3,528	1,833	28	0.79	1.53
2004	3,475	1,868	15	0.43	0.80
2005	3,386	1,858	14	0.41	0.75
2006	3,292	1,825	4	0.12	0.22
2007	3,220	1,845	6	0.19	0.33
2008	3,086	1,782	13	0.42	0.73
2009	2,923	1,723	39	1.33	2.26
2010	2,820	1,715	8	0.28	0.47
2011	2,743	1,727	6	0.22	0.35
2012	2,688	1,699	7	0.26	0.41
2013	2,730	1,736	8	0.29	0.46
2014	2,788	1,755	8	0.29	0.46
Total Sample	132,953	57,145	495	0.37	0.87

This table outlines the number of firms that filed for bankruptcy under chapter 7 or chapter 11 of the Bankruptcy Code of 1978 (No. of Failures) in the US. The sample includes US non-financial firms in the CRSP/COMPUSTAT universe with common shares listed between 1980 and 2014 (No. of Firms). Failure rate is the percentage of firms (No. of Firms or No. of Firms with Assets $\geq$ USD 100 million) that went bankrupt (No. of Failures) in a year. Bankruptcy data comes from UCLA - LoPucki Bankruptcy Research Database.

Table 2.2: Sample Observations - UK

Year	No. of Firms	No. of Failures	Failure Rate (%)
1990	851	1	0.12
1991	900	10	1.11
1992	1,063	34	3.20
1993	1,289	10	0.78
1994	1,346	8	0.59
1995	1,389	8	0.58
1996	1,460	9	0.62
1997	1,501	11	0.73
1998	1,444	15	1.04
1999	1,315	25	1.90
2000	1,272	6	0.47
2001	1,208	18	1.49
2002	1,137	30	2.64
2003	1,059	10	0.94
2004	1,076	15	1.39
2005	1,116	3	0.27
2006	1,088	16	1.47
2007	1,002	14	1.40
2008	867	19	2.19
2009	742	19	2.56
2010	627	13	2.07
2011	557	12	2.15
Total Sample	24,309	306	1.26

This table outlines the number of firms that filed for administration or receivership (bankruptcy) under the Insolvency Act of 1986 (No. of Failures) in the sample of firms listed in the Main Segment of the London Stock Exchange (LSE) between September 1990 and October 2011 (No. of Firms). Failure rate is the percentage of firms (No. of Firms) that filed for bankruptcy (No. of Failures) in a year. Bankruptcy data come from DATASTREAM dead firms, LSPD (codes 7, 16, 20 and 21), Capital Gains Tax (CGT) Capital Losses book, February 2012 and FACTIVA - Regulatory News Service (firms in receivership, administration).

Table 2.3: Logit Regressions of Bankruptcy Indicator on Variables

Variable	Shumway (2001)	Campbell et al. (2008)
NITA	-3.56***	
	(-2.15)	
TLTA	0.15*	
	(1.77)	
RSIZE	-0.40***	
	(-12.62)	
EXRET	-0.73***	
	(-9.05)	
SIGMA	2.23***	
	(5.92)	
NIMTAAVG		-0.37
		(-0.41)
TLMTA		0.87
		(1.93)
RSIZE		-0.02
		(-0.46)
EXTRETAVG		-31.19
		(-10.70)
SIGMA		0.01
		(0.66)
MB		0.04
		(0.77)
LN_PRICE		-0.58
		(-12.44)
CASHMTA		-0.85
		(-1.37)
Constant	-10.74***	-7.49***
	(-25.06)	(-11.44)
Pseudo R2 (%)	20.57	10.57
Bankruptcies	306	306

This table reports the coefficients from a logit regression of a binary indicator variable on predictor variables using UK non-financial firms listed on the main segment of the London Stock Exchange between 1990 and 2011. The first column presents results for the Shumway (2001) model. NITA refers to net income to shareholders divided by total assets. TLTA refers to total liabilities divided by total assets. RSIZE is the market value of the firm divided by the market value of FTSE All Share Index. EXRET is the log of firm excess return over the FTSE All Share Index over the past 12 months before portfolio formation (end of September). SIGMA is the standard deviation of monthly residual returns (obtained from regressing firm monthly excess returns over the risk-free rate on FTSE All Share Index returns) over the past 12 months. The second column presents results for the Campbell et al. (2008) model. NIMTAAVG and EXRETAVG refers to the moving average of NITA and EXRET over the past 12 months that assigns declining weights to higher lags, respectively. TLMTA refers to the moving average of TLTA over the past 12 months. MB refers to the market-to-book ratio computed with end of fiscal year market and book value of equity. LN_PRICE refers to the natural log of market value. CASHMTA refers to the moving average of cash and short-term investments divided by market value of total assets (book value of liabilities + market value of equity at the end of the fiscal year). The dependent indicator variable takes the value 1 (0) if a firm files for bankruptcy (lives) in the portfolio year. No observations exist for bankrupt firms after their failure.

Table 2.4: Summary Statistics - Shumway (2001) Default Risk-Sorted Portfolios for the USA

Panel A: Equally-Spaced Quintiles

Portfolio	Low	2	3	4	High
Cutoffs	0 to 20	20 to 40	40 to 60	60 to 80	80 to 100
Avg. Market Cap (USD Mil)	4669.44	1491.92	536.33	209.30	71.96
Debt/Book Equity	1.00	1.23	1.41	1.81	3.24
No. of Neg. BE Firm-Years	102	102	219	570	3,123
No. of Neg. BE Firms	9	10	21	60	737
Avg. NITA (%)	6.18	4.31	1.45	-3.84	-30.80
Avg. Default Probability (%)	0.03	0.10	0.26	0.80	12.08
Avg. Firm-Year Observations	26,657	26,651	26,653	26,649	26,636

Panel B: Right-Skewed Portfolios

Portfolio	Low	2	3	4	High
Cutoffs	0 to 60	60 to 80	80 to 90	90 to 95	95 to 100
Avg. Market Cap (USD Mil)	2232.71	209.30	92.35	55.75	47.33
Debt/Book Equity	1.22	1.81	2.49	3.49	4.95
No. of Neg. BE Firm-Years	423	570	609	630	1,884
No. of Neg. BE Firms	40	60	90	109	538
Avg. NITA (%)	3.98	-3.84	-12.70	-23.89	-74.00
Avg. Default Probability (%)	0.13	0.80	2.56	7.04	36.21
Avg. Firm-Year Observations	79,961	26,649	13,326	6,663	6,647

This table illustrates summary statistics for default risk portfolios in the US. At the end of June every year, US non-financial firms in CRSP/COMPUSTAT with common shares listed (share codes 10 and 11) between 1980 and 2014 are sorted into equally-spaced quintiles (panel A) or right-skewed quintiles (panel B) based on the one-year ex-ante default probability calculated using the Shumway (2001) model. Avg. Market Cap is the average December market capitalization (USD Millions). Debt/Book Equity is total liabilities at the end of fiscal-year t divided by book equity at the end of fiscal-year t. NITA is net income before extraordinary items at the end of fiscal-year t divided by total assets at the end of fiscal-year t. Avg. default probability (%) is the one-year ex-ante probability of default calculated using Shumway (2001) at the end of June. All values are averaged over all firm-years in a portfolio.

Table 2.5: Summary Statistics - Shumway (2001) Default Risk-Sorted Deciles for the UK

Portfolio	Low	2	3	4	5	6	7	8	9	High
Cutoffs	0 to 10	10 to 20	20 to 30	30 to 40	40 to 50	50 to 60	60 to 70	70 to 80	80 to 90	0 to 100
Avg. Market Cap (GBP '000)	5416.36	1638.21	1115.19	588.79	447.72	248.92	330.43	152.82	150.41	130.53
Avg. Debt/Equity	0.49	0.4	0.39	0.36	0.31	0.41	0.31	1.22	0.79	1.43
Avg. ROE (%)	12.67	10.34	6.75	3.14	0.08	-0.54	-2.15	-10.54	-17.24	-22.40
Avg. Default Probability (%)	0.01	0.07	0.16	0.35	0.74	1.62	3.11	4.87	7.28	9.32
Avg. Firm-Year Observations	2,149	2,149	2,149	2,149	2,149	2,149	2,149	2,149	2,149	2,149

This table presents summary statistics for default portfolios in the UK. At the end of September every year, UK non-financial firms listed on the main segment of the London Stock Exchange (LSE) between 1993 and 2012 are sorted into equally-spaced decile portfolios based on the one-year ex-ante default probability calculated using the Shumway (2001) model. Avg. Market Cap indicates the firm-level average market value of equity at the end of September in each default portfolio. Debt/Book Equity is total liabilities at the end of fiscal-year t divided by book equity at the end of fiscal-year t. Return-on-equity is net income before extraordinary items at the end of fiscal-year t divided by book equity at the end of fiscal-year t. Avg. default probability (%) is the one-year ex-ante probability of default calculated using Shumway (2001) at the end of September. All values are averaged over all firm-years in a portfolio.

Table 2.6: Fama-MacBeth (1973) Cross-Sectional Regression - USA

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10
Def. Prob. (%)	-0.12***	-0.11***	-0.10***	-0.10***	-0.10***	-0.12***	-0.11***	-0.10***		-0.06***
	(-8.21)	(-7.54)	(-6.71)	(-6.72)	(-7.67)	(-9.15)	(-7.93)	(-8.69)		(-5.44)
Dimson β_{Mkt}	0.26***	0.25***	0.37***	0.29***	0.25***	0.23***	0.24***		0.29***	
	(3.23)	(3.14)	(4.27)	(3.78)	(3.14)	(2.93)	(3.03)		(3.62)	
BM+	0.18***	0.21***	0.21***	0.16***	0.19***	0.19***		0.17***	0.21***	
	(3.85)	(5.11)	(4.34)	(3.66)	(3.87)	(3.93)		(3.61)	(4.39)	
BM-	0.00	0.09	0.04	-0.00	0.48**	-0.03		-0.08	-0.10	
	(0.01)	(0.45)	(0.19)	(-0.02)	(2.56)	(-0.18)		(-0.44)	(-0.56)	
NITA+	0.34	0.18	0.32	0.56**	0.18		0.46	0.46	1.12***	
	(1.24)	(0.64)	(1.14)	(1.97)	(0.65)		(1.61)	(1.61)	(4.12)	
NITA-	-0.25***	-0.19*	-0.14	-0.25***	-0.25***		-0.25**	-0.24***	-0.21**	
	(-2.62)	(-1.94)	(-1.38)	(-2.70)	(-2.66)		(-2.54)	(-3.12)	(-2.32)	
TLTA	0.91***	0.71***	0.82***	0.89***		0.87***	0.95***	0.93***	0.13	
	(7.81)	(4.87)	(6.93)	(7.44)		(7.85)	(8.01)	(8.16)	(1.17)	
Past Excess Ret.	-0.07***	-0.07***	-0.06***		-0.07***	-0.07***	-0.07***	-0.07***	-0.04**	
	(-4.42)	(-4.43)	(-3.74)		(-4.12)	(-4.42)	(-4.15)	(-4.42)	(-2.26)	
Residual S.D.	4.02***	4.66***		3.50***	3.84***	3.73***	4.45***	3.59***	1.30	
	(5.31)	(5.97)		(4.99)	(5.08)	(4.67)	(5.69)	(4.49)	(1.61)	
Relative Size	-0.07***		-0.11***	-0.07***	-0.04	-0.05**	-0.10***	-0.06***	-0.03	
	(-3.01)		(-5.00)	(-3.11)	(-1.64)	(-2.27)	(-4.65)	(-2.83)	(-1.31)	
Constant	-0.67***	-0.02	-0.72***	-0.66***	0.07	-0.50**	-0.94***	-0.50***	0.16	0.91***
	(-3.39)	(-0.21)	(-3.61)	(-3.34)	(0.30)	(-2.45)	(-4.57)	(-2.74)	(0.76)	(12.10)
R2 (Decimal)	0.04	0.04	0.04	0.03	0.04	0.04	0.04	0.04	0.03	0.01
N	1,403,096	1,403,096	1,403,096	1,403,096	1,403,096	1,403,096	1,403,096	1,403,096	1,403,096	1,403,096

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

This table outlines the results of a monthly cross-sectional Fama and MacBeth (1973) regression for US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1980 and end of 2014. Only for firms for which duration measure can be calculated in chapter 3 are included. The dependent variable is monthly firm-level excess returns over the three month T-bill rate. The primary independent variable is Def. Prob. (%) that corresponds to a firm's Shumway (2001) ex-ante one-year default probability (%). The control variables are as follows. Firm Dimson beta (Dimson β_{Mkt}) is calculated with one lag and one lead over a 24-month rolling window (minimum 12 observations). Book-to-market (BM+), if positive, is calculated at the default portfolio formation date (PFD), end of June. BM- is an indicator equal to 1 if Book-to-Market is negative and 0 otherwise. NITA+ is positive net income to total assets (NITA) ratio calculate at PFD. NITA- is an indicator equal to 1 if NITA is negative and 0 otherwise. TLTA is total liabilities to total assets calculated at PFD. Past Excess Ret refers to the past 12-month return skipping the last month. Residual S.D. refers to the standard deviation of the residuals from regressing firm monthly returns on the value-weighted market (NYSE/AMEX/Nasdaq) index. Relative Size is the natural log of firm's market capitalization to the market's total market capitalization. Newey-West adjusted t-statistics using six lags are in parenthesis. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Table 2.7: Fama-MacBeth (1973) Cross-Sectional Regression - UK

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8	Model9	Model10
Def. Prob.(%)	-1.00*	-0.84*	-1.00*	-0.99*	-1.00*	-1.02*	-1.01*	-0.97*		-0.81*
	(-1.89)	(-2.02)	(-1.90)	(-1.87)	(-1.88)	(-1.85)	(-1.87)	(-1.89)		(-1.69)
Dimson β_{Mkt}	0.34	0.30	0.22	0.35	0.34	0.29	0.32		0.24	
	(0.42)	(0.37)	(0.27)	(0.43)	(0.42)	(0.37)	(0.40)		(0.29)	
BM+	0.07***	0.08***	0.07***	0.08***	0.07***	0.07***		0.05**	0.08***	
	(3.26)	(3.40)	(3.31)	(3.28)	(3.26)	(3.11)		(2.33)	(3.36)	
BM-	-0.13	-0.11	-0.14	-0.12	-0.13	-0.15		-0.23	-0.09	
	(-0.72)	(-0.59)	(-0.77)	(-0.67)	(-0.68)	(-0.75)		(-1.02)	(-0.43)	
NITA+	3.19**	3.26**	3.22**	3.01**	3.22**		3.08**	2.82**	3.81**	
	(2.40)	(2.64)	(2.40)	(2.32)	(2.41)		(2.34)	(2.69)	(2.36)	
NITA-	-0.00	0.01	-0.03	0.02	0.00		0.02	0.00	-0.04	
	(-0.01)	(0.05)	(-0.20)	(0.13)	(0.02)		(0.15)	(0.02)	(-0.25)	
TLTA	-0.06*	-0.06*	-0.06*	-0.05		-0.06*	-0.10**	-0.06	-0.08**	
	(-1.89)	(-1.92)	(-1.77)	(-1.65)		(-1.75)	(-2.38)	(-1.69)	(-2.12)	
Past Excess Ret	-0.18	-0.18	-0.22*		-0.17	-0.16	-0.19	-0.21	-0.02	
	(-1.51)	(-1.38)	(-1.96)		(-1.41)	(-1.24)	(-1.55)	(-1.48)	(-0.14)	
Residual S.D.	-1.06**	-0.98**		-1.08**	-1.07**	-1.22**	-1.08**	-0.83	-1.54**	
	(-2.26)	(-2.21)		(-2.34)	(-2.23)	(-2.52)	(-2.27)	(-1.46)	(-2.88)	
Relative Size	-0.04		-0.03	-0.04	-0.04	-0.03	-0.04	-0.03	0.05*	
	(-0.94)		(-0.68)	(-1.07)	(-0.96)	(-0.67)	(-1.07)	(-0.84)	(1.79)	
Constant	-0.30	0.04	-0.28	-0.35	-0.34	-0.03	-0.28	-0.17	0.45	0.25
	(-0.63)	(0.17)	(-0.58)	(-0.73)	(-0.73)	(-0.07)	(-0.57)	(-0.36)	(1.11)	(1.65)
R2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
N	227,412	227,412	227,412	227,412	227,412	227,412	227,412	227,412	227,412	248,825

* p<0.10, ** p<0.05, *** p<0.01

This table outlines the results of a monthly cross-sectional Fama and MacBeth (1973) regression for UK non-financial firms listed on the main segment of London Stock Exchange (LSE) between 1993 and 2012. The dependent variable is monthly firm-level excess returns over the three month T-bill rate. The primary independent variable is Def. Prob. (%) that corresponds to a firm's Shumway (2001) ex-ante one-year default probability (%). The control variables are as follows. Firm Dimson beta (Dimson β_{Mkt}) is calculated with one lag and one lead over a 24-month rolling window (minimum 12 observations). Book-to-market (BM+), if positive, is calculated at the default portfolio formation date (PFD), end of June. BM- is an indicator equal to 1 if Book-to-Market is negative and 0 otherwise. NITA+ is positive net income to total assets (NITA) ratio calculate at PFD. NITA- is an indicator equal to 1 if NITA is negative and 0 otherwise. TLTA is total liabilities to total assets calculated at PFD. Past Excess Ret refers to the past 12-month return skipping the last month. Residual S.D. refers to the standard deviation of the residuals from regressing firm monthly returns on VW market (NYSE/AMEX/Nasdaq) index. Relative Size is the natural log of firm's market capitalization to the market's (FTSE All Share) total market capitalization. Newey-West adjusted t-statistics using six lags are in parenthesis. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Table 2.8: Monthly Returns on Default Risk-Sorted Quintiles - USA

Panel A: Equal-Weighted Quintiles						
Portfolio	Low	2	3	4	High	High-Low
Cutoffs	0 to 20	20 to 40	40 to 60	60 to 80	80 to 100	
$E[R_p - Rf]$	2.29***	1.15***	0.66**	0.03	-0.83*	-3.12***
	(8.04)	(4.57)	(2.37)	(0.10)	(-1.92)	(-8.73)
α	1.59***	0.37***	-0.18*	-0.85***	-1.77***	-3.36***
	(13.98)	(6.33)	(-1.94)	(-5.31)	(-6.12)	(-9.56)
β_{Mkt}	1.02***	1.00***	1.04***	1.05***	1.09***	0.08
	(38.56)	(74.72)	(48.12)	(28.19)	(16.35)	(0.93)
β_{SMB}	0.61***	0.63***	0.81***	1.02***	1.31***	0.70***
	(15.82)	(31.98)	(25.79)	(18.69)	(13.40)	(5.88)
β_{HML}	-0.12***	0.18***	0.24***	0.25***	0.21**	0.33***
	(-3.05)	(8.94)	(7.12)	(4.34)	(2.01)	(2.64)
Panel B: Value-Weighted Quintiles						
$E[R_p - Rf]$	1.29***	0.55**	0.29	-0.04	-0.14	-1.43***
	(5.77)	(2.29)	(0.96)	(-0.10)	(-0.33)	(-4.65)
α	0.71***	-0.20**	-0.61***	-1.05***	-1.24***	-1.95***
	(12.46)	(-2.42)	(-5.16)	(-6.68)	(-5.65)	(-8.12)
β_{Mkt}	0.97***	1.05***	1.19***	1.29***	1.36***	0.40***
	(73.40)	(54.29)	(43.15)	(35.59)	(26.87)	(7.10)
β_{SMB}	-0.02	0.18***	0.51***	0.85***	1.18***	1.20***
	(-0.81)	(6.28)	(12.72)	(16.02)	(15.89)	(14.69)
β_{HML}	-0.14***	0.18***	0.22***	0.22***	0.22***	0.36***
	(-6.86)	(6.06)	(5.14)	(3.86)	(2.80)	(4.19)

* p<0.10, ** p<0.05, *** p<0.01

This table shows the monthly excess returns (%) and regression alphas (%) relative to the Fama and French (1993) three-factor asset pricing model for equal-weighted (Panel A) and value-weighted (Panel B) default risk quintiles. At the end of June every year, US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1980 and 2014 are sorted into equally-spaced quintiles based on one-year ex-ante default probability calculated using the Shumway (2001) model. In the regression model,

$$R_{p,t} - R_{F,t} = \alpha + \beta_{Mkt}(R_{M,t} - R_{F,t}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \epsilon_t$$

α refers to the intercept, β_{Mkt} refers to the loading on the excess market factor $(R_{M,t} - R_{F,t})$, β_{SMB} refers to the loading on the small-minus-big factor (SMB_t), and β_{HML} refers to the loading on the value factor (HML_t). Monthly risk-free rate $(R_{F,t})$, market $(R_{M,t})$, SMB, and HML are taken from Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). T-statistics are reported in parenthesis. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Table 2.9: Monthly Returns on Default Risk-Sorted Right-Skewed Quintiles - USA

Panel A: Equal-Weighted Portfolios						
Portfolio	Low	2	3	4	High	High-Low
Cutoffs	0 to 60	60 to 80	80 to 90	90 to 95	95 to 100	
$E[R_p - Rf]$	1.37***	0.03	-0.59	-0.89*	-1.25**	-2.62***
	(5.22)	(0.10)	(-1.51)	(-1.96)	(-2.38)	(-6.55)
α	0.59***	-0.85***	-1.53***	-1.85***	-2.17***	-2.76***
	(10.66)	(-5.31)	(-6.29)	(-5.89)	(-5.54)	(-7.16)
β_{Mkt}	1.02***	1.05***	1.09***	1.12***	1.08***	0.06
	(79.03)	(28.19)	(19.31)	(15.41)	(11.93)	(0.71)
β_{SMB}	0.68***	1.02***	1.18***	1.34***	1.56***	0.87***
	(36.24)	(18.69)	(14.37)	(12.55)	(11.72)	(6.67)
β_{HML}	0.10***	0.25***	0.28***	0.21*	0.06	-0.04
	(4.98)	(4.34)	(3.22)	(1.87)	(0.41)	(-0.30)
Panel B: Value-Weighted Portfolios						
$E[R_p - Rf]$	1.07***	-0.04	-0.17	-0.40	0.11	-0.96**
	(4.78)	(-0.10)	(-0.42)	(-0.84)	(0.23)	(-2.45)
α	0.44***	-1.05***	-1.30***	-1.54***	-0.90***	-1.34***
	(10.36)	(-6.68)	(-5.99)	(-5.39)	(-2.79)	(-4.12)
β_{Mkt}	0.99***	1.29***	1.38***	1.42***	1.27***	0.28***
	(102.01)	(35.59)	(27.54)	(21.45)	(16.89)	(3.67)
β_{SMB}	0.05***	0.85***	1.07***	1.27***	1.47***	1.42***
	(3.63)	(16.02)	(14.56)	(13.14)	(13.35)	(12.84)
β_{HML}	-0.05***	0.22***	0.30***	0.19*	0.02	0.07
	(-3.35)	(3.86)	(3.93)	(1.83)	(0.15)	(0.58)

* p<0.10, ** p<0.05, *** p<0.01

This table shows the monthly excess returns (%) and regression alphas (%) relative to the Fama and French (1993) three-factor asset pricing model for equal-weighted (Panel A) and value-weighted (Panel B) default risk portfolios. At the end of June every year, US non-financial firms in CRSP/COMPUSTAT with common shares listed are sorted into right-skewed quintiles based on one-year ex-ante default probability calculated using the Shumway (2001) model. In the regression model,

$$R_{p,t} - R_{F,t} = \alpha + \beta_{Mkt}(R_{M,t} - R_{F,t}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \epsilon_t$$

α refers to the intercept, β_{Mkt} refers to the loading on the excess market factor ($R_{M,t} - R_{F,t}$), β_{SMB} refers to the loading on the small-minus-big factor (SMB_t), and β_{HML} refers to the loading on the value factor (HML_t). Monthly risk-free rate ($R_{F,t}$), market ($R_{M,t}$), SMB, and HML are taken from Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). T-statistics are reported in parenthesis. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Table 2.10: Monthly Returns on Default Risk-Sorted Deciles - UK

Panel A: Equal-Weighted Deciles

Portfolio	Low	2	3	4	5	6	7	8	9	High	High-Low
Cutoffs	0 to 10	10 to 20	20 to 30	30 to 40	40 to 50	50 to 60	60 to 70	70 to 80	80 to 90	90 to 100	
$E[R_p - Rf]$	0.87***	1.07***	1.08***	0.85***	0.74**	0.34	0.19	-0.41	-1.15***	-1.49***	-2.42***
	(3.28)	(3.69)	(3.60)	(2.79)	(2.31)	(1.06)	(0.62)	(-1.33)	(-3.34)	(-4.29)	(-7.95)
α	0.51***	0.65***	0.63***	0.37*	0.25	-0.15	-0.24	-0.82***	-1.55***	-2.04***	-2.40***
	(2.67)	(3.10)	(2.98)	(1.71)	(1.05)	(-0.61)	(-1.02)	(-3.39)	(-5.56)	(-6.49)	(-8.40)
β_{Mkt}	0.54***	0.62***	0.64***	0.65***	0.65***	0.66***	0.60***	0.60***	0.65***	0.35***	-0.18**
	(12.62)	(13.18)	(13.40)	(13.41)	(12.33)	(12.26)	(11.49)	(11.07)	(10.35)	(4.69)	(-2.59)
β_{SMB}	0.34***	0.31***	0.35***	0.32***	0.37***	0.33***	0.30***	0.30***	0.24***	0.38***	0.02
	(5.89)	(4.91)	(5.46)	(4.87)	(5.29)	(4.58)	(4.33)	(4.11)	(2.85)	(4.49)	(0.29)
β_{HML}	0.12**	0.23***	0.24***	0.35***	0.36***	0.36***	0.25***	0.20***	0.16*	0.43***	0.34***
	(2.05)	(3.42)	(3.53)	(4.94)	(4.81)	(4.69)	(3.40)	(2.60)	(1.74)	(3.62)	(3.22)
Panel B: Value-Weighted Deciles											
$E[R_p - Rf]$	1.11***	0.88***	0.84***	0.68**	0.65*	0.31	0.35	-0.11	-0.42	-0.63	-1.79***
	(4.50)	(3.05)	(2.74)	(2.03)	(1.73)	(0.74)	(0.91)	(-0.25)	(-0.90)	(-1.36)	(-4.78)
α	0.78***	0.46**	0.38*	0.18	0.08	-0.31	-0.18	-0.69**	-0.96**	-1.29***	-1.80***
	(4.49)	(2.23)	(1.77)	(0.75)	(0.30)	(-1.01)	(-0.61)	(-2.04)	(-2.60)	(-3.48)	(-4.74)
β_{Mkt}	0.56***	0.64***	0.68***	0.76***	0.80***	0.92***	0.78***	0.99***	0.89***	0.49***	-0.04
	(14.42)	(13.96)	(14.04)	(14.38)	(13.26)	(13.37)	(12.05)	(13.02)	(10.75)	(5.59)	(-0.48)
β_{SMB}	0.20***	0.23***	0.31***	0.30***	0.39***	0.33***	0.36***	0.34***	0.34***	0.63***	0.39***
	(3.89)	(3.63)	(4.76)	(4.15)	(4.74)	(3.57)	(4.16)	(3.27)	(3.10)	(6.33)	(3.86)
β_{HML}	0.09*	0.21***	0.25***	0.28***	0.35***	0.38***	0.26***	0.12	0.15	0.40***	0.23
	(1.67)	(3.21)	(3.56)	(3.69)	(4.07)	(3.84)	(2.81)	(1.14)	(1.26)	(2.88)	(1.60)

* p<0.10, ** p<0.05, *** p<0.01

This table shows the monthly excess returns (%) and regression alphas (%) relative to the Fama and French (1993) three-factor asset pricing model for equal-weighted (Panel A) and value-weighted (Panel B) default risk portfolios for the UK. At the end of September every year, UK non-financial firms listed on the main segment of London Stock Exchange (LSE) are sorted into deciles based on one-year ex-ante default probability calculated using the Shumway (2001) model. In the regression model,

$$R_{p,t} - R_{F,t} = \alpha + \beta_{Mkt}(R_{M,t} - R_{F,t}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \epsilon_t$$

α refers to the intercept, β_{Mkt} refers to the loading on the excess market factor ($R_{M,t} - R_{F,t}$), β_{SMB} refers to the loading on the small-minus-big factor (SMB_t), and β_{HML} refers to the loading on the value factor (HML_t). Monthly risk-free rate ($R_{F,t}$), market ($R_{M,t}$), SMB, and HML are taken from Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). T-statistics are reported in parenthesis. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Table 2.11: Delisting Codes for Default Events

Type	Code	No. of Delists	No. of Defaults	Type	Code	No. of Delists	No. of Defaults
Merger	200	89	1	Dropped	500	160	1
	231	1,850	9		505	1	0
	232	16	0		510	19	0
	233	3,843	26		516	5	0
	234	7	1		517	3	0
	235	2	0		520	172	9
	241	433	5		550	225	2
	242	43	1		551	79	2
	243	6	0		552	804	66
	244	12	1		560	970	37
	251	5	0		561	529	32
	252	2	0		570	249	12
	261	91	1		573	51	0
	262	4	0		575	2	0
	271	1	0		580	656	31
	280	1	0		581	49	0
	Sum	**6,405**	**45**		582	134	7
					583	4	1
Default	160	1	0		584	592	43
	400	1	0		585	113	8
	450	80	1		587	13	0
	460	17	0		591	4	0
	470	7	0		**Total**	**4,834**	**251**
	480	2	0				
	490	1	0	Others	300	251	3
	574	487	154		331	65	2
	Sum	**596**	**155**		332	2	0
					333	1	0
					341	5	0
					342	4	2
					343	1	0
	Total	**12,164**	**458**		**Total**	**329**	**7**

This table illustrates the different delisting codes under which US non-financial firms delisted between 1980 and 2014. No. of Delists is the number of unique non-financial firms in CRSP/COMPUSTAT with listed common shares that delisted under the associated delisting code between 1980 and 2014. No. of Defaults is the number of unique firms that delisted under the associated delisting code and was categorized as bankrupt in the LoPucki Bankruptcy Research Database (BRD). Delisting code types are taken from CRSP (http://www.crsp.com/products/documentation/delisting-codes).

Table 2.12: Monthly Abnormal Returns to High Default Risk Firms

Portfolio	4	High
Cutoffs	60 to 80	80 to 100
Panel A: Puzzle		
EW	-0.85***	-1.77***
	(0.24)	(-0.42)
VW	-1.05***	-1.24***
Firm-Months(%)	100	100
Panel B: Eventually Recovered		
EW	-0.54***	-0.65***
	(0.24)	(-0.42)
VW	-0.66***	-0.54*
	(-3.28)	(-1.95)
Firm-Months(%)	25.99	20.00
Panel C: Ultimately Delisted		
EW	-0.95***	-2.20***
	(-0.48)	(-6.73)
VW	-1.16***	-1.73***
	(-6.71)	(-7.10)
Firm-Months(%)	72.11	77.94
Delisting Ret(%)	-6.42	-17.27
Panel D: Status Unknown - End of Sample		
EW	-0.66	-3.13*
	(-1.31)	(-1.95)
VW	-0.91*	-0.97*
	(-1.88)	(-1.77)
Firm-Months(%)	1.90	2.06

* p<0.10, ** p<0.05, *** p<0.01

This table reports the monthly Fama and French (1993) three-factor alphas for the potential paths taken by the top 40th percentile of default risk firms. Default risk refers to the one-year ex-ante default probability for a firm based on the Shumway (2001) model. EW refers to equal-weighted alphas and VW refers to value-weighted alphas. Firm-Months refers to the proportion of firm-months in a category in comparison to total number of firm-months in the default risk portfolio, expressed in percentage. T-statistics are reported in parenthesis. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

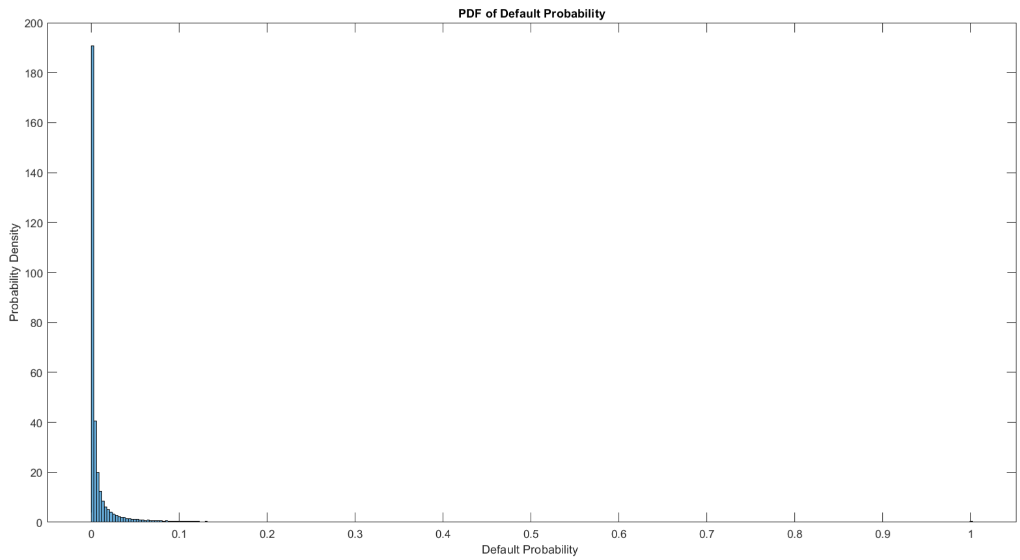
Table 2.13: Monthly Abnormal Returns to Low Default Risk Firms

Portfolio	Low	2	3
Cutoffs	0 to 20	20 to 40	40 to 60
Panel A: Puzzle			
EW	1.59***	0.37***	-0.18*
VW	0.71***	-0.20**	-0.61***
Total Firm-Months(%)	100	100	100
Panel B: Never High Default Risk			
EW	0.98***	0.13	-0.29
	(13.39)	(1.66)	(-1.83)
VW	0.61***	-0.16	-0.50***
	(12.06)	(-1.70)	(-2.78)
Firm-Months(%)	51.11	34.34	15.28
Panel C: Before High Default Risk			
EW	1.89***	0.10	-0.60***
	(10.93)	(1.28)	(-5.26)
VW	0.98***	-0.51***	-0.88***
	(6.68)	(-4.63)	(-7.04)
Firm-Months(%)	24.19	30.33	36.14
Panel D: After Recovery			
EW	2.50***	0.89***	0.19*
	(15.50)	(11.22)	(1.91)
VW	1.38***	0.36***	-0.27**
	(9.43)	(2.95)	(-2.07)
Firm-Months(%)	21.90	32.62	41.02
Panel E: Firms that recovered for one-year			
EW	3.49***	1.39***	0.19
	(7.61)	(4.70)	(1.17)
VW	2.82***	0.73**	-0.20
	(5.54)	(2.22)	(-0.91)
Firm-Months(%)	2.80	2.71	7.56

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

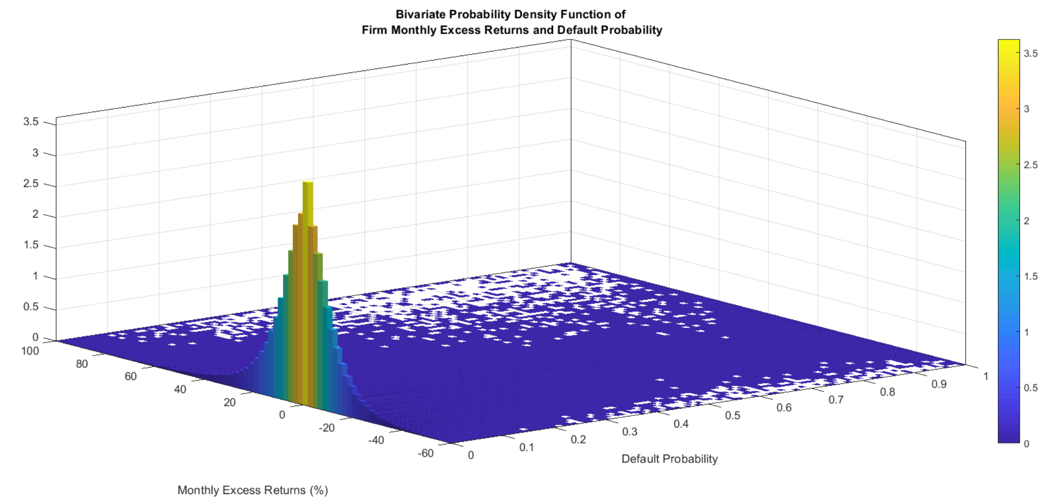
This table reports the monthly Fama and French (1993) three-factor alphas for potential paths taken by the least 60th percentile of default risk firms. Default risk refers to the one-year ex-ante default probability for a firm based on the Shumway (2001) model. EW refers to equal-weighted alphas and VW refers to value-weighted alphas. Firm-Months refers to the proportion of firm-months in a category in comparison to total number of firm-months in the default risk portfolio, expressed in percentage. T-statistics are reported in parenthesis. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Figure 2.1: PDF of Default Probability



This figure illustrates the probability density function of firm default probability calculated using Shumway (2001) for US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1980 and 2014.

Figure 2.2: Joint PDF of Firm Monthly Excess Returns (%) and Default Probability - 3D



This figure illustrates the bivariate distribution of firm monthly excess returns (%) over risk-free rate and default probability. The 3D figure plots firm default probability on the x-axis, firm monthly excess returns on the y-axis, and probability density on the vertical axis. The color coding indicates increasing density from dark blue to bright yellow. Hence, the color coding and the vertical axis are equivalent. Plotting the frequency distribution instead of probability density yields similar results. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed between July 1980 and June 2015.

Chapter 3

AN EQUITY DURATION-BASED RATIONALE FOR THE DEFAULT RISK PUZZLE

3.1 Introduction

The risk-return relationship is a central tenet in asset pricing, and it posits that financial markets reward higher systematic risk with higher expected returns. In this context, distress risk has been examined for many years. Fama and French (1992) find that firms that are small and have high book-to-market (BM) ratios earn higher returns than firms that are big and have low BM ratio. Fama and French (1996) state that their HML factor that buys high BM and sells low BM firms, may capture distress risk because companies with high probability of failure may fail to meet their financial obligations in bad times and their stock prices may move together, making their risk non-diversifiable or systematic. By this argument, high default risk firms should earn higher returns than low default risk firms. However, chapter 2 of this dissertation and other studies document that firms with high default risk load positively on the HML factor (e.g., Dichev (1998), Campbell et al. (2008)) yet earn lower returns than firms with low default risk (e.g., Griffin and Lemmon (2002), Ferguson and Shockley (2003), Agarwal and Taffler (2008)).

Why do firms with high default risk earn lower returns than firms with low default risk? I partially resolve this puzzle by showing that high default risk (HDR) firms have longer equity duration than low default risk (LDR) firms (default-duration hypothesis). In expectation, HDR firms take longer than LDR firms to generate cash flows for shareholders because HDR firms may use most of their near-term cash flows to cover their debt obligations. When aggregate dividends are negatively correlated to expected aggregate dividends, the stochastic discount factor will produce a downward-sloping term structure of returns. That is, long-duration dividends will earn lower returns than short-duration dividends (e.g., Van Binsbergen and Koijen (2017)). Hence, long-duration HDR firms earn lower returns than short-duration LDR firms.

I demonstrate the intuition behind equity duration using an example. Consider two firms, A and B, with a life span of 10 years, and each having a coupon bond outstanding with the same face value, coupon rate, and time to maturity. Firm B generates little cash-flows for the next four years that may just be sufficient to meet coupon obligations, but is expected to deliver ample cash-flows starting five years from now. On the other hand, firm A generates ample and reliable cash-flows for all ten years. Assume that a firm will default if it misses a coupon payment. Then, firm B has more default risk than firm A between today and next year.[1]

Now, consider the shareholders. Firm B delivers lower cash-flows to shareholders (residual cash flows) than firm A because most of the former's cash-flows are used to pay coupons. Intuitively, equity duration of a firm is a measure of time, similar to payback period, and is generally defined as the weighted average time for shareholders to receive cash-flows from the firm with weights are the ratio of discounted future cash-flows from the firm to the firm's price (see Chapter 1 for further explanation.). Then, excluding firms that are expected to

[1] In my example, difference in cash-flows (value) between firms A and B drives default risk. In reality, differences in firm leverage can also influence firm default risk. However, market expectation regarding cash-flows may be the primary driver of default risk. This hypothesis can be corroborated with some empirical observations. For instance, market variables that capture expectation about a firm's future cash-flows increase the predictive ability of accounting-based default risk models significantly (Shumway (2001); Bharath and Shumway (2008)). If leverage alone determined default, then accounting variables-based models such as Altman (1968); Ohlson (1980) should predict default in the data accurately. Further, if leverage was the only contributor to default risk, and the firm's fundamental value as determined through its cash-flows is good, then a firm should be able to raise equity to bring down leverage and thus default risk. Alternatively, I can observe the persistence of leverage and cash flows. The variable with lower persistence will drive default risk because a persistent variable will generally not vary much. I find that leverage is much more persistent than cash-flows implying that cash-flows drive default risk more than leverage does.

default tomorrow, HDR firm B that is expected to generate lower residual cash-flows in the short term will have longer equity duration than LDR firm A that is expected to generate larger residual cash-flows in the short term.

Having verified the default puzzle in my sample in chapter 2, I calculate equity duration for default risk quintiles employing the BM modified DSS method from chapter 1.[2] Then, I examine whether a duration factor based on the BM modified DSS method explains the abnormal returns to the default risk quintiles documented under various asset pricing models (e.g., Fama and French (1996); Carhart (1997); Fama and French (2015); Barillas and Shanken (2018)).

My results are consistent with the default-duration hypothesis. I employ equally-spaced quintiles in the US to document my baseline results. In this context, HDR and LDR portfolios refer to the top and bottom quintiles of default risk, respectively. First, I find that HDR firms have longer equity duration than LDR firms. The average equity duration of the HDR portfolio is 4.03 years longer than that of the LDR portfolio under the BM modified DSS method. Secondly, the Fama and French (1993) three-factor (FF3) model augmented with the equity duration factor reduces the default puzzle by 57% (30%) in the value-(equal-) weighted arbitrage portfolio that buys HDR and sells LDR firms.

My results are robust to different constructions of the duration factor, default risk models, and countries. Firstly, a duration factor based on BM modified DSS method with a constant discount rate also reduces the default puzzle. Specifically, such a factor augmented to the FF3 model reduces the default puzzle by 41.93% (22.56%) in the value-(equal-) weighted arbitrage portfolio that buys HDR and sells LDR firms. Secondly, under the Campbell et al. (2008) default prediction model, the HDR portfolio has longer equity duration than LDR portfolio, and the duration factor augmented to the FF3 model reduces the default puzzle by

[2]Refer to chapter 2 section for a description of how default risk portfolios are constructed.

74%. Finally, the qualitative results also hold for the default risk deciles of firms listed on the main segment of the London Stock Exchange in the UK. Precisely, the duration factor augmented to the FF3 model reduces the default puzzle by 36.67%.

My results have important implications for several research themes. First, this chapter contributes to the empirical literature surrounding the default risk puzzle from the perspective of timing of cash-flow to shareholders which I capture through duration, a widely studied concept in the fixed-income literature. This chapter highlights an important distinction in duration between equities and fixed-income securities in the context of default. When firm default probability and interest rates are not positively correlated, high default risk bonds have shorter duration than low default risk bonds (e.g., Chance (1990); Acharya and Carpenter (2002); Xie et al. (2009)). However, my results show that high default risk firms have longer equity duration than low default risk firms, on average. The key differentiating factor is the perpetual nature of equities that allows for the possibility of cash-flows to occur at a distant future as opposed to a bond that would be considered default if cash-flows did not occur within its time to maturity.

Second, distinct from existing explanations for the default risk puzzle that focus on mispricing stories, I focus on an economic rationale for the puzzle. Many studies appeal to either limits to arbitrage (e.g., Taffler, Lu, and Kausar (2004); Chu, Hirshleifer, and Ma (2017); Eisdorfer, Goyal, and Zhdanov (2018)) or lottery stocks (e.g., Blume and Stambaugh (1983); Asparouhova, Bessembinder, and Kalcheva (2013)) based explanations, but do not attempt to explain alternative economic hypothesis. My economic rationale based on the timing of cash-flows is closely related to Garlappi and Yan (2011) hypothesis on shareholder advantage. The authors claim that shareholders can strategically default on debt because they can either renegotiate debt or liquidate assets amongst themselves, thereby decreasing the equilibrium returns to default risk firms. However, their hypothesis implies that equity duration decreases with an increase in default risk which is contradictory to my results.

Third, my results also have implications for default risk firms' exposures to market risk components. Cornell (1999) adopt Amgen Corporation as an example of a long-duration firm and show that the firm has greater exposure to the discount rate component of market risk than to the cash-flow component. Additionally, Campbell and Vuolteenaho (2004) acknowledge that the reason behind small-growth stocks' greater exposure to discount rate risk than to cash-flow risk could be due to the stocks' long duration. Indeed, Lettau and Wachter (2007) propose a model with long-duration growth stocks having greater exposure to discount rate shocks than to cash-flow shocks that is sufficient to generate the empirically observed value premium. In this context, my duration results imply that HDR firms may have higher exposure to discount rate risk than to cash-flow risk.

3.2 Related Literature

In this section, I review prior explanations for the default risk puzzle.

Limits to Arbitrage: Taffler et al. (2004) examine UK non-financial firms listed on the London Stock Exchange (LSE) between 1995 and 2000 whose auditors expressed concerns through their audit reports over the firms' ability to continue in the future. The paper documents a robust under-performance to the audit report disclosures in the calendar year subsequent to publication due to costly arbitrage. Kausar, Taffler, and Tan (2009) reach a similar conclusion with US non-financial firms. Chu et al. (2017) show that the average causal effect of limits to arbitrage for 11 puzzles, including the default risk puzzle, is 79 bps per month. The weakest version of the default risk puzzle in my sample earns 195 absolute bps per month. So, limits to arbitrage can explain only 40.51% of the weakest version of the default risk puzzle. Lastly, Eisdorfer et al. (2018) find mixed support for the role of limits to arbitrage in explaining the puzzle in international markets. In brief, limits to arbitrage partially explains the default risk puzzle.

Shareholder Advantage: Garlappi and Yan (2011) argue through a theoretical model that equity beta increases with an increase in leverage under low default risk but equity beta decreases with an increase in leverage under high default risk because high default risk firms can renegotiate debt and redistribute liquidated assets to shareholders. This shareholder advantage results in a hump-shaped relation between default risk and equity returns. Hackbarth et al. (2015) show that the 1978 Bankruptcy Reform Act (BRA) amplified shareholders bargaining power, thereby providing empirical support to Garlappi and Yan (2011). However, several studies (e.g., Dichev (1998); Agarwal and Taffler (2008); Campbell et al. (2008)) including chapter 2 of this dissertation find no evidence for a hump-shaped relationship between default risk and returns. Hence, shareholder advantage is not empirically supported as an explanation for the default risk puzzle.

Lottery Stocks: Statman (2002) discusses how lotteries and stock trading are the only avenues for certain individuals to promote themselves to an upper social class, and discuss how lotteries and stock trading, as opposed to stock buying, are negative-sum games. In this context, Coelho, John, Kumar, and Taffler (2014) explore Chapter 11 filings employing non-financial firms between 1979 and 2005 listed on NYSE, AMEX, and Nasdaq post their bankruptcy announcement. The paper finds that Chapter 11 firms share characteristics of lottery stocks such as high individual investors ownership (90% of firms that file for Chapter 11) and negative returns (-28% over the year following Chapter 11 filing). This paper is the only empirical study that directly connects default risk with lottery stocks but the paper does not provide comprehensive information on the time elapsed between bankruptcy announcement and delisting date or the number of months of returns available post bankruptcy filing. Hence, the conjecture that high default risk firms are lottery stocks has not been robustly verified.

Other Explanations: Boualam, Gomes, and Ward (2017) develop a model to show that a bias in high default risk firms' CAPM beta and return non-linearity resulting from high default risk firms delisting can partially explain the default risk puzzle under firm-level cumulative default probability. However, existing literature does not study default risk under cumulative basis because current default models cannot predict cumulative default probability as accurately as conditional one-year default probability (e.g., Shumway (2001)).

Summarizing, existing hypotheses cannot explain the default risk puzzle completely and do not consider a rational explanation of the puzzle. The default-duration hypothesis explained in section 3.1 presents a rational alternative hypothesis for the default risk puzzle which the rest of the chapter investigates.

3.3 Equity Duration

Having discussed the data employed to construct the default quintiles in chapter 2 (refer to section 2.4), I examine whether HDR firms differ in the timing of their cash-flows from LDR firms in this section.

Chapter 2 suggested that there might exist a missing pricing factor in explaining the returns to firms differing in default risk. If HDR firms indeed have longer equity duration than LDR firms like the intuition in section 3.1, then the downward-sloping term structure of equity risk premium may help price the returns to the cross-section of default risk firms.

3.3.1 Methodology: Summary from Chapter One

This section briefly summarizes the equity duration methodology developed in chapter 1.

From chapter 1, equity duration is measured similar to the Macaulay (1938) duration of bonds adjusted for the stock's expected cash-flows and perpetual nature.

$$\text{Equity Duration}_0 = \underbrace{\frac{\sum_{t=1}^{T} t \times E_0[CF_t]/(1+r)^t}{P_0}}_{\substack{\text{Duration of expected cash-flows, } E_0[CF_t], \\ \text{maturing in T periods (Term A)}}} + \underbrace{(T + \frac{1+r}{r})}_{\substack{\text{Duration of perpetuity} \\ \text{starting T periods from now (Term B)}}} \times \underbrace{\frac{P_0 - \sum_{t=1}^{T} E_0[CF_t]/(1+r)^t}{P_0}}_{\substack{\text{Difference between price and} \\ \text{sum of present-value of expected cash-flows (Term C)}}} \quad (3.1)$$

where $E_0[CF_t]$ is the expected cash-flows to shareholders as of $t = 0$ and paid at time t, T is the number of projection years, P_0 is the firm's price at $t = 0$, and r is the discount rate at which cash-flows are discounted.

Chapter 1 established that cross-sectional variation in parameters (modified DSS methods) are preferred over constant parameters (DSS method) to estimate equity duration. Further, book-to-market specific parameters (BM modified DSS method) predict firm cash-flows more accurately than the DSS method, and more precisely than the industry modified DSS method, that yielded a steeper sloped term structure of equity risk premium with a higher Sharpe ratio (See Chapter 1). Hence, I calculate equity duration under the BM modified DSS method in this chapter.

Equity Duration at the Portfolio Level

Term C in the equity duration formula (Equation 3.1) can turn negative when the sum of present-value (PV) of projected cash-flows is greater than the price today. A large negative term C can render equity duration negative and economically meaningless.

Additionally, valuation models are inherently optimistic. Valuation models forecast cash-flows assuming that a firm does not default. This assumption can mechanically increase a firm's equity duration if the firm defaults within the projection horizon.

One solution is to compute equity duration at the portfolio level. The key idea is that while firms can default, it is unlikely that all firms in a portfolio will default. This idea is more consistent with the optimistic nature of valuation models. I aggregate expected firm cash-flows and firm market value up to each default quintile, and calculate equity duration at the quintile level. The empirical results in the next section are based on quintile level duration.[3][4]

3.3.2 Results

This sub-section shows that HDR firms indeed have longer equity duration than LDR firms.

I present portfolio-level equity duration under the BM modified DSS method with various discount rates namely, median long-run ROE, constant (10.03%), and median ICC, in sequence. The median long-run ROE and median ICC are computed across firm-years for each default quintile. Equity duration calculated for each quintile-year results in autocorrelated observations due to overlapping cash-flow projection years. I account for this lack of independence by computing Hansen-Hodrick standard errors based on which I evaluate the statistical significance of my results.

Table 3.1 and table 3.2 illustrate portfolio-level equity duration for equally-spaced and right-skewed default quintiles, respectively. Panels A, B, and C present results under median long-run ROE, constant, and median ICC discount rates, respectively. Each panel presents the median and mean duration summarized over the time dimension in a quintile, and the Hansen-Hodrick standard errors that evaluate the mean's statistical significance. Additionally, panels A and C present the median long-run ROE and the median ICC in the last row,

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[3] In undocumented results, I show that firm level equity duration increases with an increase in default risk.

[4] Note that there are two ways to calculate duration at the portfolio level. I forecast firm cash-flows, and aggregate firm cash-flows to the portfolio level to calculate duration. Alternatively, I can also forecast parameters and cash-flows at the portfolio level and then calculate duration for the portfolio. My qualitative results do not change when I use the alternate approach.

respectively.

Panel A of table 3.1 shows that equity duration monotonically increases from low to high default risk quintiles. The high default risk quintile has an equity duration that is 4.03 years longer than that of the low default risk quintile on average. Panels B and C of table 3.1 show that the high default risk quintile's equity duration is 2.73 years and 1.85 years longer than that of the low default risk quintile even though the relation between default risk and equity duration is not monotonic. Similarly, panels A, B, and C of table 3.2 show that equity duration for the highest right-skewed default quintile is longer by 6.52, 5.26, and 4.69 years, respectively. The relationship between default risk and equity duration is monotonic across all panels for the right-skewed quintiles. Hence, high default risk firms have longer equity duration than low default risk firms.

It is important to consider the effect of discount rates because they can introduce biases. Panel A of both tables show that the long-run ROE for LDR firms is lower than that of HDR firms for both equal and right-skewed quintiles. This relationship can mechanically increase the duration differential between low and high default risk portfolios. Similarly, Panel C of both tables show that the median ICC is higher for LDR firms than HDR firms for both default quintile types, thereby mechanically driving the duration differential between LDR and HDR portfolios down. Constant discount rate, although free from such biases, does not account for the variation in cost of equity capital across default quintiles. Which is the correct equity duration? One way to answer this question is to compare the estimated equity duration to that computed with realized cash-flows, both discounted at a constant rate.

Table 3.3 presents the realized duration under a constant discount rate of 10.03% for equally-spaced quintiles. The expected average equity durations from table 3.1 do not match the realized equity duration differential of 16.73 years between the LDR and HDR portfolios. One potential reason for the mismatch between estimated and realized equity duration is that the BM modified DSS method does not estimate cash-flows for default portfolios accurately. The cash-flows error term (%) computed similar to chapter 1 at the portfolio-level (Figure 3.1) indicates that the BM modified DSS method over-predicts cash-flows by 12% for the HDR portfolio and by 1% for the LDR equally-spaced quintiles. This over-prediction can lower equity duration for the HDR portfolio and reduce the differential between HDR and LDR portfolios. One solution is to predict cash-flows based on default risk specific parameters.[5] However, a modified DSS method with default risk specific parameters would be an endogenous explanation of default. Hence, the inconsistency between expected equity duration and realized equity duration highlights the trade-off between projecting cash-flows accurately and providing an endogenous explanation for the cross-section of returns that I seek to explain.

Overall, HDR firms have longer equity duration than LDR firms across the default risk spectrum and across different discount rates that might bias firm duration upwards or downwards.

3.4 Equity Duration Factor

Having documented that equity duration for the HDR portfolio is longer than that for the LDR portfolio, I examine whether equity duration helps price the cross-section of default risk firms in this section.

I employ time-series regression of default quintiles monthly excess returns over the risk-free rate on a duration factor to capture the average exposure to equity duration over the spectrum of default risk and document the abnormal returns after controlling for duration exposure. First, I explain the construction of the duration factor. Second, I present the exposure to the duration factor, and the factors ability to explain the FF3 alphas to the default quintiles.

[5] Such a method predicts cash-flows for the equally-spaced default quintiles more accurately than the BM modified DSS method (results not shown).

Finally, I augment recent asset-pricing models with the duration factor to show that duration captures a component of default risk independent of recent risk factors.

3.4.1 Methodology

In this sub-section, I explain the construction of the duration factor that is then augmented to the Fama and French (1993) three-factor model. Chapter 1 introduces different versions of the return spread between duration deciles. Which is the correct duration factor? The answer depends on what is the appropriate benchmark duration for the purpose. The purpose of constructing an universal duration factor is to capture the duration differential accurately. Hence, projecting cash-flows based on growth opportunities, such as book-to-market ratio is appropriate (See Chapter 1, Sub-section 1.5.2). Further, a discount rate that accurately reflects the long-run cost of equity is appropriate. Most importantly, the discount rate should be exogenous to duration itself. In chapter 1, I show that ICC depends on duration. On the other hand, a constant discount rate does not capture cross-sectional differences in cost of equity. Hence, a duration factor constructed using BM modified DSS method with ROE discount rate (baseline BM modified DSS) is the appropriate duration factor that captures duration differential in the cross-section more accurately than the alternatives.

One concern regarding equity duration is that there may not be enough variation in the data to distinguish between default risk and duration. That is, there might be no firms that have as high a duration as HDR firms but are independent of default risk implying that default may drive the duration factor. To ensure that default does not drive my duration results, I construct a duration factor by removing firms with default risk higher than 60th percentile default risk.

At the end of June each year, I sort the least 60th percentile default risk firms into deciles based on the baseline BM modified DSS equity duration. The baseline duration factor is the difference between equal-weighted returns on the highest duration decile and the lowest duration decile.[6] As the main result, I augment the FF3 model with the duration factor.

$$R_{p,t+1} = \alpha + \beta_{Duration} Duration_{t+1} + \beta_{Mkt} Mkt\_rf_{t+1} + \beta_{SMB} SMB_{t+1} + \beta_{HML} HML_{t+1} \epsilon_{t+1} \tag{3.2}$$

where $E[R_{p,t+1}]$ is the monthly excess returns on default quintile p, $\beta_{Duration}$ is the loading on the baseline duration factor, β_{Mkt} is the loading on the excess market, β_{SMB} is the loading on the small-minus-big factor, and β_{HML} is the loading on the value factor, high-minus-low. $Duration_{t+1}$, Mkt_rf_{t+1}, SMB_{t+1} , and HML_{t+1} represent the monthly returns on the baseline duration factor, excess market, size, and value factors at $t+1$, respectively. I refer to this model as the duration-FF3 model, henceforth.

The baseline duration factor earns an equal-weighted monthly return of -1.63% (t-stat = -8.09) for a duration differential of 5.85 years. Removing long-duration high default risk firms reduces the duration differential from 11.98 years and the return spread from -1.83% (See Chapter 1, Table 1.8).

3.4.2 Results

This sub-section discusses how well the duration-FF3 asset pricing model explains the default risk puzzle.

Tables 3.4 and 3.5 present alphas and risk exposures under the duration-FF3 model for equally-spaced and right-skewed quintiles, respectively. Panels A and B of the both tables present equal-weighted and value-weighted returns for each default quintile, respectively. In each panel, the first row presents FF3 alphas, the second row presents alphas from the

[6] An alternate method to separate default and duration is to sequentially double sort on default and duration, and construct a factor based on the double sort. In unreported results, I show that duration mitigates default risk under such a construction.

duration-FF3 model, α, and the last four rows present the exposure to risk factors namely, duration(β_{Dur}), the market (β_{Mkt}), size (β_{SMB}), and value (β_{HML}). In each panel, the arbitrage portfolio that buys the "High" default risk portfolio and sells the "Low" default risk portfolio summarizes the spread in alphas and risk exposures between firms that fall under the bottom and top default risk portfolios.

Panel A of table 3.4 shows that the equal-weighted highest default risk portfolio experiences a significant reduction in FF3 alpha of 60% (-2.35% vs -3.36%) once the baseline duration factor is included. Panel B of table 3.4 shows that the baseline duration factor subsumes the significant negative returns for value-weighted highest default risk portfolio by reducing the FF3 alpha by 89%, and earning an insignificant -13 bps per month. Similarly, Panels A and B together suggest that the FF3 alpha on arbitrage default portfolio is reduced by 30% for equal-weighted and 57% for value-weighted portfolios, respectively. Hence, the baseline duration factor mitigates the default risk puzzle for equally-spaced quintiles.

Panel A table 3.5 shows that the equal-weighted highest default risk portfolio experiences a significant reduction in FF3 alpha of 55.79% (-1.22% vs -2.76%) once the baseline duration factor is included. Panel B of table 3.5 shows that the model yields significant positive returns for value-weighted highest default risk portfolio by earning 72 bps per month. Both panels suggest that the FF3 alpha on the arbitrage default portfolio is reduced by 55.79% for equal-weighted and by 100% for value-weighted portfolios, respectively.

Hence, the baseline duration factor mitigates the default risk puzzle for right-skewed quintiles to a greater extent than for equally-spaced quintiles. This improved performance on the right tail of default risk suggests that equity duration is particularly relevant for firms with elevated default risk.

Duration Augmented to Other Factor Models

This section presents asset pricing results when the baseline duration factor is augmented to recent factor models.

Table 3.6 presents the results. The first five rows present alphas under the various asset pricing models. The next five rows present alphas after including the baseline duration factor. The last five rows present the exposure to the baseline duration factor. Collectively, the baseline duration factor adds explanatory power over and above the recent asset pricing factors. However, the incremental information added by the baseline duration factor decreases as additional factors are included in the duration-FF3 model. Indeed, the loading on the baseline duration factor decreases by a half which is consistent with the result in the first chapter that the existing asset pricing models can explain 43% of the baseline duration factor.

In conclusion, equity duration has implications for the cross-section of default risk firms. Specifically, I find support for the hypothesis that HDR firms have longer equity duration than LDR firms and that duration partially explains the default risk puzzle. By controlling for exposures to well-known risk factors, I rule out that duration is a manifestation of other risk factors and vice-versa. In the next section, I perform further robustness checks.

3.5 Robustness

In this section, I address the criticism that my results maybe specific to the baseline duration factor, Shumway (2001) default prediction model, and to the US version of the default risk puzzle.

3.5.1 Duration Models

In this sub-section, I examine whether my results are robust to a duration factor based on BM modified DSS method with a constant discount rate. Like the baseline duration factor, I sort the least 60th percentile default risk firms into deciles at the end of every June based on equity duration implied from BM modified DSS method with a constant discount rate. The arbitrage portfolio that buys the top and sells the bottom duration deciles is the constant discount rate (DR) duration factor.

Table 3.7 presents the results and is organized similar to table 3.4. Panel B shows that the constant DR duration factor reduces the FF3 alpha on the value-weighted HDR portfolio by 42% and reduces the default risk puzzle by 22.56%. Similar to the main results, the default risk puzzle is subsumed in value-weighted terms for right-skewed quintiles (Table 3.8, Panel B).

3.5.2 Default Models

In this sub-section, I examine whether my results hold under the default risk puzzle documented using the Campbell et al. (2008) model in the US.

Table 3.9 shows the expected equity duration (Panel B) and the asset pricing results with the baseline duration factor (Panel A). Panel A is organized similar to Panel A of Table 3.4. Panel A of Table 3.9 shows that the arbitrage value-weighted portfolio that buys the top quintile and sells the bottom quintile of firms differing in Campbell et al. (2008) implied default risk earns a monthly FF3 alpha of -1.58%. Panel B shows that the equity duration of the top quintile of default risk firms is 9.80 years longer than that of the bottom quintile of default risk firms. Panel A also shows that the baseline duration factor explains the default risk puzzle by 74% when augmented to the FF3 model. This result suggests that the baseline duration factor explains a greater portion of the default risk puzzle documented under the Campbell et al. (2008) model. However, this result could be mechanically driven by BM and price entering the Campbell et al. (2008) model as predictive variables. Hence, these results should be interpreted with caution.

Overall, the default-duration hypothesis holds under Campbell et al. (2008) model of default risk.

3.5.3 Shumway (2001) in UK

In this sub-section, I address the challenge that my results are restricted to the default risk puzzle in the US. Garlappi and Yan (2011) and Hackbarth et al. (2015) document that shareholder advantage increased in the US following the Bankruptcy Act in 1978 that may have contributed to the default risk puzzle. Hence, I examine my duration hypothesis in the UK market under the Shumway (2001) model.

Panels A and B of Table 3.10 show the asset pricing results with the baseline duration factor for equal-weighted and value-weighted default risk deciles, respectively, and are organized similar to panels A and B of Table 3.4. Panel C illustrates the expected equity duration computed with the baseline BM modified DSS method.

Panels A and B show that the baseline duration factor reduces the default risk puzzle by 8.75% and 36.67% for equal-weighted and value-weighted deciles, respectively. Panel C shows that the expected equity duration for the top decile is 3.68 years longer than that for the bottom decile of default risk firms. Hence, the duration-default hypothesis is valid in the UK data.

In conclusion, I find robust support for the duration-default hypothesis that HDR firms have longer equity duration than LDR firms. My results underscore the implications of equity duration in explaining the cross-section of returns.

3.6 Conclusion

The novel contribution of this chapter is that equity duration has implications for the cross-section of returns. In particular, high default risk (HDR) firms differ from low default risk firms (LDR) in the timing of their cash-flows to shareholders. Specifically, HDR firms have longer equity duration than LDR firms. Consistent with the literature documenting the downward-sloping term structure of equity risk premium, long duration HDR firms earn lower returns than short duration LDR firms. Further, a factor based on equity duration computed under the BM modified DSS method explained in Chapter 1 reduces the default risk puzzle. Across different default quintiles and duration factors in the US data, duration explains, on average, 58.94% of the value-weighted default risk puzzle documented under the Fama and French (1993) three-factor model.

Table 3.1: Equity Duration of Default Risk-Sorted Quintiles - BM Modified DSS Method

Portfolio	Low	2	3	4	High	High-Low
Cutoffs	0 to 20	20 to 40	40 to 60	60 to 80	80 to 100	
Panel A: Expected Equity Duration - ROE Discount Rate						
Median	17.75	18.46	19.31	19.73	22.50	4.75
Mean	17.95	18.41	19.22	19.94	21.98	4.03***
Hansen-Hodrick Std. Errs.	0.28	0.27	0.56	0.65	0.66	0.32
LR ROE (%)	10.52	9.89	9.45	9.12	8.96	
Panel B: Expected Equity Duration - Constant Discount Rate						
Median	18.37	18.36	18.51	19.00	20.74	2.37
Mean	18.15	18.13	18.37	18.95	20.88	2.73***
Hansen-Hodrick Std. Errs.	0.42	0.41	0.35	0.33	0.31	0.22
Panel C: Expected Equity Duration - ICC Discount Rate						
Median	18.20	17.72	17.84	18.24	20.18	1.98
Mean	17.18	16.82	16.85	17.20	19.03	1.85***
Hansen-Hodrick Std. Errs.	0.41	0.33	0.30	0.28	0.35	0.59
ICC	11.74	12.50	12.84	12.94	12.51	
N Years	36	36	36	36	36	36

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

This table illustrates equity duration computed under BM modified DSS model. The model in brief is

$$\text{Equity Duration}_0 = \frac{\sum_{t=1}^{T} t \times E_0[CF_{sh,t}]/(1+r)^t}{P_0}(T + \frac{1+r}{r}) \times \frac{P_0 - \sum_{t=1}^{T} E_0[CF_{sh,t}]/(1+r)^t}{P_0}$$

where expected cash-flows, $E_0[CF_{sh,t}]$, is the sum of expected cash-flows for each firm in a default quintile at t, discount rate,r, projection horizon, T*=10 years*, and share price, P_0, is the market value of each default quintile. Expected cash-flows for each firm are computed according to BM modified DSS method. Default quintile-specific long-run ROE refers to the median long-run ROE of firms, the median is computed across all firm-years in a default quintile. Panel A, B, and C present results for equity duration computed with ROE, a constant (10.03%), and ICC discount rates, respectively. ROE and ICC discount rates are computed as the median long-run ROE and median ICC computed across firm-years in each default quintile. Refer to section 1.5.2 for a detailed explanation of the BM modified DSS method and the discount rates long-run ROE and ICC. Default quintiles are constructed as follows. At the end of June every year, US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1980 and 2014 are sorted into equally-spaced quintiles based on their one-year ex-ante probability of default calculated using Shumway (2001) model. Hansen-Hodrick standard errors that adjust standard errors for autocorrelation due to overlapping year observations with a lag of 10 years (the projection horizon) are reported. Newey-West adjustment for heteroskedasticity in addition to autocorrelation correction does not make much difference.

Table 3.2: Equity Duration of Default Risk-Sorted Right-Skewed Quintiles - BM Modified DSS Method

Portfolio	Low	2	3	4	High	High-Low
Cutoffs	0 to 60	60 to 80	80 to 90	90 to 95	95 to 100	
Panel A: Expected Equity Duration - ROE Discount Rate						
Median	18.35	20.22	21.14	22.31	23.97	5.62
Mean	18.31	20.03	21.10	22.27	24.83	6.52***
Hansen-Hodrick Std. Errs.	0.38	0.55	0.35	0.46	0.81	0.32
LR ROE (%)	9.95	9.12	8.97	8.93	8.96	
Panel B: Expected Equity Duration - Constant Discount Rate						
Median	18.40	19.00	19.94	21.39	23.45	5.05
Mean	18.16	18.94	20.05	21.42	23.42	5.26***
Hansen-Hodrick Std. Errs.	0.41	0.33	0.30	0.35	0.62	0.22
Panel C: Expected Equity Duration - ICC Discount Rate						
Median	17.38	17.48	18.40	19.56	21.48	4.10
Mean	16.92	17.20	18.26	19.61	21.52	4.60***
Hansen-Hodrick Std. Errs.	0.71	0.58	0.61	0.73	0.90	0.59
ICC	12.66	13.40	13.11	12.72	12.42	
N Years	36	36	36	36	36	36

* p<0.10, ** p<0.05, *** p<0.01

This table illustrates equity duration computed under BM modified DSS model. The model in brief is

$$\text{Equity Duration}_0 = \frac{\sum_{t=1}^{T} t \times E_0[CF_{sh,t}]/(1+r)^t}{P_0}(T + \frac{1+r}{r}) \times \frac{P_0 - \sum_{t=1}^{T} E_0[CF_{sh,t}]/(1+r)^t}{P_0}$$

where expected cash-flows, $E_0[CF_{sh,t}]$, is the sum of expected cash-flows for each firm in a default quintile at t, discount rate,r, projection horizon, *T=10 years*, and share price, P_0, is the market value of each default quintile. Expected cash-flows for each firm are computed according to BM modified DSS method. Default quintile-specific long-run ROE refers to the median long-run ROE of firms, the median is computed across all firm-years in a default quintile. Panel A, B, and C present results for equity duration computed with ROE, a constant (10.03%), and ICC discount rates, respectively. ROE and ICC discount rates are computed as the median long-run ROE and median ICC computed across all firm-years in each default quintile. Refer to section 1.5.2 for a detailed explanation of the BM modified DSS method and the discount rates long-run ROE and ICC. Default quintiles are constructed as follows. At the end of June every year, US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1980 and 2014 are sorted into five right-skewed portfolios based on their one-year ex-ante probability of default calculated using Shumway (2001) model. Hansen-Hodrick standard errors that adjust the standard errors for autocorrelation due to overlapping year observations with a lag of 10 years (the projection horizon) are reported. Newey-West adjustment for heteroskedasticity in addition to autocorrelation correction does not materially impact standard errors.

Table 3.3: Realized Equity Duration of Default Risk-Sorted Quintiles

Portfolio	Low	2	3	4	High	High-Low
Cutoffs	0 to 20	20 to 40	40 to 60	60 to 80	80 to 100	
Median	16.99	20.04	21.47	24.13	31.74	14.75
Mean	17.16	18.99	21.58	24.63	33.89	16.73***
HH Std. Errs.	1.67	1.25	0.77	0.89	1.97	3.17
N Years	26	26	26	26	26	26

* p<0.10, ** p<0.05, *** p<0.01

This table illustrates equity duration computed with realized cash-flows in the projection horizon. The model in brief is

$$\text{Equity Duration}_0 = \frac{\sum_{t=1}^{T} t \times CF_{sh,t}/(1+r)^t}{P_0}(T + \frac{1+r}{r}) \times \frac{P_0 - \sum_{t=1}^{T} CF_{sh,t}/(1+r)^t}{P_0}$$

where realized cash-flows, $CF_{sh,t}$, is the sum of realized cash-flows for each firm in a default quintile at t, discount rate,$r = 10.03\%$, projection horizon, *T=10 years*, and share price, P_0, is the market value of each default quintile. Default quintiles are constructed as follows. At the end of June every year, US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1980 and 2014 are sorted into equally-spaced quintiles based on their one-year ex-ante probability of default calculated using Shumway (2001) model. Hansen-Hodrick standard errors that adjust the standard errors for autocorrelation due to overlapping year observations with a lag of 10 years (the projection horizon) are reported. Newey-West adjustment for heteroskedasticity in addition to autocorrelation correction does not materially impact standard errors.

Table 3.4: Performance of BM Modified Duration Factor with BM ROE Discount Rate on Default Risk-Sorted Quintiles

Portfolio Cutoffs	Low 0 to 20	2 20 to 40	3 40 to 60	4 60 to 80	High 80 to 100	High-Low
			Panel A: Equal-Weighted Quintiles			
α_{FF3}	1.59***	0.37***	-0.18*	-0.85***	-1.77***	-3.36***
α	1.62***	0.31***	-0.09	-0.42**	-0.72**	-2.35***
	(12.43)	(4.69)	(-0.85)	(-2.37)	(-2.31)	(-6.02)
β_{Dur}	0.02	-0.03*	0.05*	0.25***	0.61***	0.59***
	(0.47)	(-1.74)	(1.74)	(4.95)	(6.83)	(5.34)
β_{Mkt}	1.01***	1.01***	1.02***	0.98***	0.93***	-0.09
	(35.76)	(70.47)	(44.35)	(25.23)	(13.59)	(-1.03)
β_{SMB}	0.60***	0.64***	0.79***	0.92***	1.07***	0.46***
	(14.56)	(30.51)	(23.47)	(16.11)	(10.68)	(3.72)
β_{HML}	-0.11**	0.17***	0.26***	0.38***	0.52***	0.64***
	(-2.55)	(7.34)	(7.19)	(6.16)	(4.85)	(4.76)
			Panel B: Value-Weighted Quintiles			
α_{FF3}	0.71***	-0.20**	-0.61***	-1.05***	-1.24***	-1.95***
α	0.71***	-0.23**	-0.49***	-0.57***	-0.13	-0.83***
	(10.83)	(-2.45)	(-3.61)	(-3.31)	(-0.57)	(-3.32)
β_{Dur}	-0.00	-0.02	0.07*	0.28***	0.65***	0.65***
	(-0.08)	(-0.70)	(1.87)	(5.63)	(10.16)	(9.12)
β_{Mkt}	0.97***	1.06***	1.17***	1.22***	1.19***	0.22***
	(68.39)	(50.85)	(39.68)	(32.36)	(24.29)	(3.95)
β_{SMB}	-0.01	0.19***	0.48***	0.74***	0.92***	0.93***
	(-0.72)	(6.10)	(11.22)	(13.43)	(12.85)	(11.68)
β_{HML}	-0.14***	0.17***	0.25***	0.36***	0.56***	0.70***
	(-6.22)	(5.16)	(5.46)	(6.03)	(7.20)	(8.06)
N	420	420	420	420	420	420

* p<0.10, ** p<0.05, *** p<0.01

This table shows the monthly percent regression alphas and loadings on the duration factor for equal-weighted (Panel A) and value-weighted (Panel B) default risk portfolios. At the end of June every year, US non-financial firms in CRSP/COMPUSTAT with common shares listed are sorted into equally-spaced quintiles based on one-year ex-ante default probability calculated using the Shumway (2001) model (default risk). β_{Dur} refers to loading on the duration factor, $Duration_t$, in the model below.

$$R_{p,t} - R_{F,t} = \alpha + \beta_{Dur}Duration_t + \beta_{Mkt}(R_{M,t} - R_{F,t}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \epsilon_t$$

$Duration_t$ is computed as the difference in monthly returns between the top and bottom decile of firms differing in equity duration constructed using the BM modified DSS method with a discount rate equal to the BM decile specific long-run ROE. Refer to section 1.5.2 for details on the BM modified DSS method. Only firms with the least 60th percentile default risk are used to construct the equity duration factor. Monthly risk-free rate ($R_{F,t}$), market ($R_{M,t}$), SMB and HML are taken from Kenneth French's website. T-statistics are reported in parenthesis. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Table 3.5: Performance of BM Modified Duration Factor with BM ROE Discount Rate on Default Risk-Sorted Right-Skewed Quintiles

Portfolio Cutoffs	Low 0 to 60	2 60 to 80	3 80 to 90	4 90 to 95	High 95 to 100	High-Low
		Panel A: Equal-Weighted Portfolios				
α_{FF3}	0.59***	-0.85***	-1.53***	-1.85***	-2.17***	-2.76***
α	0.61***	-0.42**	-0.79***	-0.69**	-0.60	-1.22***
	(9.64)	(-2.37)	(-2.95)	(-2.04)	(-1.44)	(-2.95)
β_{Dur}	0.01	0.25***	0.43***	0.68***	0.92***	0.90***
	(0.68)	(4.95)	(5.66)	(6.99)	(7.66)	(7.67)
β_{Mkt}	1.02***	0.98***	0.97***	0.94***	0.83***	-0.19**
	(73.40)	(25.23)	(16.62)	(12.65)	(9.10)	(-2.06)
β_{SMB}	0.68***	0.92***	1.01***	1.06***	1.19***	0.51***
	(33.51)	(16.11)	(11.83)	(9.82)	(8.88)	(3.86)
β_{HML}	0.10***	0.38***	0.50***	0.56***	0.53***	0.43***
	(4.78)	(6.16)	(5.45)	(4.79)	(3.70)	(3.02)
		Panel B: Value-Weighted Portfolios				
α_{FF3}	0.44***	-1.05***	-1.30***	-1.54***	-0.90***	-1.34***
α	0.44***	-0.57***	-0.35	-0.28	0.72**	0.28
	(9.13)	(-3.31)	(-1.51)	(-0.92)	(2.15)	(0.83)
β_{Dur}	0.00	0.28***	0.56***	0.74***	0.95***	0.95***
	(0.19)	(5.63)	(8.55)	(8.60)	(9.99)	(9.92)
β_{Mkt}	0.99***	1.22***	1.23***	1.21***	1.01***	0.02
	(94.95)	(32.36)	(24.73)	(18.58)	(13.92)	(0.22)
β_{SMB}	0.05***	0.74***	0.84***	0.97***	1.08***	1.03***
	(3.31)	(13.43)	(11.60)	(10.17)	(10.22)	(9.70)
β_{HML}	-0.05***	0.36***	0.59***	0.57***	0.51***	0.56***
	(-2.94)	(6.03)	(7.53)	(5.49)	(4.45)	(4.85)
N	420	420	420	420	420	420

* p<0.10, ** p<0.05, *** p<0.01

This table shows the monthly percent regression alphas and loadings on the duration factor for equal-weighted (Panel A) and value-weighted (Panel B) default risk portfolios. At the end of June every year, US non-financial firms in CRSP/COMPUSTAT with common shares listed are sorted into right-skewed quintiles based on one-year ex-ante default probability calculated using the Shumway (2001) model (default risk). β_{Dur} refers to loading on the duration factor, $Duration_t$, in the model below.

$$R_{p,t} - R_{F,t} = \alpha + \beta_{Dur} Duration_t + \beta_{Mkt}(R_{M,t} - R_{F,t}) + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \epsilon_t$$

$Duration_t$ is computed as the difference in monthly returns between the top and bottom decile of firms differing in equity duration constructed using the BM modified DSS method with a discount rate equal to the BM decile specific long-run ROE. Refer to section 1.5.2 for details on the BM modified DSS method. Only firms with the least 60th percentile default risk are used to construct the equity duration factor. Monthly risk-free rate ($R_{F,t}$), market ($R_{M,t}$), SMB and HML are taken from Kenneth French's website. T-statistics are reported in parenthesis. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Table 3.6: Performance of BM Modified Duration Factor with BM ROE Discount Rate on Default Risk-Sorted Quintiles - Recent Asset Pricing Factors

Panel A: Equal-Weighted Quintiles

Portfolio	Low	2	3	4	High	High-Low
Cutoffs	0 to 20	20 to 40	40 to 60	60 to 80	80 to 100	
α_{FF3}	1.59***	0.37***	-0.18*	-0.85***	-1.77***	-3.36***
$\alpha_{FF3+Mom}$	1.44***	0.46***	0.05	-0.48***	-1.22***	-2.66***
α_{FF5}	1.47***	0.28***	-0.14	-0.62***	-1.25***	-2.73***
$\alpha_{FF5+Mom}$	1.39***	0.35***	0.01	-0.39***	-0.94***	-2.33***
$\alpha_{Barillas}$	1.45***	0.32***	-0.03	-0.40***	-0.84***	-2.30***
$\alpha_{FF3+Dur}$	1.62***	0.31***	-0.09	-0.42**	-0.72**	-2.35***
$\alpha_{FF3+Mom+Dur}$	1.56***	0.35***	0.00	-0.28*	-0.52*	-2.08***
$\alpha_{FF5+Dur}$	1.56***	0.34***	-0.00	-0.33*	-0.67**	-2.22***
$\alpha_{FF5+Mom+Dur}$	1.53***	0.37***	0.05	-0.25*	-0.56*	-2.09***
$\alpha_{Barillas+Dur}$	1.53***	0.30***	-0.03	-0.29**	-0.52*	-2.05***
$\beta_{FF3+Dur}$	0.02	-0.03*	0.05*	0.25***	0.61***	0.59***
$\beta Dur_{FF3+Mom+Dur}$	0.07**	-0.07***	-0.03	0.13***	0.44***	0.37***
$\beta Dur_{FF5+Dur}$	0.06	0.05**	0.10***	0.21***	0.43***	0.37***
$\beta Dur_{FF5+Mom+Dur}$	0.11**	0.02	0.03	0.11**	0.29***	0.18
$\beta Dur_{Barillas+Dur}$	0.07*	-0.02	0.00	0.11**	0.31***	0.24**

* p<0.10, ** p<0.05, *** p<0.01

Panel B: Value-Weighted Quintiles

Portfolio Cutoffs	Low 0 to 20	2 20 to 40	3 40 to 60	4 60 to 80	High 80 to 100	High-Low
α_{FF3}	0.71***	-0.20**	-0.61***	-1.05***	-1.24***	-1.95***
$\alpha_{FF3+Mom}$	0.64***	0.00	-0.28***	-0.59***	-0.70***	-1.34***
α_{FF5}	0.64***	-0.22**	-0.54***	-0.80***	-0.81***	-1.44***
$\alpha_{FF5+Mom}$	0.60***	-0.08	-0.32***	-0.53***	-0.49***	-1.09***
$\alpha_{Barillas}$	0.66***	-0.11	-0.33***	-0.54***	-0.43**	-1.09***
$\alpha_{FF3+Dur}$	0.71***	-0.23**	-0.49***	-0.57***	-0.13	-0.83***
$\alpha_{FF3+Mom+Dur}$	0.68***	-0.14*	-0.35***	-0.39***	0.07	-0.61***
$\alpha_{FF5+Dur}$	0.66***	-0.18*	-0.37***	-0.47***	-0.09	-0.75***
$\alpha_{FF5+Mom+Dur}$	0.65***	-0.13*	-0.29***	-0.38***	0.01	-0.63***
$\alpha_{Barillas+Dur}$	0.69***	-0.15**	-0.34***	-0.39***	0.01	-0.68***
$\beta Dur_{FF3+Dur}$	-0.00	-0.02	0.07*	0.28***	0.65***	0.65***
$\beta Dur_{FF3+Mom+Dur}$	0.02	-0.09***	-0.05	0.13***	0.49***	0.46***
$\beta Dur_{FF5+Dur}$	0.02	0.03	0.12***	0.24***	0.53***	0.51***
$\beta Dur_{FF5+Mom+Dur}$	0.03	-0.04	0.02	0.11***	0.38***	0.35***
$\beta Dur_{Barillas+Dur}$	0.03	-0.05*	-0.01	0.15***	0.42***	0.39***
N	420	420	420	420	420	420

* p<0.10, ** p<0.05, *** p<0.01

This table shows the monthly percent excess returns and regression alphas relative to various asset pricing models for equal-weighted (Panel A) and value-weighted (Panel B) default risk portfolios. At the end of June every year, US non-financial firms in CRSP/COMPUSTAT with common shares listed are sorted into equally-spaced quintiles based on one-year ex-ante default probability calculated using the Shumway (2001) model (default risk). α_{FF3} refers to the intercept in the Fama and French (1996) model $[R_{M,t} - R_{F,t}\ SMB\ HML]$. $\alpha_{FF3+Mom}$ refers to the intercept in the Carhart (1997) model $[R_{M,t} - R_{F,t}\ SMB\ HML\ MOM]$. α_{FF5} refers to the intercept in the Fama and French (2015) model $[R_{M,t} - R_{F,t}\ SMB\ HML\ CMA\ RMW]$. $\alpha_{FF5+Mom}$ refers to the intercept in the momentum augmented Fama and French (2015) model $[R_{M,t} - R_{F,t}\ SMB\ HML\ MOM\ CMA\ RMW]$. $\alpha_{Barillas}$ refers to the intercept in the Barillas and Shanken (2018) model $[R_{M,t} - R_{F,t}\ SMB\ HMLm\ MOM\ IA\ ROE]$. α_{i+Dur} refers to the loading on the Duration factor when the model i is augmented with duration. The following regression framework presents a comprehensive representation of the model.

$$\begin{aligned} R_{p,t} - R_{F,t} = \quad & \alpha_{i+Dur} + \beta_{Mkt}(R_{M,t} - R_{F,t}) + \beta_{SMB}SMB_t + \beta_{value}Value_t + \beta_{MOM}MOM_t + \beta_{prof}Profitability_t \\ & + \beta_{inv}Investment_t + \beta_{i+Dur}Duration_t + \epsilon_t \end{aligned}$$

α_{i+Dur} refers to the intercept in the asset pricing model i augmented with the duration factor, $Duration_t$. $HMLm$ refers to the HML devil factor from Asness and Frazzini (2013). ROE and IA refer to the profitability and investment factor respectively from Hou, Xue, and Zhang (2015). $Duration_t$ is computed as the difference in monthly returns between the top and bottom decile of firms differing in equity duration constructed using the BM modified DSS method with a discount rate equal to the BM decile specific long-run ROE. Refer to section 1.5.2 for details on the BM modified DSS method. Only firms with the least 60th percentile default risk are used to construct the equity duration factor. I thank Professor Avraham Kamara for providing me with the $HMLm$, ROE, and IA. Monthly risk-free rate $(R_{F,t})$, market $(R_{M,t})$, size premium (SMB), value premium (HML), momentum premium (MOM), investment premium (CMA), and profitability premium (RMW) are taken from Kenneth French's website. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Table 3.7: Performance of BM Modified Duration Factor with BM Constant Discount Rate on Default Risk-Sorted Quintiles

Portfolio Cutoffs	Low 0 to 20	2 20 to 40	3 40 to 60	4 60 to 80	High 80 to 100	High-Low
			Panel A: Equal-Weighted Quintiles			
α_{FF3}	1.59***	0.37***	-0.18*	-0.85***	-1.77***	-3.36***
α	1.82***	0.33***	-0.23**	-0.76***	-1.38***	-3.20***
	(15.45)	(5.25)	(-2.31)	(-4.41)	(-4.51)	(-8.50)
β_{Dur}	0.21***	-0.04*	-0.04	0.09	0.35***	0.14
	(5.45)	(-1.83)	(-1.39)	(1.52)	(3.53)	(1.15)
β_{Mkt}	0.97***	1.01***	1.05***	1.03***	1.01***	0.04
	(35.56)	(70.98)	(45.70)	(25.99)	(14.35)	(0.48)
β_{SMB}	0.52***	0.64***	0.83***	0.98***	1.16***	0.64***
	(12.79)	(30.10)	(24.20)	(16.53)	(11.02)	(4.92)
β_{HML}	0.03	0.16***	0.20***	0.31***	0.46***	0.43***
	(0.57)	(6.27)	(5.02)	(4.43)	(3.70)	(2.82)
			Panel B: Value-Weighted Quintiles			
α_{FF3}	0.71***	-0.20**	-0.61***	-1.05***	-1.24***	-1.95***
α	0.79***	-0.30***	-0.67***	-0.92***	-0.72***	-1.51***
	(13.11)	(-3.41)	(-5.30)	(-5.49)	(-3.20)	(-6.01)
β_{Dur}	0.07***	-0.09***	-0.06	0.11**	0.47***	0.40***
	(3.66)	(-3.12)	(-1.36)	(2.10)	(6.40)	(4.85)
β_{Mkt}	0.95***	1.07***	1.20***	1.26***	1.25***	0.30***
	(68.67)	(52.58)	(41.02)	(32.83)	(24.21)	(5.18)
β_{SMB}	-0.05**	0.22***	0.54***	0.80***	0.98***	1.03***
	(-2.22)	(7.07)	(12.21)	(13.88)	(12.66)	(11.86)
β_{HML}	-0.09***	0.12***	0.18***	0.30***	0.55***	0.64***
	(-3.58)	(3.20)	(3.42)	(4.38)	(6.09)	(6.31)
N	420	420	420	420	420	420

* p<0.10, ** p<0.05, *** p<0.01

This table shows the monthly percent regression alphas and loadings on the duration factor for equal-weighted (Panel A) and value-weighted (Panel B) default risk portfolios. At the end of June every year, US non-financial firms in CRSP/COMPUSTAT with common shares listed are sorted into equally-spaced quintiles based on one-year ex-ante default probability calculated using the Shumway (2001) model (default risk). β_{Dur} refers to loading on the duration factor, $Duration_t$, in the model below.

$$R_{p,t} - R_{F,t} = \alpha + \beta_{Dur}Duration_t + \beta_{Mkt}(R_{M,t} - R_{F,t}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \epsilon_t$$

$Duration_t$ is computed as the difference in monthly returns between the top and bottom decile of firms differing in equity duration constructed using the BM modified DSS method with a discount rate equal to a constant 10.03%. Refer to section 1.5.2 for details on the BM modified DSS method. Only firms with the least 60th percentile default risk are used to construct the equity duration factor. Monthly risk-free rate ($R_{F,t}$), market ($R_{M,t}$), SMB and HML are taken from Kenneth French's website. T-statistics are reported in parenthesis. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Table 3.8: Performance of BM Modified Duration Factor with BM Constant Discount Rate on Default Risk-Sorted Right-Skewed Quintiles

Portfolio Cutoffs	Low 0 to 60	2 60 to 80	3 80 to 90	4 90 to 95	High 95 to 100	High-Low
Panel A: Equal-Weighted Portfolios						
α_{FF3}	0.59***	-0.85***	-1.53***	-1.85***	-2.17***	-2.76***
α	0.64***	-0.76***	-1.32***	-1.40***	-1.45***	-2.09***
	(10.78)	(-4.41)	(-5.10)	(-4.22)	(-3.55)	(-5.18)
β_{Dur}	0.04**	0.09	0.19**	0.41***	0.65***	0.60***
	(2.20)	(1.52)	(2.20)	(3.77)	(4.84)	(4.57)
β_{Mkt}	1.01***	1.03***	1.04***	1.02***	0.93***	-0.08
	(73.78)	(25.99)	(17.45)	(13.40)	(9.83)	(-0.89)
β_{SMB}	0.67***	0.98***	1.10***	1.16***	1.28***	0.62***
	(32.45)	(16.53)	(12.33)	(10.15)	(9.07)	(4.42)
β_{HML}	0.13***	0.31***	0.41***	0.50***	0.52***	0.39**
	(5.36)	(4.43)	(3.91)	(3.72)	(3.14)	(2.39)
Panel B: Value-Weighted Portfolios						
α_{FF3}	0.44***	-1.05***	-1.30***	-1.54***	-0.90***	-1.34***
α	0.47***	-0.92***	-0.91***	-0.90***	-0.02	-0.49
	(10.55)	(-5.49)	(-4.01)	(-3.05)	(-0.07)	(-1.50)
β_{Dur}	0.03**	0.11**	0.35***	0.58***	0.80***	0.76***
	(2.32)	(2.10)	(4.76)	(6.03)	(7.46)	(7.08)
β_{Mkt}	0.99***	1.26***	1.30***	1.28***	1.08***	0.09
	(95.48)	(32.83)	(24.88)	(18.90)	(14.30)	(1.20)
β_{SMB}	0.04**	0.80***	0.92***	1.03***	1.13***	1.09***
	(2.41)	(13.88)	(11.77)	(10.11)	(10.00)	(9.58)
β_{HML}	-0.03	0.30***	0.56***	0.60***	0.59***	0.61***
	(-1.41)	(4.38)	(6.04)	(5.03)	(4.43)	(4.58)
N	420	420	420	420	420	420

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

This table shows the monthly percent regression alphas and loadings on the duration factor for equal-weighted (Panel A) and value-weighted (Panel B) default risk portfolios. At the end of June every year, US non-financial firms in CRSP/COMPUSTAT with common shares listed are sorted into right-skewed quintiles based on one-year ex-ante default probability calculated using the Shumway (2001) model (default risk). β_{Dur} refers to loading on the duration factor, $Duration_t$, in the model below.

$$R_{p,t} - R_{F,t} = \alpha + \beta_{Dur} Duration_t + \beta_{Mkt}(R_{M,t} - R_{F,t}) + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \epsilon_t$$

$Duration_t$ is computed as the difference in monthly returns between the top and bottom decile of firms differing in equity duration constructed using the BM modified DSS method with a discount rate equal to a constant 10.03%. Refer to section 1.5.2 for details on constructing BM deciles. Firms with annual default risk greater than 60th percentile default probability are removed before factor construction. Monthly risk-free rate ($R_{F,t}$), market ($R_{M,t}$), SMB and HML are taken from Kenneth French's website. T-statistics are reported in parenthesis. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Table 3.9: Performance of BM Modified Duration Factor with BM ROE Discount Rate on Campbell et al. (2008) Default Risk-Sorted Deciles

Portfolio	Low	2	3	4	5	6	7	8	9	High		
Cutoffs	0 to 5	5 to 10	10 to 20	20 to 40	40 to 60	60 to 80	80 to 90	90 to 95	95 to 99	99 to 100	>90 - <10	>80 - <20
Panel A: Asset Pricing Results												
α_{FF3}	0.38***	0.09	0.03	-0.05	-0.25***	-0.49***	-1.06***	-1.40***	-1.69***	-1.50***	-1.77***	-1.58***
α	0.46***	0.07	-0.03	-0.08	-0.15*	-0.13	-0.33*	-0.39	-0.32	0.05	-0.49	-0.41
	(4.12)	(0.75)	(-0.43)	(-1.11)	(-1.66)	(-0.93)	(-1.70)	(-1.49)	(-1.05)	(0.12)	(-1.60)	(-1.54)
β_{Dur}	0.05	-0.02	-0.04	-0.02	0.06**	0.23***	0.46***	0.64***	0.87***	0.98***	0.81***	0.74***
	(1.51)	(-0.55)	(-1.61)	(-0.86)	(2.29)	(5.37)	(7.78)	(7.92)	(9.36)	(7.72)	(8.73)	(8.97)
β_{Mkt}	1.02***	1.01***	1.00***	0.99***	1.09***	1.17***	1.25***	1.19***	1.16***	0.95***	0.08	0.13**
	(41.48)	(49.52)	(57.74)	(65.12)	(55.07)	(38.33)	(29.46)	(20.44)	(17.44)	(10.41)	(1.23)	(2.16)
β_{SMB}	0.39***	0.25***	0.20***	0.20***	0.34***	0.56***	0.83***	0.90***	1.05***	1.16***	0.72***	0.70***
	(10.80)	(8.31)	(8.00)	(8.75)	(11.59)	(12.45)	(13.23)	(10.61)	(10.68)	(8.69)	(7.33)	(8.12)
β_{HML}	-0.05	-0.05	0.00	0.10***	0.22***	0.28***	0.43***	0.45***	0.58***	0.69***	0.63***	0.57***
	(-1.26)	(-1.56)	(0.14)	(4.08)	(6.74)	(5.48)	(6.14)	(4.74)	(5.30)	(4.60)	(5.70)	(5.88)
Panel B: Expected Equity Duration												
Mean	17.65	17.27	17.26	18.05	18.91	20.84	25.74	28.25	30.63	352.92	13.95***	9.80***
Median	17.80	17.37	17.43	18.28	19.17	21.12	25.80	28.34	30.61	363.37	14.07	9.46***
LR ROE (%)	11.32	11.91	11.75	10.16	9.13	7.65	5.52	5.35	5.19	0.30		
Avg. Default Probability (%)	0.01	0.02	0.03	0.04	0.05	0.09	0.17	0.29	0.54	1.35		

* p<0.10, ** p<0.05, *** p<0.01

This table illustrates equity duration (Panel B) and asset pricing tests (Panel A) for default risk portfolios formed under the Campbell et al. (2008) default risk model. At the end of December every year, US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1980 and 2014 are sorted into decile portfolios based on their one-year ex-ante probability of default calculated using Campbell et al. (2008) model. The equity duration model in brief is

$$\text{Equity Duration}_0 = \frac{\sum_{t=1}^{T} t \times E_0[CF_{sh,t}]/(1+r)^t}{P_0}(T + \frac{1+r}{r}) \times \frac{P_0 - \sum_{t=1}^{T} E_0[CF_{sh,t}]/(1+r)^t}{P_0}$$

where expected cash-flows, $E_0[CF_{sh,t}]$, is the sum of expected cash-flows for each firm in a default quintile at t, discount rate,r, projection horizon, *T=10 years*, and share price, P_0, is the market value of each default quintile. Expected cash-flows for each firm are computed according to BM modified DSS method. Default quintile-specific long-run ROE refers to the median long-run ROE of firms, the median is computed across all firm-years in a default quintile. Refer to section 1.5.2 for details on the BM modified DSS method. Panel A presents asset pricing results when the Fama and French (1993) three-factor model is augmented with a duration factor. The duration factor is computed as the difference in monthly returns between the top and bottom decile of firms differing in equity duration constructed using the BM modified DSS method with a discount rate equal to the BM decile specific long-run ROE. Only firms with the least 60th percentile default risk are used to construct the equity duration factor. α_{FF3} and α refer to the intercept from regressing default portfolio monthly excess returns over the risk-free rate on the Fama and French (1993) three-factors, and on duration factor and Fama and French (1993) three-factors, respectively. β_{Dur}, β_{Mkt}, β_{SMB}, and β_{HML} refer to the loadings on the duration factor, market, size premium, and value premium, respectively. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

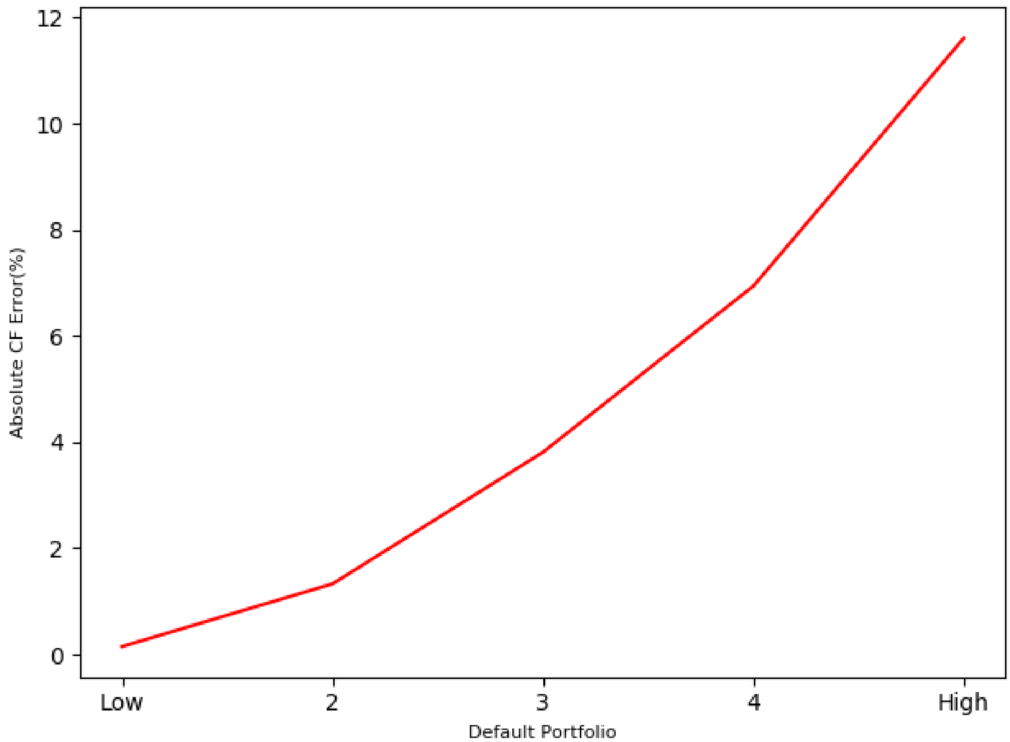
Table 3.10: Performance of BM Modified Duration Factor with BM ROE Discount Rate on UK Shumway (2001) Default Risk-Sorted Deciles

Portfolio	Low	2	3	4	5	6	7	8	9	High	High-Low
Cutoffs	0 to 10	10 to 20	20 to 30	30 to 40	40 to 50	50 to 60	60 to 70	70 to 80	80 to 90	90 to 100	
					Panel A: Equal-Weighted Deciles						
α_{FF3}	0.51***	0.65***	0.63***	0.37*	0.25	-0.15	-0.24	-0.82***	-1.55***	-2.04***	-2.40***
α	0.74***	0.79***	0.75***	0.49**	0.37	-0.05	-0.04	-0.61**	-1.29***	-1.42***	-2.19***
	(3.57)	(3.40)	(3.19)	(2.02)	(1.43)	(-0.18)	(-0.14)	(-2.27)	(-4.18)	(-4.27)	(-6.77)
β_{Dur}	0.16***	0.10	0.08	0.08	0.09	0.07	0.14*	0.15*	0.19**	0.43***	0.14
	(2.60)	(1.39)	(1.16)	(1.11)	(1.10)	(0.86)	(1.78)	(1.83)	(1.98)	(3.91)	(1.36)
β_{Mkt}	0.47***	0.58***	0.60***	0.62***	0.61***	0.63***	0.54***	0.54***	0.57***	0.18**	-0.23***
	(9.34)	(10.35)	(10.64)	(10.68)	(9.77)	(9.83)	(8.74)	(8.36)	(7.68)	(2.18)	(-2.93)
β_{SMB}	0.27***	0.27***	0.32***	0.29***	0.34***	0.30***	0.25***	0.24***	0.17*	0.11	-0.07
	(4.41)	(3.94)	(4.53)	(4.01)	(4.40)	(3.84)	(3.26)	(3.04)	(1.83)	(1.10)	(-0.67)
β_{HML}	0.23***	0.29***	0.30***	0.40***	0.42***	0.41***	0.35***	0.30***	0.28**	0.59***	0.40***
	(3.19)	(3.60)	(3.56)	(4.69)	(4.58)	(4.33)	(3.82)	(3.19)	(2.57)	(5.02)	(3.51)
					Panel B: Value-Weighted Deciles						
α_{FF3}	0.78***	0.46**	0.38*	0.18	0.08	-0.31	-0.18	-0.69**	-0.96**	-1.29***	-1.80***
α	0.86***	0.54**	0.48**	0.38	0.38	-0.02	0.23	-0.05	-0.38	-0.57	-1.14***
	(4.46)	(2.36)	(2.02)	(1.45)	(1.29)	(-0.06)	(0.74)	(-0.13)	(-0.95)	(-1.44)	(-2.78)
β_{Dur}	0.06	0.06	0.07	0.14*	0.21**	0.20*	0.29***	0.45***	0.40***	0.50***	0.45***
	(0.95)	(0.81)	(0.97)	(1.77)	(2.34)	(1.95)	(2.98)	(4.07)	(3.31)	(3.84)	(3.40)
β_{Mkt}	0.53***	0.62***	0.65***	0.70***	0.71***	0.83***	0.66***	0.80***	0.72***	0.29***	-0.23**
	(11.60)	(11.29)	(11.28)	(11.18)	(9.99)	(10.25)	(8.69)	(9.12)	(7.45)	(3.03)	(-2.24)
β_{SMB}	0.18***	0.20***	0.28***	0.24***	0.30***	0.25**	0.25***	0.16	0.19	0.32**	0.11
	(3.18)	(2.99)	(3.97)	(3.10)	(3.44)	(2.50)	(2.67)	(1.46)	(1.56)	(2.62)	(0.86)
β_{HML}	0.13*	0.25***	0.29***	0.37***	0.49***	0.51***	0.45***	0.42***	0.42***	0.59***	0.40***
	(1.91)	(3.09)	(3.47)	(4.05)	(4.71)	(4.29)	(4.05)	(3.30)	(2.95)	(4.24)	(2.78)
					Panel C: Equity Duration						
Mean Duration	17.35	18.12	21.77	21.38	23.02	26.54	23.76	29.85	22.43	21.03	3.68***
Median Duration	17.33	18.12	20.74	21.39	23.00	25.81	23.68	29.51	22.23	20.87	3.54
Long-Run ROE (%)	15.76	14.08	10.26	9.64	8.35	6.77	7.91	5.42	8.95	10.30	

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

This table illustrates asset pricing tests (Panels A, B), and equity duration (Panel C) for default risk portfolios formed under the Shumway (2001) default risk model in the United Kingdom. At the end of September every year, UK non-financial firms listed on the main segment of the London Stock Exchange (LSE) are sorted into decile portfolios based on their one-year ex-ante default probability from Shumway (2001) model (default risk). Equity duration is based on the BM modified DSS method. Long-run ROE refers to the median long-run ROE of firms, the median is computed across all firm-years in a default decile. Refer to section 1.5.2 for a detailed explanation of the method. Panels A and B present asset pricing results when the Fama and French (1993) three-factor model is augmented with a duration factor for equal- and value-weighted default deciles, respectively. The duration factor is computed as the difference in monthly returns between the top and bottom decile of firms differing in equity duration constructed using the BM modified DSS method with a discount rate equal to the BM decile specific long-run ROE. Only firms with the least 60th percentile default risk are used to compute the equity duration factor. α_{FF3} and α refer to the intercept from regressing default portfolio monthly excess returns over the risk-free rate on the Fama and French (1993) three-factors, and on duration factor and Fama and French (1993) three-factors, respectively. β_{Dur}, β_{Mkt}, β_{SMB}, and β_{HML} refer to the loadings on the duration factor, market, size premium, and value premium, respectively. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.

Figure 3.1: Default Risk-Sorted Portfolios - Cash-Flow Comparison



This figure plots the average error term computed across all portfolio-years. The error term is the absolute difference between expected cash-flows and realized cash-flows for each portfolio-year scaled by the portfolio market value observed at the beginning of the projection horizon of ten years. Firm expected cash-flows are computed using BM modified DSS method and aggregated to the portfolio level each year to form portfolio expected cash-flows. Similarly, realized cash-flows for firms are aggregated to the portfolio level each year. Portfolio refers to one of the equally-spaced default quintiles constructed by sorting firms based on their one-year ex-ante default probability from Shumway (2001) model. Refer to section 1.5.2 for details on the BM modified DSS method. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1980 and 2004.

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Appendix A

CHAPTER 1

Table A.1: Cross-correlations for Equity Duration

	BM Modified			Ind Modified			DSS	
Variables	CONST	ROE	ICC	CONST	ROE	ICC	CONST	ICC
CONST	1.00							
ROE	0.94	1.00						
ICC	0.77	0.65	1.00					
CONST	0.07	0.06	0.08	1.00				
ROE	0.05	0.04	0.06	0.93	1.00			
ICC	0.08	0.06	0.13	0.72	0.61	1.00		
CONST	0.29	0.22	0.38	0.06	0.04	0.08	1.00	
ICC	0.33	0.25	0.56	0.09	0.07	0.13	0.63	1.00

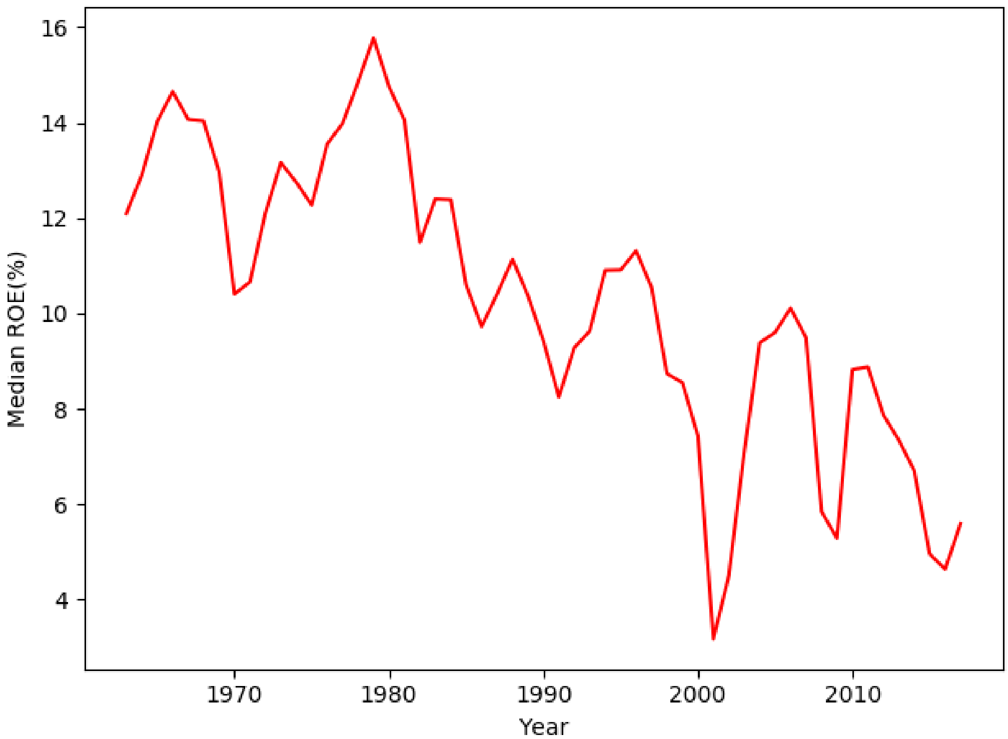
This table presents the correlations across firm equity duration computed based on the DSS and modified DSS methods for US non-financial firms in CRSP/COMPUSTAT with listed common shares between 1963 and 2017. CONST, ROE, and ICC refer to firm equity duration computed with constant, ROE, and ICC discount rates, respectively. The first three rows and columns refer to BM modified DSS method, the next three rows and columns refer to industry modified DSS method, and the last two columns refer to the DSS method. Refer to sections 1.5.1 and 1.5.2 for details on the DSS and BM modified DSS methods. All correlations are significant at the 5% level.

Table A.2: Equity Duration with Realized Cash-Flows

	Expected Duration		Realized Duration
Portfolio	DSS	BM Modified DSS	
	Const	Const	Const
Growth	20.23	20.00	22.20
2	19.56	19.33	21.00
3	19.10	18.67	20.51
4	18.67	18.59	20.30
5	18.22	18.00	20.12
6	17.73	17.81	19.76
7	17.23	17.33	19.46
8	16.66	17.16	19.46
9	15.77	16.33	19.06
Value	13.74	15.63	19.48
Growth-Value	6.48***	4.38***	2.72***

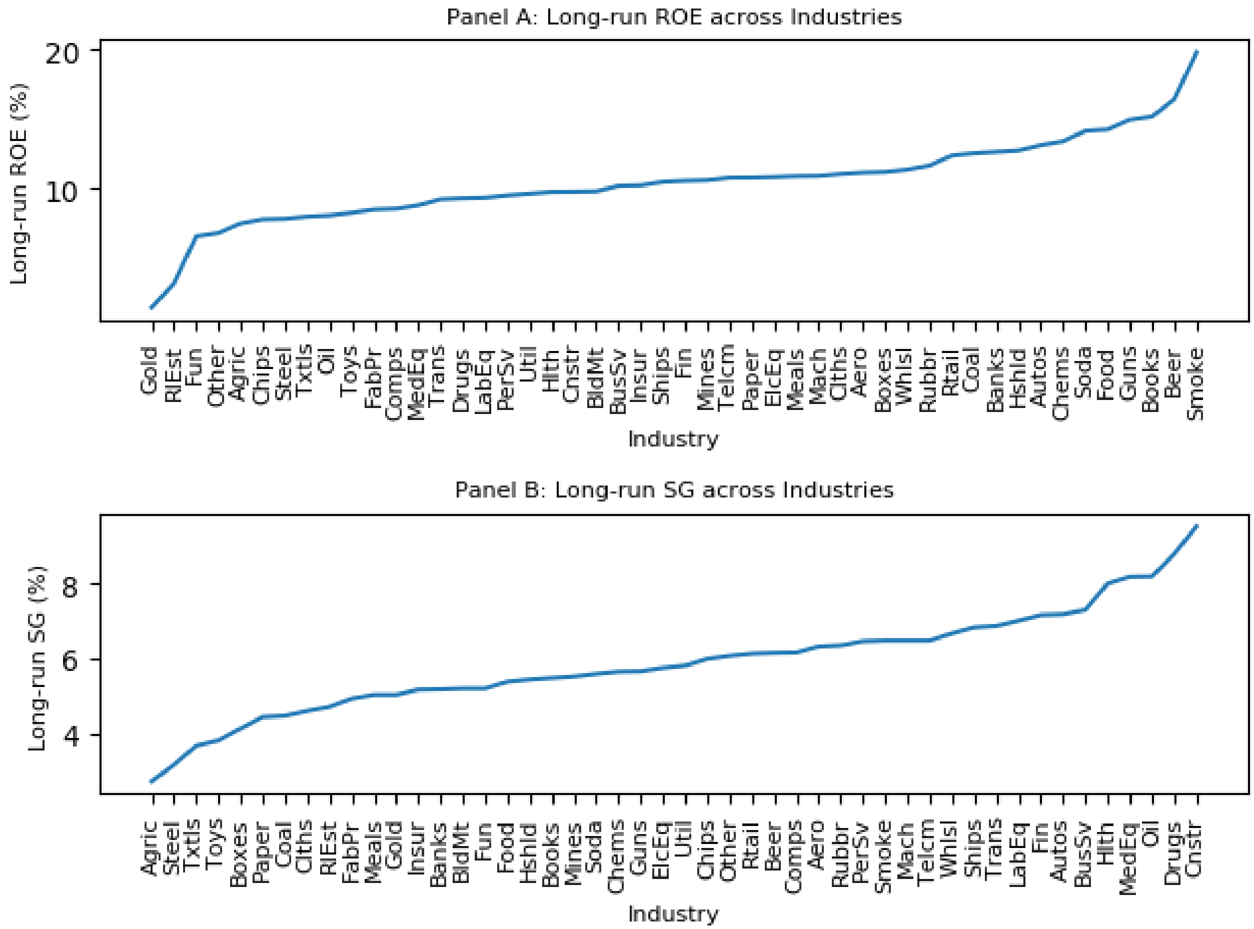
This table presents firm-level equity duration computed with realized cash-flows in the projection horizon and a constant discount rate of 10.03% for US non-financial firms in CRSP/COMPUSTAT with listed common shares between 1963 and 2017 under DSS and BM modified DSS methods. Refer to sections 1.5.1 and 1.5.2 for details on the DSS and BM modified DSS methods.

Figure A.1: Median Firm-Level Return-on-Equity



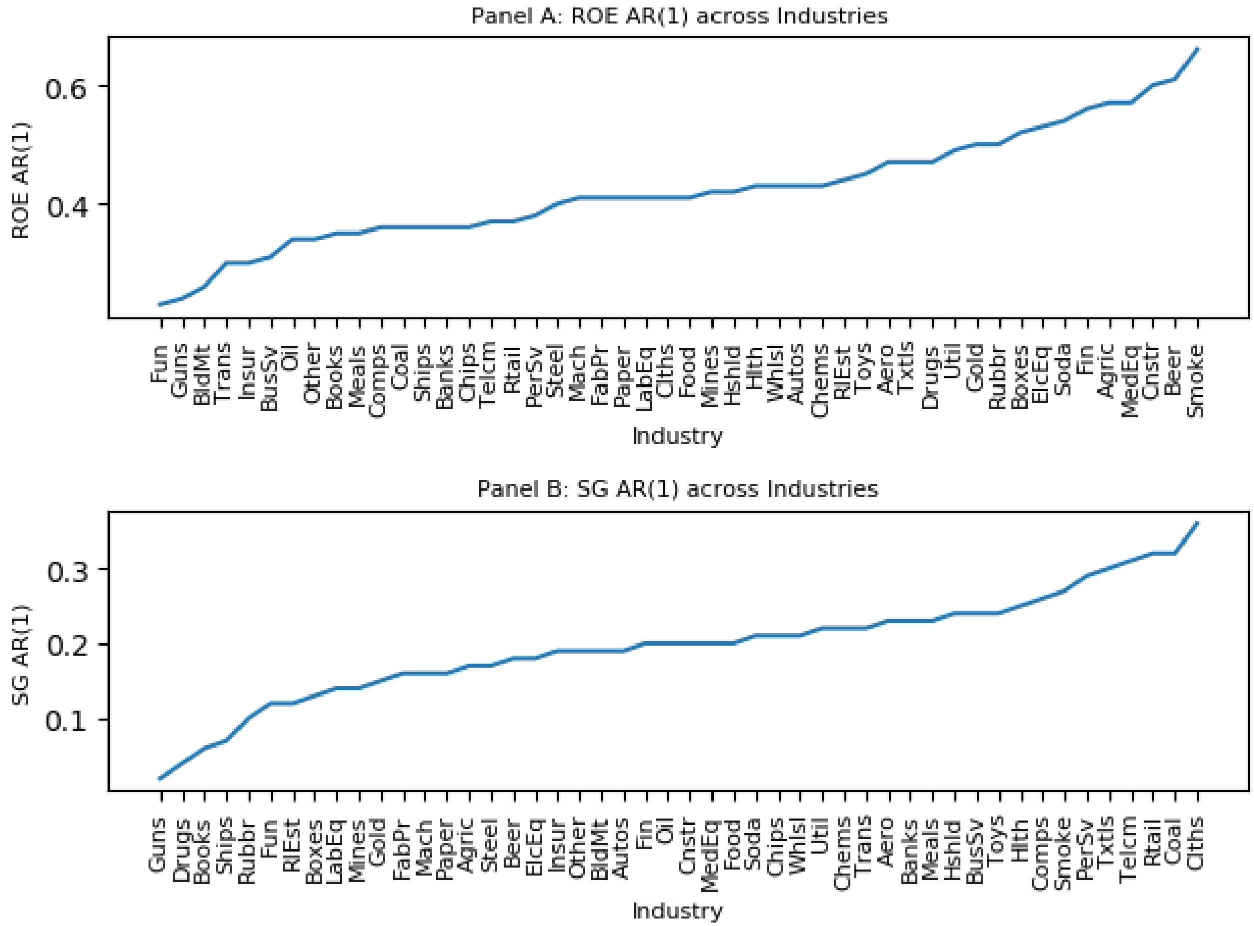
This figure plots the median return-on-equity for US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1963 and 2017. Return-on-equity is defined as net income before extraordinary items divided by previous fiscal year's book value of equity. Negative book value of equity is replaced with market value at the end of the corresponding fiscal year.

Figure A.2: Median Long-run Cash-flow Prediction Parameters across Industries



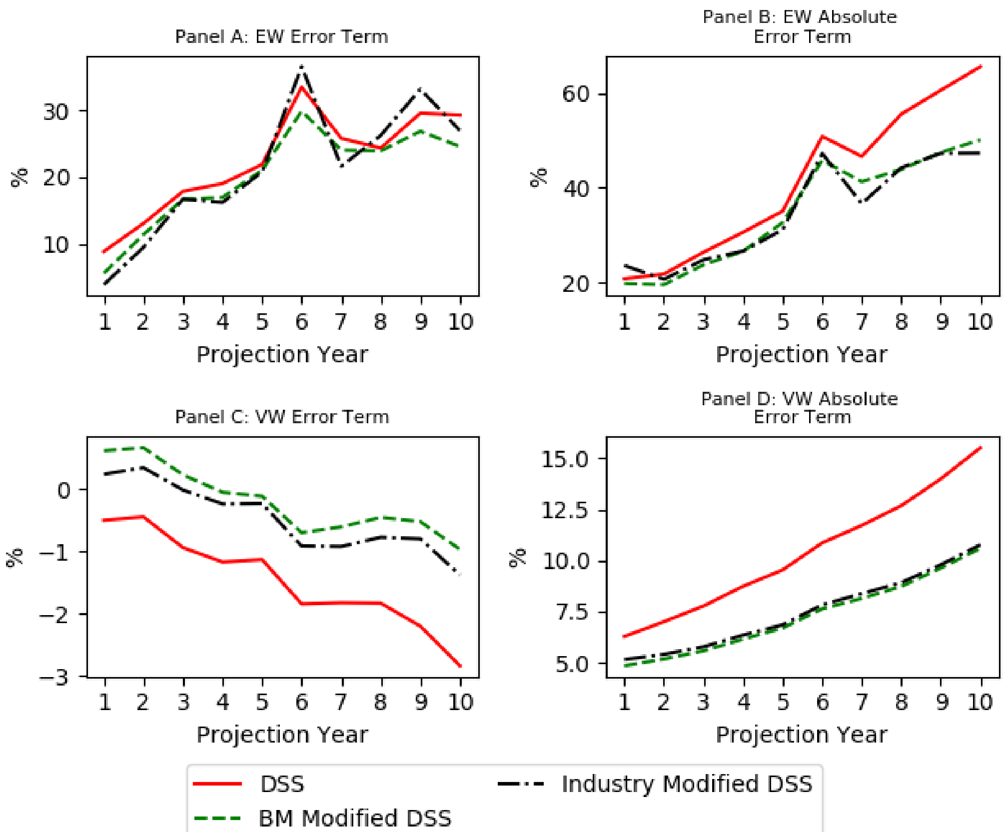
This figure plots differences in parameters that predict cash-flows across industries. Industry refers to one of the 48 Fama-French industries. At the end of June every year, firms are sorted into 48 industries based on their Fama-French industry classification. Return-on-equity (ROE) is computed as the income before extra-ordinary items (IB) over the previous year's book value of equity. Sales growth (SG) is computed as current sales divided by previous year's sales. Each year, I follow firms in each portfolio 15 years into the future and compute ROE for each firm at the end of 15 years (future ROE). The median of the future ROE computed across all firm-years within each industry portfolio is the portfolio's long-run ROE. Similarly, I compute the long-run sales growth (LR SG) for each portfolio. ROE AR(1) and SG AR(1) are computed from regressing current values on past values averaged across all firm-years within each portfolio. Data includes non-financial firms in CRSP/COMPUSTAT with common shares listed (10 and 11) between 1963 and 2017.

Figure A.3: Persistence in Cash-flow Prediction Parameters across Industries



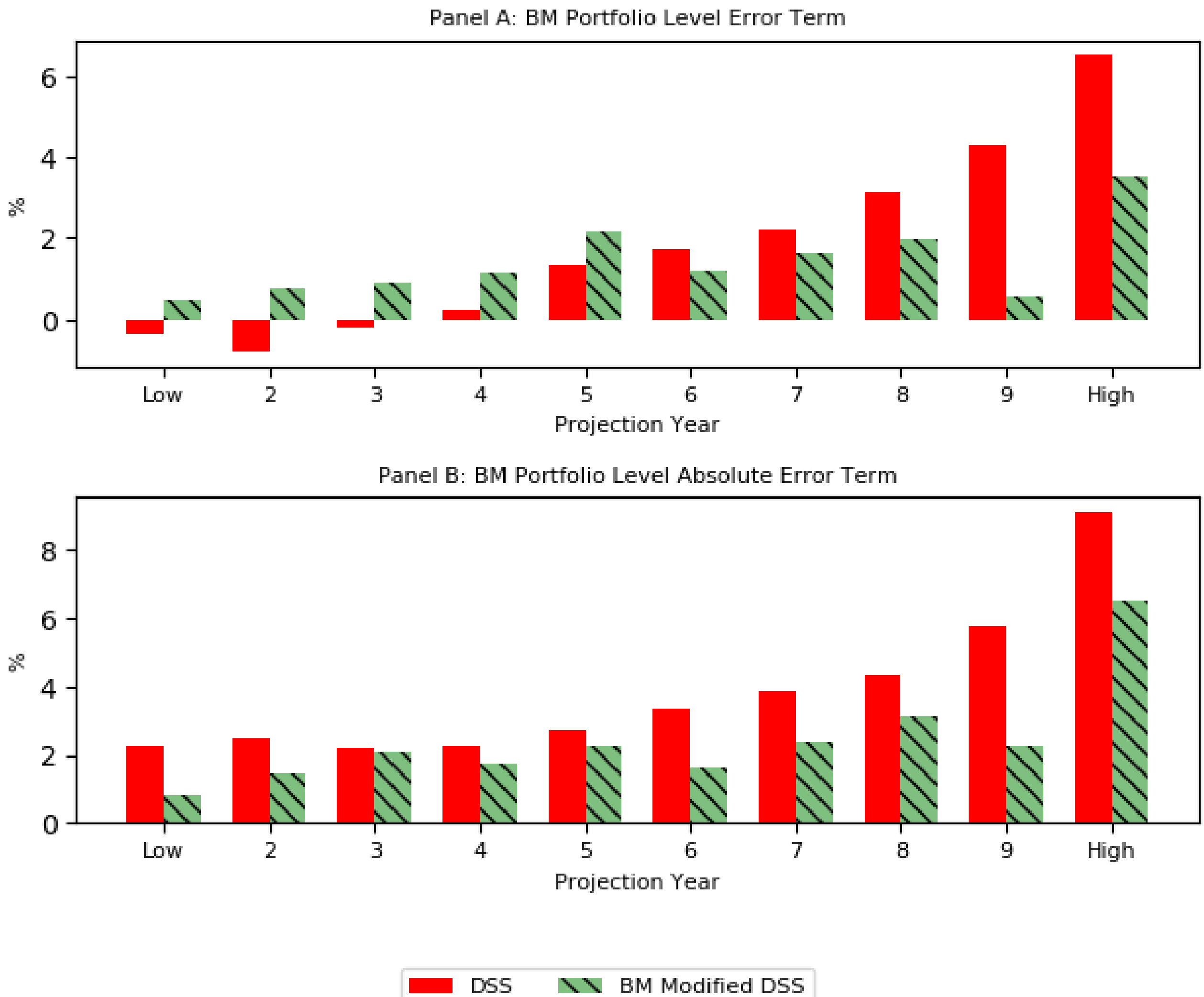
This figure plots differences in persistence of parameters that predict cash-flows across industries. Industry refers to one of the 48 Fama-French industries. At the end of June every year, firms are sorted into 48 industries based on their Fama-French industry classification. Return-on-equity (ROE) is computed as the income before extra-ordinary items (IB) over the previous year's book value of equity. Sales growth (SG) is computed as current sales divided by previous year's sales. ROE AR(1) and SG AR(1) are computed from regressing current values on past values averaged across all firm-years within each industry portfolio. Data includes non-financial firms in CRSP/COMPUSTAT with common shares listed (10 and 11) between 1963 and 2017.

Figure A.4: Detailed Cash-Flow Comparison - Firm-Level



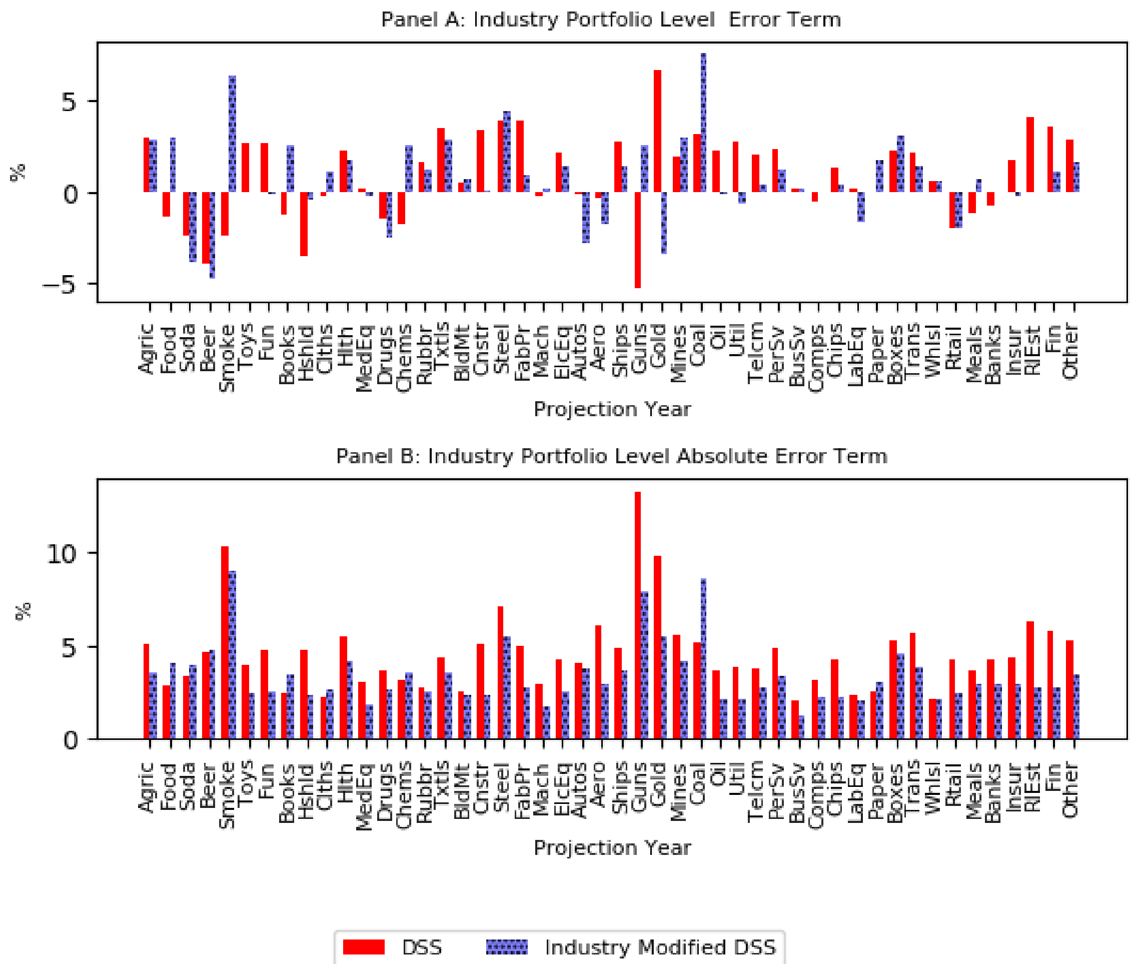
This figure plots an error term - the difference between expected cash-flows and realized cash-flows scaled by beginning total market value. Panel A plots firm-level equal-weighted mean error term. Panel C plots firm-level value-weighted mean error term. Panels B and D plot the absolute error-term equivalents of panels A and C. Expected firm cash-flows are projected employing one of the models - Dechow et al. (2004), modified DSS using book-to-market decile specific parameters, or modified DSS using industry decile specific parameters. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1963 and 2007.

Figure A.5: Cash-Flow Comparison - Book-to-Market Portfolios



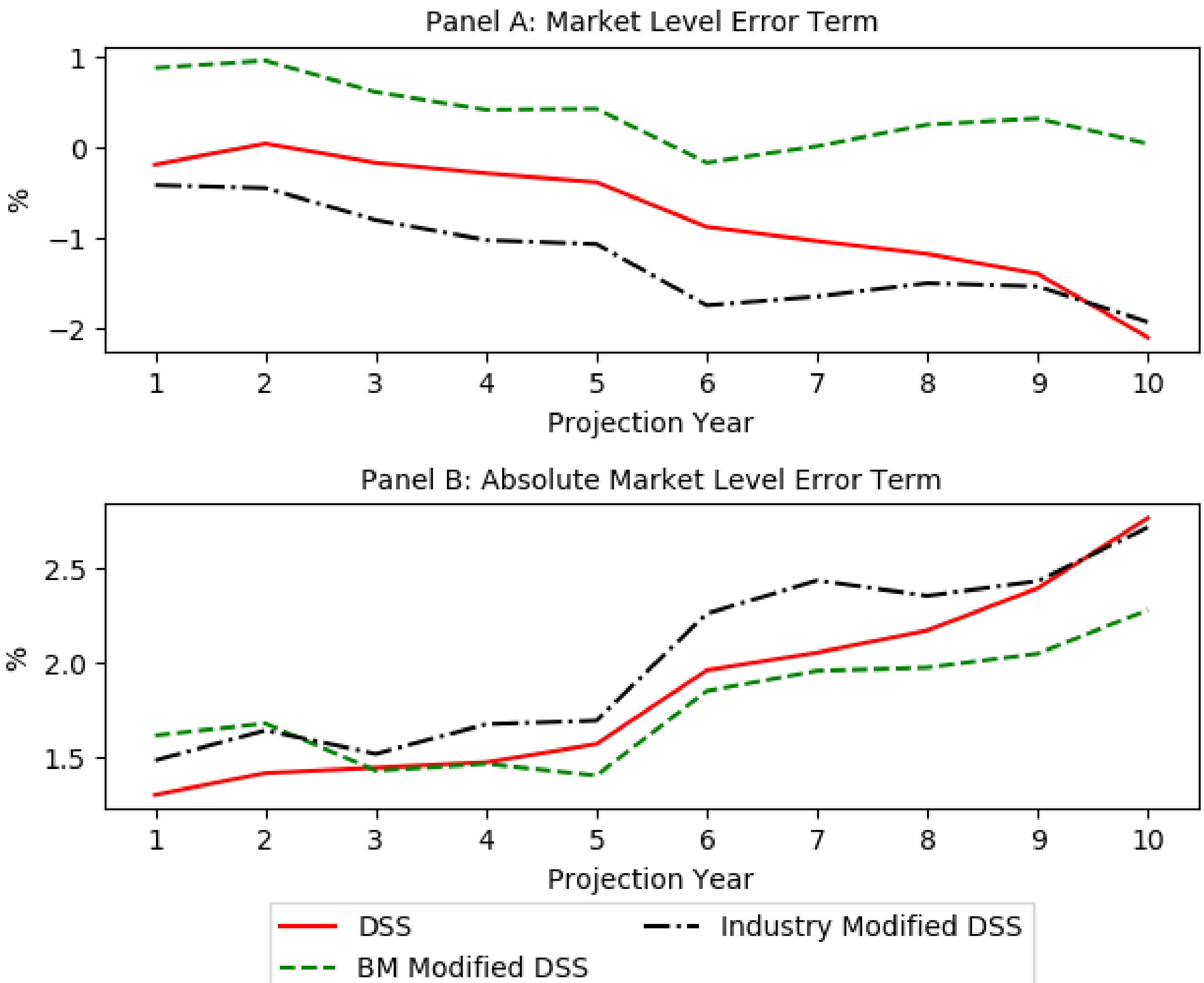
This figure plots an error term - the difference between portfolio expected cash-flows and realized cash-flows scaled by beginning total market value at the portfolio level. Panel A (B) plots the (absolute) mean error term at the book-to-market decile level. Expected firm cash-flows are projected employing one of the models - Dechow et al. (2004), modified DSS using book-to-market decile specific parameters, or modified DSS using industry decile specific parameters. These firm cash-flows are then aggregated to the corresponding portfolio levels. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1963 and 2007.

Figure A.6: Cash-Flow Comparison - Industry Portfolios



This figure plots an error term - the difference between portfolio expected cash-flows and realized cash-flows scaled by beginning total market value at the portfolio level. Panel A (B) plots the (absolute) mean error term at the book-to-market decile level. Panel C (D) plots the (absolute) mean error term at the industry portfolio level. Expected firm cash-flows are projected employing one of the models - DSS, modified DSS using book-to-market decile specific parameters, or modified DSS using industry portfolio specific parameters. These firm cash-flows are then aggregated to the corresponding portfolio levels. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1963 and 2007.

Figure A.7: Cash-Flow Comparison - Market-Level



This figure plots an error term - the difference between expected cash-flows and realized cash-flows scaled by beginning total market value at the market level. Expected firm cash-flows, realized cash-flows, and market capitalization are aggregated to the market level before calculating the error term at the aggregate level. Panel A plots the error term while panel B plots the absolute error term. Expected firm cash-flows are projected employing one of the models - DSS, modified DSS using book-to-market decile specific parameters, or modified DSS using industry portfolio specific parameters. Data include US non-financial firms in CRSP/COMPUSTAT with common shares listed between 1963 and 2007.

Appendix B

CHAPTER 2

B.1 Merging LoPucki BRD and CRSP/COMPUSTAT

Table B.1: Summary of Firm Sample - Merging LoPucki BRD and CRSP/COMPUSTAT

No. of Observations in LoPucki (Includes Multiple Bankruptcies)	1,087
Matched with CRSP/Compustat through GVKEY (Includes Multiple Bankruptcies)	1,050
Matched Permno in the year or within the past two years of default (link table on WRDS)	634
Matched by Name Comparison	151
Total Matched Permno	785
Information available on CRSP	684
Common shares	671
Non-financial firms	550
Accounting and market information available to compute default probability	508
Within the sample period 1980 - 2014	458

B.2 Comparative Statistics for Default Prediction Models

B.2.1 Receiver Operating Characteristic

Receiver operating characteristic (ROC) summarizes a default prediction model's ability to separate default and non-default firms. Consider a contingency table for a binary-default model that predicts whether a firm is non-default or default. A true positive (TP) is a predicted default that occurs, a true negative (TN) is a correctly predicted non-default, a false positive (FP) is an incorrectly predicted default, and a false negative (FN) is an incorrectly predicted non-default. FN represents type 1 error and FP represents type II error. The ROC curve plots the false positive rate (FPR), the number of incorrectly predicted defaults as a fraction of actual non-defaults, on the x-axis and the true positive rate (TPR), the number of correctly predicted defaults as a fraction of actual defaults, on the y-axis.

Default probability from the default prediction model is converted to binary measure, based on a default probability threshold, T. A default probability $X \geq T$ represents a default outcome and a probability $X < T$ represents a non-default outcome. The ROC curve then plots TPR(T) vs FPR(T) with T as the varying parameter.

A model is evaluated by the area under the ROC curve (AUROC) that ranges between 0 and 1. The AUROC represents the degree of non-overlap between the bad and good firm distributions and hence implies the ability of the model to separate the two distributions. A perfect model has an AUROC of 1 while a model based on chance has an AUROC of 0.5. An AUC of 0 represents a model that perfectly reverses the classification (default as non-default and vice-versa).

B.2.2 Accuracy Ratio

The accuracy ratio (AR) measures the number of default firms within the first x percentile of firms reverse sorted on predicted default probability. An accurate model would classify all default firms within a small percentile, λ. Formally, let $\theta = \frac{M}{N}$, where M is the number of default firms and N is the number of firms in the sample. Let $f(\lambda) = \frac{\lambda}{\theta}$. For a perfect model,

$$f(\lambda) = \frac{\lambda}{\theta}, \lambda < \theta \quad \text{(B.1)}$$

$$= 1, \lambda \geq \theta \quad \text{(B.2)}$$

A cumulative accuracy profile (CAP) that plots average $f(\lambda)$, computed over all months in the sample, against λ. The model's informative power is measured by the area under the average $f(\lambda)$ and above the 45 deg line. The AR itself is defined as the ratio between the area pertaining to a model's average $f(\lambda)$ function and the one pertaining to the perfect model's average $f(\lambda)$ function. Therefore, a perfect model's AR is 1 while that of a zero-information model is 0.

The direct relation between AR and area under the receiver operating characteristic (AUROC) is,

$$AR = 2 * AUROC - 1 \tag{B.3}$$

B.2.3 Kolmogorov-Smirnov Test

Kolmogorov-Smirnov (KS) test is a generic non-parametric, goodness-of-fit test to check whether two data samples come from different distributions - default and non-default. The measure is a summary statistic, like AR. The KS statistic is the maximum difference between the true positive rate and the false negative rates enumerated over all possible thresholds of predicted default probability, T, that distinguishes non-default and default firms.

$$KS = \max_{T}(TPR - FNR) \tag{B.4}$$

A perfect model segregates the two distributions perfectly resulting in a KS statistic of 1. Unlike the AR, KS is not a global measure because it focuses only on the maximum discrepancy.

Appendix C

CHAPTER 3

Table C.1: Performance of Weber (2018) on Default Risk-Sorted Quintiles

Portfolio	Low	2	3	4	High	High-Low
Cutoffs	0 to 20	20 to 40	40 to 60	60 to 80	80 to 100	
Panel A: Equal-Weighted Quintiles						
α_{FF3}	1.62***	0.37***	-0.18*	-0.84***	-1.72***	-3.34***
α	1.58***	0.38***	-0.03	-0.43***	-0.76***	-2.35***
	(13.16)	(6.10)	(-0.34)	(-2.90)	(-3.23)	(-7.45)
β_{Dur}	-0.02	0.00	0.14***	0.37***	0.86***	0.88***
	(-0.93)	(0.31)	(6.50)	(11.29)	(16.31)	(12.58)
β_{Mkt}	1.02***	1.00***	1.01***	0.97***	0.91***	-0.11
	(37.37)	(71.71)	(47.25)	(28.74)	(16.93)	(-1.58)
β_{SMB}	0.63***	0.63***	0.75***	0.86***	0.96***	0.33***
	(15.25)	(29.84)	(23.42)	(16.93)	(11.84)	(3.05)
β_{HML}	-0.14***	0.19***	0.35***	0.57***	0.95***	1.09***
	(-3.05)	(7.81)	(9.58)	(9.78)	(10.24)	(8.85)
Panel B: Value-Weighted Quintiles						
α_{FF3}	0.73***	-0.20**	-0.62***	-1.05***	-1.25***	-1.98***
α	0.71***	-0.19**	-0.52***	-0.71***	-0.54***	-1.25***
	(11.79)	(-2.14)	(-4.18)	(-4.65)	(-2.90)	(-5.94)
β_{Dur}	-0.01	0.02	0.10***	0.30***	0.63***	0.65***
	(-0.99)	(0.94)	(3.62)	(8.99)	(15.47)	(13.89)
β_{Mkt}	0.97***	1.05***	1.17***	1.23***	1.23***	0.26***
	(71.04)	(52.07)	(41.48)	(35.64)	(29.31)	(5.37)
β_{SMB}	-0.01	0.17***	0.47***	0.73***	0.91***	0.92***
	(-0.45)	(5.71)	(11.15)	(13.97)	(14.41)	(12.79)
β_{HML}	-0.15***	0.20***	0.31***	0.48***	0.77***	0.92***
	(-6.45)	(5.76)	(6.32)	(8.06)	(10.65)	(11.22)
N	408	408	408	408	408	408

* p<0.10, ** p<0.05, *** p<0.01

This table shows the monthly percent regression alphas and loading on duration factor for equal-weighted (Panel A) and value-weighted (Panel B) default risk portfolios. At the end of June every year, US non-financial firms in CRSP/COMPUSTAT with common shares listed are sorted into equally-spaced quintiles based on one-year ex-ante default probability calculated using the Shumway (2001) model. β_{Dur} refers to loading on the duration factor, $Duration_t$, in the model below.

$$R_{p,t} - R_{F,t} = \alpha + \beta_{Dur} Duration_t + \beta_{Mkt}(R_{M,t} - R_{F,t}) + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \epsilon_t$$

$Duration_t$ is the monthly return on the duration factor from Weber (2018) and available on http://faculty.chicagobooth.edu/michael.weber/research/data.html. The factor is available until June 2014. Monthly risk-free rate ($R_{F,t}$), market ($R_{M,t}$), SMB and HML are taken from Kenneth French's website. T-statistics are reported in parenthesis. ***, **, and * denote significance at 1%, 5% and 10% levels, respectively.