Understanding the Behavior of Distressed Stocks

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Abstract

The paper argues that the behavior of distressed stocks is not a puzzle. This is because in equilibrium expected excess returns are not well captured by the simple linear factor model used in many empirical studies. Instead this popular reduced form approach produces potentially important biases in the both estimated factor loadings and excess returns for portfolios of highly distressed stocks. Empirically we find that these biases can be quite large for abnormal excess returns but are generally small for factor loadings. This is because delisting events are largely uncorrelated with systematic risk factors. After we correct for these biases we see little evidence of underperformance for portfolios of distressed stocks.

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1 Introduction

Understanding the behavior of distress stocks has proved a challenge. Earlier thought, going back to at least Fama and French (1992), suggested financial distress could be the source of the higher expected returns of value stocks. However, recent research suggests that portfolios of highly distressed stocks tend to severely underperform other stocks.\(^1\) Equally surprising, estimated loadings of distress portfolios on standard risk factors, especially size, are often large, making it even more difficult to explain returns to distressed stocks with conventional multi-factor models.

In this paper we develop a general equilibrium asset pricing model with explicit default or delisting events to help us understand these facts. Our main finding is that there is no real distress puzzle. Instead, much of the existing evidence is based on a fundamental misunderstanding of the effect of distress on returns and a failure to recognize biases in the estimated factor loadings and, especially, portfolio alphas.

Our starting point is the observation that delisting is an extreme event that often implies a discrete jump in the expected (and realized) stock return of a firm that is not well captured by a smooth diffusion process. A second issue is the need to separate the exposure to distress risk into systematic and idiosyncratic components. This is paramount to any discussion on the impact of distress on expected equity returns but is rarely acknowledged explicitly in the literature. In fact, in the extreme case where defaults are driven solely by diversifiable firm-level shocks we should not see any sort of premium for highly distressed stocks.

The general equilibrium model in Section 2 is developed around these two observations. We obtain two key results. First, conditioning a stock’s return on well-known risk factors effectively prices the stock’s exposure to the systematic component of default, leaving only the idiosyncratic residual of default to be diversified away. As in Jarrow, Lando, and Yu (2005) this result rests on the validity of the conditions required for conditional diversification to hold. These conditions are commonly assumed in the

credit risk literature and we provide novel evidence for their validity in the context of equity returns.\footnote{See, for example, Duffee (1999), Duffie and Singleton (1999), Liu, Longstaff, and Mandell (2006), and Bai, Collin-Dufresne, Goldstein, and Helwege (2015).}

Second, equilibrium firm-level expected excess returns are driven by three components: (1) the usual risk compensation for systematic risk; (2) a risk compensation the investor demands for the covariation of the firm’s return with the systematic component of default; and (3), an adjustment for the firm’s idiosyncratic default intensity. The last point is particularly important for empirical work since portfolios of distressed stocks are explicitly constructed and ranked from their underlying stocks’ default probabilities. We then show theoretically that expected returns are not well captured by the simple linear factor model used in many empirical studies. Instead this reduced form approach produces potentially important biases in both the estimated factor loadings and the abnormal excess returns for portfolios of highly distressed stocks, when default probabilities are large.

Section 3 sheds light on the likely empirical magnitude of these biases by explicitly identifying and separating idiosyncratic and systematic components of distress in the data. Estimating default probabilities accurately is a significant step in any study of financial distress. Here we follow the reduced-form logit approach introduced by Shumway (2001) and Campbell, Hilscher, and Szilagyi (2008). We show that our predicted estimates of the likelihood of default do an excellent job of predicting actual default of distressed stocks and take this to be evidence of the accuracy of our estimates. Importantly, these probabilities show little, if any, covariation with our usual risk factors, suggesting these probabilities are driven largely by firm-level shocks.

In Section 4 we use a Monte Carlo simulation to illustrate these biases quantitatively. Using the estimated default probabilities we show how fitting a simple linear model leads to biased coefficient estimates, and more specifically, produces sizably negative portfolio alphas. This happens even though the true underlying data generating process is assumed to have zero excess returns. These findings help us formalize a relatively simple procedure to adjust portfolio returns to account for the extreme effects
of a delisting event and that produces unbiased estimates for both excess returns and factor loadings.

Section 5 implements our suggested theoretical corrections and compares the results with those from the linear models that are standard in the literature. Our findings confirm that the correct excess returns are much smaller than previously estimated and in most cases not statistically different from zero. In particular, it is no longer true that the portfolios of the most highly distressed stocks exhibit strongly negative alphas when simply controlling for the excess return on the market. In addition, we also show that after adopting our correction the estimated price of distress risk is essentially zero.

Although we find our evidence compelling, there are a few subtle, but potentially important, issues that we do not entirely resolve in this paper. Perhaps the most significant has to do with the fact that detecting financial distress is inherently difficult. It is common in the literature to identify a “distress” or a “default” event, with stock delistings for performance-related reasons, and we will follow this practice here too. As a result, we will use the terms distress, default, and delisting more or less interchangeably, although the latter is the more accurate one. Practically, this means that we will identify highly distressed stocks as those with a very high probability of being delisted for performance-related reasons.

The literature on distress risk covers empirical work documenting its negative return patterns from Dichev (1998), Griffin and Lemmon (2002), and Campbell, Hilscher, and Szilagyi (2008), to the more recent theoretical justifications of this effect in George and Hwang (2010), Garlappi and Yan (2011), Opp (2013), and Ozdagli (2013). However, Vassalou and Xing (2004) find a positive return pattern but only to the extent that distressed firms are small, value stocks. Chava and Purnanandam (2010) also find a positive return pattern while measuring expected returns with an implied cost of capital developed in Pástor, Sinha, and Swaminathan (2008). Our study is the first to model the non-linear return behavior of distressed stocks, accounting for both idiosyncratic and systematic distress risk; once accounted for, we find no anomalous return pattern across distressed firms.
We now turn to discuss our work and findings in detail.

2 Equilibrium Equity Returns with Default

In this section we study a general equilibrium economy with explicit default events and derive the implied endogenous process for expected stock returns. We then use this framework to characterize analytically the theoretical biases in estimated linear factor models. Specifically, we establish that these biases will depend on both the likelihood of the default events and their correlation with systematic risk factors.

2.1 Production Technologies

Consider an economy comprised of \(N\) firms with identical linear production technologies that produce the single consumption good. Each technology offers an instantaneous rate of return \(dS_i/S_i\) given by the expression:

\[
\frac{dS_i}{S_i} = \mu dt + \sigma_0 \sqrt{\lambda} dz + \sigma_1 \sqrt{\lambda_i} dz_i - \Gamma dq_i,
\]

where \(dz\) is a Brownian motion common to all firms, the \(dz_i\) are idiosyncratic Brownian motions orthogonal to each other and to \(dz\), and the \(dq_i\) are Poisson processes with time-varying intensities \(\lambda_i\) that are also firm-specific.\(^3\)

Related to Ahn and Thompson (1988) and Bai, Collin-Dufresne, Goldstein, and Helwege (2015), the term \(\Gamma dq_i\) captures a default or delisting event associated with firm \(i\), something that occurs with a time-varying instantaneous probability \(\lambda_i\). In this case the expected equity return changes by a discrete amount \(-\Gamma < 0\).\(^4\)

The volatility of the systematic risk factor \(dz\) is scaled by the square root of a time-varying systematic default intensity \(\lambda\), so in times where default is more likely for all firms, the volatility of the market is higher as well. A firm’s idiosyncratic volatility is similarly scaled by its own default intensity. Neither scaling is crucial for the results but they permit a closed-form solution of the model.

\(^3\)Note that in this world the rate of return can be viewed either as the percentage change in an asset price (Merton (1971)), or as the return from investing a unit of the consumption good into a stochastic constant returns to scale technology (Cox, Ingersoll, and Ross (1985)).

\(^4\)Many theoretical models of endogenous default (e.g. Merton (1974), Leland (1994)) effectively imply that \(\Gamma = 1\), although in practice this is probably a worst case scenario (see Garlappi and Yan (2011)).
2.2 The Components of Distress

We now discuss the stochastic processes governing stock delistings. The process for the aggregate default intensity, $\lambda$, follows a Cox-Ingersoll-Ross (CIR) process:

$$d\lambda = \kappa(\bar{\lambda} - \lambda)dt - \sigma\lambda\sqrt{\lambda}dz.$$  \hspace{1cm} (2)

We set $\kappa > 0$ and $\bar{\lambda} > 0$ to ensure a stationary Gamma distribution which is highly skewed, and choose $\sigma > 0$ to satisfy the Feller condition guaranteeing that the processes only take positive values. We similarly assume that the idiosyncratic default intensity follows the CIR process:

$$d\lambda_i = \kappa(\lambda - \lambda_i)dt - \sigma\lambda\sqrt{\lambda_i}dz_i.$$  \hspace{1cm} (3)

For the sake of clarity in exposition we assume that the drifts of all firms' idiosyncratic default intensities revert to a common default intensity, $\lambda$. For the same reason, we keep the parameters across these $N + 1$ processes common, leaving only their diffusions to govern any differences. Neither assumption affects our results.

The two processes (2)-(3) imply that negative realizations of the common risk factor, $dz$, coincide with increases in the probability of default for all firms. Because of this and the fact that all firms' intensities revert to a common default intensity, we interpret $\lambda$ as the systematic component of default. Moreover, since high values of the square-root term raise the volatility of the process, further high realizations are more likely than those governed by a homoskedastic process. Consequently, this process implies periods where defaults cluster but also that they are rare. In addition, as we show below, the correlation between aggregate returns and default probabilities can lead to potentially biased estimates of factor loadings.

2.3 Household’s Problem

The economy is populated by a continuum of identical agents with Epstein-Zin-Weil preferences. Define continuation utility for the representative agent in the economy as:

$$J_t = \mathbb{E}_t \left[ \int_t^\infty f(C_s, J_s)ds \right],$$  \hspace{1cm} (4)
where \( C_t \) denotes household consumption. Under the assumption that the agent has an intertemporal elasticity of substitution equal to one we have:

\[
f(C, J) = \rho (1 - \gamma) J \left( \log C - \frac{1}{1 - \gamma} \log((1 - \gamma)J) \right). \tag{5}\]

where parameter \( \rho > 0 \) is the rate of time preference and we interpret \( \gamma > 1 \) as the coefficient of relative risk aversion.

Let \( W \) denote the (financial) wealth of the representative agent which evolves according to the law of motion:

\[
dW = \left\{ rW - C + W \left( \sum_{i=1}^N \pi_i \right) (\mu - r) \right\} dt + W \sigma_0 \sqrt{\lambda} \left( \sum_{i=1}^N \pi_i \right) dz
+ W \sigma_1 \left( \sum_{i=1}^N \pi_i \sqrt{\lambda} dz_i \right) - WT \left( \sum_{i=1}^N \pi_i dq_i \right). \tag{6}\]

Here \( \pi_i \geq 0 \) is defined as the proportion of wealth invested into the stock of firm \( i \) and \( r \) is the risk-free rate.

Applying Ito’s lemma, the value function, \( J(W_t, \lambda_t, \{\lambda_i\}) \), satisfies the Hamilton-Jacobi-Bellman equation

\[
0 = \max_{C_t, \pi} \left\{ f(C, J) - \rho J + J_W \left[ rW - C + W \left( \sum_{i=1}^N \pi_i \right) (\mu - r) \right] 
+ \frac{1}{2} W^2 J_{WW} \left[ \lambda \sigma^2_0 \left( \sum_{i=1}^N \pi_i \right)^2 + \sigma_1^2 \left( \sum_{i=1}^N \lambda_i \pi_i^2 \right) \right]
+ \sum_{i=1}^N \lambda_i \left[ J(W - WT \pi_i, \lambda, \{\lambda_i\}) - J(W, \lambda, \{\lambda_i\}) \right]
+ J_{\lambda_k} (\lambda - \lambda) + \frac{1}{2} J_{\lambda_k \lambda} \sigma_{\lambda}^2 \lambda - \left( \sum_{i=1}^N \pi_i \right) J_{\lambda W \lambda} \sigma_{\lambda} \sigma_0 W \lambda
+ \sum_{i=1}^N \left[ J_{\lambda_k \lambda} (\lambda - \lambda_i) + \frac{1}{2} J_{\lambda_k \lambda} \sigma_{\lambda}^2 \lambda_i \right] - \left( \sum_{i=1}^N \lambda_i \pi_i J_{\lambda_k W} \right) \sigma_{\lambda} \sigma_1 W \right\}, \tag{7}\]

and the first-order conditions are:

\[
f_C = J_W \tag{8}\]

\[
0 = W J_W (\mu - r) + W^2 J_{WW} \left[ \lambda \sigma^2_0 \left( \sum_{i=1}^N \pi_i \right) + \lambda_k \sigma_1^2 \pi_k \right]
- \lambda_k \Gamma W J' (W - WT \pi_k, \lambda, \{\lambda_i\}) - \lambda J_{\lambda W} \sigma_{\lambda} \sigma_0 W - \lambda_k W \sigma_1 \sigma_{\lambda} J_{\lambda k W}. \tag{9}\]
We conjecture and verify that the solution to the value function takes the form:

\[ J(W, \lambda, \{\lambda_i\}) = \frac{W^{1-\gamma}}{1-\gamma} e^{a+b\lambda + \sum_{i=1}^{N} b_i \lambda_i}, \]  

(10)

where the coefficient \( b \) is the negative root of the equation that solves\(^5\)

\[ 0 = \lambda \left( -b \rho - \frac{1}{2} \gamma (1-\gamma) \sigma_0^2 - b \kappa + \frac{1}{2} b^2 \sigma^2 - \sigma \lambda_0 b(1-\gamma) + \kappa \sum_{i=1}^{N} b_i \right) \]  

(11)

and the constant \( a \) obeys

\[ \rho a = \rho (1-\gamma) \log \rho - \rho + (1-\gamma)(\mu - \rho) + b \kappa \lambda \]  

(12)

The values of the coefficients \( b_i \) are discussed in the text below.

Given the value function, equation (8) implies that the consumption-wealth ratio equals \( C/W = \rho \). As in Duffie and Skiadas (1994), it then follows that the state-price density \( \Lambda_t \) in our environment with recursive preferences takes the form:

\[ \Lambda_t = \exp \left\{ vt - \rho b \int_0^t \lambda_s ds - \rho \sum_{i=1}^{N} b_i \int_0^t \lambda_{is} ds \right\} W_t^{-\gamma} e^{a+b\lambda t + \sum_{i=1}^{N} b_i \lambda_i}, \]  

(13)

where \( v = \rho (1-\gamma) \log \rho - \rho a - \rho \). It follows that:

\[ \frac{d\Lambda}{\Lambda} = -r dt - \sqrt{\lambda} \gamma \sigma_0 dz - \sqrt{\lambda} b \sigma \lambda dz - \gamma \sigma_1 \sum_{i=1}^{N} \sqrt{\lambda_i} \pi_i dz_i - \sigma_\lambda \sum_{i=1}^{N} \sqrt{\lambda_i} \pi_i dz_i + \sum_{i=1}^{N} [(1-\Gamma \pi_i)^{-\gamma} - 1] (d\pi_i - \lambda_i dt). \]  

(14)

### 2.4 A Large Economy

We now focus on a large economy, akin to Ross’s (1976), where the number of firms in the economy \( N \) goes to infinity. In this case the household’s value function ceases to depend on the joint distribution of firms’ idiosyncratic default intensities. To see this note that the optimality condition (9) implies that each coefficient \( b_i \) must satisfy the equation:

\[ 0 = \lim_{N \to \infty} -b_i \rho - \frac{1}{2} \gamma (1-\gamma) \sigma_1^2 \pi_i^2 + [(1-\Gamma \pi_i)^{1-\gamma} - 1] - b_i \kappa + \frac{1}{2} b_i^2 \sigma^2 - (1-\gamma) \sigma_1 \lambda_0 b_i \pi_i \]

\[ = -b_i \rho - b_i \kappa + \frac{1}{2} b_i^2 \sigma^2. \]  

(15)

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\(^5\)The negative root of \( b \) guarantees that with log utility and \( N \to \infty \) the agent does not price variation in systematic distress risk and only cares about wealth. Additionally, the value of the parameter \( b \) under the negative root is smaller than under the positive root and is therefore more conservative.
where the second expression follows from the fact that \( \pi \to 0 \) as \( N \to \infty \). Because we think it is reasonable that in equilibrium all sources of idiosyncratic risk will be diversified away, and thus should not be priced, we therefore pick the solution of \( b_i = 0 \). Thus we restrict our analysis of the equilibrium to a representative agent whose value function does not depend on the joint distribution of firms’ idiosyncratic default intensities.\(^6\)

With a continuum of firms, the stochastic discount factor collapses to:

\[
\lim_{N \to \infty} \frac{d\Lambda}{\Lambda} = -rdt - \sqrt{\lambda} \gamma \sigma_0 dz - \sqrt{\lambda} b \sigma_\lambda dz. \tag{16}
\]

It follows that the only source of uncertainty in the pricing kernel is the systematic component of productivity \( dz \) and default jump risk is not priced. The conditional diversification of default jump risk has also been studied before in the credit risk literature, most notably by Jarrow, Lando, and Yu (2005). This result is essentially in the spirit of Ross (1976) and boils down to two key assumptions:

- **Conditional** on the state variables driving the intensities, the event of default is independent across firms
- The number of firms in the economy is infinite.\(^7\)

### 2.5 Equilibrium Equity Returns

Given the value function, equation (9) implies that the equilibrium excess return for each firm \( i \) obeys:\(^8\)

\[
\mu - r = \gamma \lambda \sigma_0^2 + \gamma \lambda_i \pi_i \sigma_1^2 + b \lambda \sigma_\lambda \sigma_0 + b_i \lambda_i \sigma_\lambda \sigma_1 + \lambda_i \Gamma [1 - \Gamma \pi_i]^{-\gamma}. \tag{17}
\]

Unsurprisingly, an increase in the common default intensity \( \lambda \) raises the expected excess returns on all stocks. An increase in a firm’s idiosyncratic default intensity \( \lambda_i \) will not only increase its own required excess return, but also will decrease its relative market

\(^6\)When the number of firms in the economy is finite, the solution to \( b_i \) produces two positive roots, so we pick the smallest root which corresponds to the solution \( b_i = 0 \) in the large economy.

\(^7\)The term \((1 - \Gamma \pi_i)^{-\gamma} - 1\) will not vanish if \( N < \infty \) but it should nevertheless be negligible for large enough \( N \).

\(^8\)In equilibrium, the risk free security is in zero net supply therefore \( \sum_{i=1}^{N} \pi_i = 1. \)
share \( \pi_i \). Therefore, we would expect increases in default intensities, to be empirically correlated with size, so that distressed firms will have positive loadings on the size factor.

Consistent with standard APT arguments, as \( N \) becomes very large the idiosyncratic diffusive component, \( \gamma \lambda_i \pi_i \sigma^2 \), becomes negligible, as does the source of compensation arising from the firm’s return covariation with its idiosyncratic default intensity, \( b_i \lambda_i \sigma \lambda_1 \). It follows from (17) that:

\[
\lim_{N \to \infty} (\mu - r) = \gamma \lambda \sigma^2_0 + b \lambda \sigma \lambda_0 + \lambda_i \Gamma.
\]

The first term in this expression reflects the usual reward for exposure to systematic risk, while the second component compensates the investor for the covariation of a firm’s stock return with the systematic component of default. The final term adjusts expected returns for the firm’s idiosyncratic default intensity. We now show that failure to account for these additional terms can pose a number of challenges to understanding the effects of distress on equity returns.

### 2.6 Theoretical Biases in Estimated Expected Returns

The typical procedure to estimate the impact of financial distress on equity returns is as follows:

- Estimate default probabilities, usually using firm-level data.
- Create \( p \) portfolios of firms sorted by estimated default probabilities.
- Construct portfolio excess returns, \( r^{e}_{pt} = \mu_{pt} - r_t \), and estimate a reduced-form, discrete-time, regression that is linear in priced factors, \( F_t \),

\[
r^{e}_{pt} = a_p + b'_p F_t + \epsilon_{pt} \quad (19)
\]

- Compute average excess returns, \( \hat{a}_p \) and factor loadings, \( \hat{b}_p \), and investigate whether there are excess returns for high distress portfolios.

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9To see this, the implicit function theorem on (17) gives \( \frac{\partial \pi_i}{\partial \lambda_i} < 0 \).
Our model shows that this procedure is incorrect and generally leads to biased estimates for both excess returns, $\hat{a}_p$’s, and factor betas, $\hat{b}_p$’s. To see this, rewrite the specification for excess returns for firm $i$ by expressing (18) as a single time series equation:

$$\lim_{N \to \infty} (\mu - r) = \sigma_0^2 \gamma \beta_i - \sigma_0^2 b \beta_\lambda + \lambda_i \Gamma. \quad (20)$$

where $\beta_\lambda = \frac{\text{cov}(d\lambda, dW)}{\text{var}(dW)}$. As discussed above, the first piece of the equity risk premium is the usual risk compensation, the quantity of risk measured by factor loading $\beta_i$ multiplied by the factor’s price of risk $\sigma_0^2 \gamma$. The two additional terms however suggest we will have two types of potential biases in the linear factor estimates of returns on distressed portfolios.

First, there is a slope bias since the reduced-form estimates of factor loadings are linked to the structural loadings by the equation: \(^{10}\)

$$\hat{b}_p = \beta_i - \frac{b}{\gamma} \beta_\lambda. \quad (21)$$

If distress intensities load negatively on risk factors ($\beta_\lambda < 0$), the estimated linear loadings $\hat{b}_p$ will be above their true factor $\beta_i$’s. Effectively this is a classic case of omitted variable bias. Only in the extreme case where defaults are driven entirely by idiosyncratic shocks will there be no return compensation for these exposures.

Second, excess returns must also be adjusted for the effects of individual default, $\lambda_i \Gamma$. Failure to make this adjustment generates an intercept bias in the linear regression equation (19). In particular, when the true excess return is zero this equation implies negative estimates of $\alpha_p$’s which are equal to:

$$\hat{a}_p = -\lambda_i \Gamma. \quad (22)$$

Equation (22) shows how the well documented underperformance of stocks with a high probability of delisting can arise from estimating a misspecified linear factor model. In the next two sections we discuss how large this bias is in practice and whether the “underperformance” of distressed stocks survives after we correct for it.

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\(^{10}\)Of course, beta loadings at the portfolio level would be value-weighted averages of the constituent firm’s betas. We ignore this fact for clarity.
More broadly, equations (21) and (22) also suggest a potentially important modifier to Shumway’s (1997) well-known argument about the role of delisting biases. While adding delisting returns to the CRSP sample is clearly important, the introduction of these sharply non-linear events should be modeled with great care. Continuing to assume that the process for expected stock returns obeys a simple linear factor model creates large potential biases in parameter estimates, something that is likely exacerbated by sorting portfolios on the distress probabilities themselves. In particular, as we show below this approach can generates sizable, and spurious, negative alphas to high distress portfolios.

3 Estimating Default Probabilities

The quantitative magnitude of these theoretical biases discussed above depends on the empirical properties of the stochastic processes for the delisting intensities (2)-(3). In this section we seek to infer these properties from estimated probabilities of stock delisting or default event, denoted \( p_{it} \). In what follows we identify a default event with a stock delisting for performance-related reasons. Specifically we use the following delisting flags from the CRSP monthly file: 500, 550, 552, 560, 561, 574, 580, and 584. Appendix A discusses these classifications and their properties at length. For the sample period model discussed in this section this classification yields 7,393 delistings out of over 210,000 firm-year observations.

3.1 Data Overview

Our data covers the period 1950 to 2013, although most of the analysis focuses on the period from 1970 on. Firm-level data comes from combining annual and quarterly accounting data from COMPUSTAT with monthly and daily data from CRSP. We prefer annual over quarterly accounting data.

We use all industrial, standard format, consolidated accounts of USA headquartered firms in COMPUSTAT. We follow Campbell et al. (2008) and align each company’s fiscal year with that of the calendar year, and then lag the accounting data by two months. Our measure of book equity follows Davis, Fama, and French (2005). From
the CRSP monthly and daily file we use all stocks in NYSE, AMEX, and NASDAQ. The S&P500 index comes from the annual MSI file and data on the Fama and French size and book-to-market factors come from Ken French’s website. Details about the data and our approach to construct the key variables are included in Appendix B. Table I reports the summary statistics for the variables used in our regressions.

### 3.2 Logistic Regressions

We forecast delisting events using an updated version of the reduced-form logistic model proposed by Campbell, Hilscher, and Szilagyi (2008). As we will see this measure offers a very good forecast of delisting events over this period, at least at the portfolio level.

Formally we use maximum likelihood methods to estimate a logistic function on eight explanatory variables in a pooled estimation across all firm-years. Our methodology here differs somewhat from that of Campbell, Hilscher, and Szilagyi (2008). They use monthly regressions and focus on predicting the probability of defaulting 12 months ahead, \textit{conditional} on no default occurring in the 11th month. Instead, we use annual rolling logit regressions that can be interpreted as estimating the probability of defaulting, at any time \textit{within the next year}, given the information available at the beginning of the year. More precisely, we estimate these rolling regressions on an annual basis starting in December 1970 up to December 2011 to avoid any look-ahead bias.

Formally we define $p_{it} = 1/(1 + \exp(-y_{it}))$, where $y_{it}$ can be approximated by the following empirical specification:

$$
y_{it} = \gamma_0 + \gamma_{EXRETAVG}EXRETAVG_{it} + \gamma_{SIGMA}SIGMA_{it}$$
$$+ \gamma_{PRICE}PRICE_{it} + \gamma_{NIMTAAVG}NIMTAAVG_{it} + \gamma_{TLMTA}TLMTA_{it}$$
$$+ \gamma_{CASHMTA}CASHMTA_{it} + \gamma_{RSIZE}RSIZE_{it} + \gamma_{MB}MB_{it}$$

(23)

where $EXRETAVG_{it}$ is a measure of average excess returns over the S&P500 index, $SIGMA_{it}$ is the volatility of equity returns, $MB_{it}$ is the market to book ratio, $NIMTAAVG_{it}$ is a measure of profitability, $TLMTA_{it}$ is a measure of firm leverage, $CASHMTA_{it}$ is a measure of cash holdings, $RSIZE_{it}$ is the relative size of the firm, and $PRICE_{it}$ is the log stock price, capped at $15.
The full sample logistic regression results are shown in Table II. They do not differ materially from those in Campbell, Hilscher, and Szilagyi (2008). The McFadden pseudo R-squared for these firm level estimates is 40% and all of these financial and accounting ratios are immensely significant.

3.3 Probability Portfolios

Based on the estimated probabilities \( \hat{p}_{it} \) each firm is then ranked and assigned a percentile on a scale of zero to one-hundred in this empirical distribution. Next we form nine portfolios every year in December and each firm is placed in the correct percentile portfolio. These portfolios are ranked in a symmetric and increasing order as follows:\(^{11}\)

- Portfolio 1: Percentiles between 0% and 5%
- Portfolio 2: Percentiles between 5% and 10%
- Portfolio 3: Percentiles between 10% and 20%
- Portfolio 4: Percentiles between 20% and 40%
- Portfolio 5: Percentiles between 40% and 60%
- Portfolio 6: Percentiles between 60% and 80%
- Portfolio 7: Percentiles between 80% and 90%
- Portfolio 8: Percentiles between 90% and 95%
- Portfolio 9: Percentiles between 95% and 100%

Although the portfolio composition is fixed over the course of a calendar year, both the probabilities and the value weights on each stock are allowed to fluctuate monthly over the year with the change in each firm’s accounting variables and returns, respectively.

We use value weights to construct portfolio returns and incorporate the delisting returns into our portfolio return calculations we also follow Campbell, Hilscher, and

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11 As usual there is a degree of arbitrariness about these classifications. In practice nearly all delistings come from the stocks ex-ante classified in the percentiles 60-100 so the breakdowns for the first 5 portfolios are not particularly important. It is sometimes useful to create finer portfolios for the upper percentiles but there is also a concern that the number of firms in each of them will become quite low, particularly as so many are then delisted over the calendar year.
Szilagyi (2008) and simply use the CRSP delisting return when available or the lagged monthly returns otherwise.

Average delisting probabilities for each portfolio are computed using equal weights. Formally, the portfolio’s December-to-December average predicted probability for portfolio $p$ equals:

$$\hat{p}_{pt} = \frac{\sum_{\text{firm } i \text{ in portfolio } p} \hat{p}_{it}}{N_{pt}}$$ (24)

where $N_{pt}$ is the number of stocks in portfolio $p$ at time $t$.

Table III documents the basic patterns of delisting probabilities, stock returns and other characteristics across our nine delisting portfolios. Average delisting probabilities, $p_{pt}$ are quite low for the first five portfolios. Excess returns (over the market) are generally negative for the portfolios with a high probability of delisting. Return volatility and skewness is also much higher for these stocks. The sharp increase in return skewness is consistent with our view of delistings as highly non-linear events. As documented extensively distress portfolios are also generally made of small firms.

### 3.4 Actual and Predicted Delistings

Before proceeding it is instructive to investigate the accuracy of our estimated average delisting probabilities. To this effect we also construct a yearly time series of actual annual delisting events and compute the ex-post delisting frequencies for each portfolio. These time series for the four highest-risk portfolios are shown in Figure 2. As can be seen these probabilities exhibit significant time variation. Visually, the two time series for each portfolio seems to match up remarkably well, suggesting that our logit-based probability model performs well when estimating the realized delisting frequencies.

More formally, Table IV reports the results of regressing the realized delisting frequencies $p_{pt}$ on our average predicted probabilities, $\hat{p}_{p,t-1}$. Although the quality of fit might seem poor for the first four portfolios it should be noted that there is virtually no variation in the dependent variable (delistings) here. By contrast for the remaining portfolios where default is concentrated the fit seems much more accurate. Indeed, the estimated R-squareds for the last four portfolios are all close to 90 percent. For all but
the first four portfolios the estimated coefficients are also very close to 1 as we would expect if the fit is accurate.\textsuperscript{12}

3.5 Systematic Components of Delisting Probabilities

Section 2 shows that when delisting probabilities have a systematic component there is a potential source of bias in our estimates of the factor loadings. To investigate this issue we now regress the average predicted portfolio delisting probabilities, $p_{pt}$, on the systematic risk factors. The theoretical discussion on bias of the factor loadings in (21) suggests that the correct analysis looks at

$$b \cdot \text{cov}_t \left( d\lambda, \frac{dW}{W} \right) = \frac{\text{cov}_t \left( d\lambda, \frac{dW}{W} \right)}{\text{var}_t \left( \frac{dW}{W} \right)} \cdot \sigma_0^2 b.$$ 

The decomposition gives a familiar result in the study of asset risk compensation: the left term in the product prescribes a regression of the estimated delisting probabilities on the risk factors, the quantity of risk; the right term is the price of that risk.

To implement this equation empirically we first convert our logit’s annual predicted probabilities to monthly probabilities using the following formula:

$$\hat{p}_{pt}^{mth} = 1 - (1 - \hat{p}_{pt}^{ann})^{1/12} \quad (25)$$

We then estimate the following empirical regression for the average delisting probabilities across portfolios on the four Carhart (1997) factors:

$$\hat{p}_{pt} = \eta_{p,0} + \eta_{p,m} MKT_t + \eta_{p,s} SMB_t + \eta_{p,h} HML_t + \eta_{p,o} MOM_t + \xi_{pt} \quad (26)$$

Table V reports both our coefficient estimates and the $R^2$ for each of the nine distress portfolios. Somewhat curiously, in light of the suggestive evidence on the time variation of delisting probabilities presented earlier, there is remarkably little evidence of covariance between delisting probabilities and risk factors.

These findings have two important implications. First, from a practical standpoint, it suggests that this covariance between factors and probabilities is unlikely to produce

\textsuperscript{12}No intercept is included in these regressions to force the regression line through the origin. This assumes that if we predict a zero probability of delisting (which never occurs), then we are also predicting the actual delisting probability to be zero. Including an intercept reduces the highest R-squared to 0.75.
a significant bias in our estimates of factor loadings, at least not when using these baseline logistic default probabilities.

More broadly however, this evidence of little actual systematic risk in delistings indicates that equity investors should not care very much about these events. As a result we should not expect to see much risk compensation for them. With this interpretation any empirical findings of negative excess returns in high distress portfolios must be the result of some form of mis-pricing.\textsuperscript{13}

In the next two sections we investigate the empirical implications of these findings. We proceed in two complementary steps. First we combine these estimated probabilities with numerical simulation methods to attempt to quantify the likely bias in empirical estimates. We also propose a return correction that accounts for the non-linear role of delistings on portfolio returns. Finally, in Section 5 we use this correction to provide more accurate estimates of factor loadings and excess returns across distress portfolios.

4 Numerical Simulation

The analysis in the previous two sections raises two questions:

1. Are the theoretical biases in factor loadings and excess returns quantitatively significant?
2. How do we obtain more accurate estimates of these coefficients?

We now tackle both of them.

4.1 Implementation

Suppose that we have a cross-section of firms that is made \( p = 1, 2, \ldots, 9 \) portfolios each made of 250 individual stocks. Each portfolio is ranked in increasing order of default probabilities, \( p_{pt} \). For simplicity we assume that each firm \( i \) in portfolio \( p \) has an equal ex-ante default probability, that is equal to the average probability for

\textsuperscript{13}Of course it is also possible, although unlikely, that we left out an important risk factor from this regression.
the entire portfolio; formally, $p_{it} = p_{pt}$. To account for the turnover of stocks within a portfolio, once a stock is delisted, it is excluded from its portfolio for the rest of the year. We assume that each delisted stock is only replaced by a new stock at the beginning of the following year.

Assuming firm-level stock excess returns follow the stochastic process (1), we can draw inference from a discrete-time counterpart and generate an artificial panel of 504 months of excess stock returns for each stock $i$ in portfolio $p$ by drawing realizations from the process:

$$r_{ipt}^e = \begin{cases} 
\beta_i'F_t + \epsilon_{it} & \text{if } U[0, 1] > p_{pt} \\
-\Gamma - r_{ft} + \epsilon_{it} & \text{otherwise}
\end{cases}$$

(27)

where $U[0, 1]$ denotes a uniform random number on the unit interval, and $r_{ft}$ is the reference rate of return.\(^{14}\)

The upper branch of the stochastic process (27) describes the familiar multi-factor linear representation of expected equity returns. Here $F_t$ is a vector of priced factors, $\beta_i$ is a vector of factor loadings, and $\epsilon_{it}$ is idiosyncratic noise with mean zero. For most practical applications we can think of $F_t$ as including the popular Fama and French (1993) factor although in our empirical analysis we also discuss the role of the momentum factor (Jegadeesh and Titman (1993)).

By construction there are no abnormal excess returns to these returns ($\alpha_i = 0$). The exact values of the true factor loadings, $\beta_i$ turn out not to be particularly important. For consistency however we assume that they are also equal to their empirical counterparts (reported below in Section 5).

The law of large numbers implies that the (equally-weighted) average excess returns of stocks in each portfolio $p$ are given by:\(^{15}\)

$$r_{pt}^e = \sum_i r_{ipt}^e \approx \beta_p'F_t(1 - p_{pt}) - (\Gamma + r_{ft})p_{pt}$$

(28)

We now use our estimates of the properties of the delisting probabilities $p_{pt}$ in Section 3 to inform our choice of the stochastic process for $p_{pt}$. Specifically, we set

\(^{14}\) Although (27) is quite general it is common in this literature to work with excess returns over the market portfolio and not the risk-free rate.

\(^{15}\) For the artificial sample it makes no difference whether we report equal or value-weighted returns.
the value of $p_{pt}$ for each portfolio $p$ equal to the unconditional average of the default probabilities shown in Table III. As we will see, the low covariance between factors and probabilities renders the practical difference between specifying these probabilities either as constant or as time-varying processes small.

For each of these cases we then estimate the following reduced-form four-factor model to these artificial portfolios:

$$r_{pt} = \alpha_p + \beta_{p,m} \times MKT_t + \beta_{p,s} \times SMB_t + \beta_{p,h} \times HML_t + \beta_{p,o} \times MOM_t + \epsilon_{pt}$$  (29)

and examine the accuracy of our estimated factor loadings and alphas.

### 4.2 Findings

Table VI shows our findings. Panel A shows the estimates from the linear factor model (29). And Panel B lists “corrected” returns to be discussed shortly.

Clearly the most striking result is the finding of large negative alphas for the last three portfolios where the delisting probabilities are also quite high. These are quantitatively large and, as we show in the next section, very similar to the estimates found in the data.

On the other hand the biases in the factor loadings seem negligible, as seen in Table VIII. This is perhaps as expected. We know from (21) that when delisting probabilities weakly covary with factors ($\text{cov}(p_{pt}, F_t) \approx 0$) the magnitude of slope bias will be small.

Taken together these two tables confirm our impression that linear factor models are likely to lead to potentially important biases when the underlying process is highly non-linear, as is likely the case when we focus on portfolios with many delisting stocks. Most significantly, estimated excess returns can easily, and spuriously, appear large and negative for the high delistings portfolios. Biases in factor loadings, however, seem largely irrelevant.

### 4.3 Empirical Implications

We now discuss possible corrections to allow for proper identification of the underlying parameters of the true stochastic process for expected returns.
We start with the observation that although (27) cannot be directly estimated using linear models on the excess returns $r_{it}^e$, we can easily re-write a corrected excess return as

$$\hat{r}_{it} = r_{it} - r_{ft} + (\Gamma + r_{ft})p_{it}$$

(30)

where by definition $\hat{r}_{it}^e$ now follows the linear factor model\(^{16}\)

$$\hat{r}_{it}^e = \beta_i^T F_t (1 - p_{it}) + \epsilon_{it}$$

(31)

Only if the delisting probability equals zero will we have the traditional linear factor regression for unadjusted excess returns $r_{it}^e$, which obtains as a special case of this.

This then suggests adopting the following approach to estimate a factor model on expected equity returns:

1. Estimate the default probability process $\hat{p}_{it}$ for each firm $i$
2. Use the estimated probabilities to compute the adjusted excess returns as:

$$\tilde{r}_{it} = r_{it} - r_{ft} + (\Gamma + r_{ft})\hat{p}_{it}$$

(32)

3. Estimate a linear regression of the adjusted excess returns $\tilde{r}_{it}^e$ on the corrected pricing factors, $F_t (1 - \hat{p}_{it})$.

In practice of course, we will first group stocks into $p = 1, 2, \ldots, P$ portfolios before estimating the factor model to reduce estimation and measurement errors and to isolate the common risk factors driving stock returns.

Panel B of Table VI shows how this correction works in our artificial panel. It reports the results of estimating the same four-factor model (29) but using instead the corrected excess returns in (32). We see that with this adjustment the estimated alphas are now essentially equal to its true value of zero across both sets of portfolios.\(^{17}\)

Next we investigate the results of implementing this procedure to actual return data.

\(^{16}\)Recall that we are normalizing $\alpha_i = 0$ for simplicity.

\(^{17}\)None are statistically significant at the 10% level.
5 Portfolio Excess Returns

We now use our theoretical insights to re-examine the empirical evidence on distressed stocks. As background, we first report the results of estimating a standard linear factor model on the nine empirical distress portfolios constructed in Section 3. This confirms that our portfolios exhibit the usual pattern of large negative excess returns for distressed portfolios. We then report the results of using the theoretical return correction proposed in the previous section.

5.1 Standard Linear Regressions

Table III documents the basic patterns of stock returns and characteristics across the nine empirical delisting portfolios. We now use these data to estimate monthly excess return regressions for four different empirical models: on an intercept (average excess return), the CAPM, the three-factor Fama and French (1992) regression, and a four-factor Carhart (1997) regression. Recall that, as is common in this literature, we mean excess returns over the return over the market portfolio - as measured by the CRSP VWRETD variable.

The estimated average excess returns for each of these regressions are documented in Panel A of Table VII. They are very much in line with much of the available evidence from other authors. In particular we find that portfolios with high probabilities of delistings - recall that these were fairly negligible for the first five portfolios - average negative excess returns over the market portfolio. Although these are not statistically significant they become much larger once we control for the market and, especially, the Fama-French factors. The last column also shows that much of this “distress” puzzle seems to be linked to the momentum factor. Controlling for this factor reduces abnormal excess returns significantly, to the point where only two portfolios exhibit statistically significant alphas.

For completeness, Panel A in Table IX shows the estimated loadings of each portfolio on the market, size and book-to-market factors. As we can see there is a significant size effect across delisting portfolios. Unfortunately however, distressed stocks, which load strongly on size have sizably negative excess returns. Although this pattern of
loading more strongly on the risk factors can also be observed for the market and HML
the effects are fairly insignificant.

5.2 Non-Linear Model

Panels B for Tables VII and IX report the results of incorporating our proposed ad-
justment that explicitly accounts for the non-linearity introduced by a time-varying
probability of delisting.

Formally these panels are constructed from estimating a second set of monthly
excess return regressions but where we now adjust the excess return on portfolio \( p \) as
follows:

\[
\tilde{r}_{pt}^e = r_{pt} - r_{ft} + (\Gamma_t - r_{ft})\hat{p}_{pt} \quad p = 1, 2, \ldots, 9 \quad (33)
\]

Each portfolio’s probabilities, \( \hat{p}_{pt} \), are the equal-weighted averages of the estimated
annual delisting firm level probabilities using the logit regression (23) and converted
to monthly probabilities using the relation (25). As discussed earlier under the null
hypothesis that returns follow the true stochastic process (27) this adjustment cor-
correctly removes the non-linear component of returns from the factor regressions, and is
suitable to be fitted by a linear factor model. The delisting return \( \Gamma_t \) is time-varying to
capture the fact that these returns are often larger in magnitude during recessions.\(^{18}\)

In estimation, we use the value-weighted delisting return of last year to adjust this
year’s excess returns to avoid look ahead bias.

Panel B in Table VII shows the estimated alphas corrected for delisting bias. These
are significantly smaller (in absolute value) than those in Panel A for virtually all
models. They are also essentially zero except for a few portfolios when using the
Fama-French model. However these middle portfolios are not where we see a significant
incidence of default, suggesting these remaining alphas could be driven by something
other than financial distress.

Panel B in Table IX shows the factor loading estimates from the corrected model.
Again, although potentially important in theory these corrections are, in practice,

\(^{18}\)The average correlation between yearly delisting return and yearly predicted delisting probability across
portfolios is -0.13. We plot the time series of our average delisting return in Figure 1.
negligible. As we can see the estimates are nearly identical across both panels and continue to exhibit a pronounced size effect across delisting portfolios.

To conclude, our results confirm our view that estimation bias is an important driver of the perception that distressed stocks underperform. This result largely, although perhaps not entirely, survive even after we adjust excess returns for various risk factors. Based on this evidence the case for a distress “puzzle” seems considerably weaker. Existing estimates of factor loadings however seem fairly accurate and in particular the conclusion that highly distress stocks load heavily on size is confirmed.

5.3 The market price of distress risk

The results in Table V highlighting the lack of covariance between distress probabilities and risk factors suggests something of a puzzle in the study of distressed stock returns. It appears that distress risk is largely unsystematic, and thus should not be priced at all as a risk factor. Previous studies, on the other hand, have largely found that distress risk to have a negative price of risk, although Vassalou and Xing (2004) and Chava and Purnanandam (2010) are the exceptions and find it to be positive.

It is possible to have a risk be pervasive and be unpriced, however. If the CAPM holds, for example, then each firm’s risk is fully captured by its covariation with the market portfolio, and the risk is unpriced to the extent that it is uncorrelated with that portfolio. This is, in essence, the prediction of the model in Section 2. In this section, we investigate how much this pervasiveness of distress risk is priced in stock returns.

As is usual in the literature, estimates of factors’ market prices of risk can be estimated by time series averages of excess returns on factor-mimicking portfolios. That said, we form three mimicking portfolios that vary by their degree of which they sample from the tails of the distress risk distribution:

- LS2080 - buys stocks in the 0 to 20 percentile, and shorts stocks in the 80 to 100 percentile
- LS1090 - buys stocks in the 0 to 10 percentile, and shorts stocks in the 90 to 100 percentile
• LS0595 - buys stocks in the 0 to 5 percentile, and shorts stocks in the 95 to 100 percentile

Each stock is bought in proportion to its market value within its portfolio. In order to correct for the non-linearity that is likely to be present in the upper tail of the risk distribution, we adjust these mimicking portfolio returns similarly to that employed in (33). More specifically, we define returns on the linear model, on say the LS2080 portfolio, as

\[
\tilde{r}_{LS2080,t} = \tilde{r}_{20,t} - \tilde{r}_{80,t} = r_{20,t} - r_{80,t} + (\Gamma_t + \hat{r}_{ft})(\hat{p}_{20,t} - \hat{p}_{80,t}).
\] (34)

In order to assess the degree to which distress risk is captured by another risk factor, we regress these factor-mimicking portfolio returns on traditional risk factors. The corrected regression specifies the regressors not as simply \( F_t \) but as \( F_t(\hat{p}_{20,t} - \hat{p}_{80,t}) \).

The results in the simulation are reported in Table X and the empirical results are reported in Table XI, which reports estimates of intercepts. In Panel A, the raw portfolio returns across finer tails of the risk distribution have an increasing pattern of mean excess returns, in accordance with the majority of studies that find a negative price of distress risk. Indeed, the 0595 portfolio estimates over a 7 percent market price of risk, a sizable risk premium when compared to common estimates of the return on the market or the value factor. Furthermore, traditional sources of risk cannot account for the fluctuations in distress risk, as estimates become statistically significant when controlling for the CAPM, the three-factor model and even the four-factor model.

In Panel B, the corrected returns are tabled. First, the signs of the estimates of mean excess returns flip, now showing a modest, *positive* 2.62 percent for the price of distress risk in the 0595 portfolio. Second, when controlling for the return on the market portfolio the estimates of the intercepts are no longer rejected from being different from zero. It appears the CAPM fully describes the pricing of distressed stocks. This is also because distressed stocks display modestly increasing patterns of CAPM betas. Further controlling for the returns on small stocks, value stocks, and past winners and losers does nothing to alter this conclusion.

These two results we believe are important contributions in the study of distress
stock returns. The lack of covariance of distress probabilities with risk factors suggest that distress risk is not compensated and should therefore not appear anomalous over and above traditional risk factors. Accordingly, we find that the CAPM explains distress factor-mimicking portfolio with corrected returns.

6 Conclusion

This paper shows how non-linearities in returns induced by delisting events can affect the inference about the behavior of delisting stocks. Because these events are both extreme and introduce a floor on expected stock returns, the correct factor model is also non-linear. As a result the estimated alphas and loadings in standard linear models are biased. We show that although these biases can be significant for excess returns they are generally quite small for factor loadings. Empirically this occurs largely because the covariance between delisting events and the systematic risk factors is quite small. After we correct these biases we see little evidence of underperformance for portfolios of distressed stocks.
References


Ozdagli, Ali, 2013, Distress, but not risky: Reconciling the empirical relationship between financial distress, market-based risk indicators, and stock returns (and more), working paper.


A Appendix: Delistings

Figure 1 shows the evolution of average delisting returns (both equal and value-weighted) from 1970 to 2013, for the following performance-related delisting codes:\textsuperscript{19,20}

- 500 - Issue stopped trading on exchange - reason unavailable
- 550 - Delisted by current exchange - insufficient number of market makers
- 552 - Delisted by current exchange - price fell below acceptable level
- 560 - Delisted by current exchange - insufficient capital, surplus, and/or equity
- 561 - Delisted by current exchange - insufficient (or non-compliance with rules of) float or assets
- 574 - Delisted by current exchange - bankruptcy, declared insolvent
- 580 - Delisted by current exchange - delinquent in filing, non-payment of fees
- 584 - Delisted by current exchange - does not meet exchange’s financial guidelines for continued listing

We remove all delisting returns, $\Gamma_t$, greater than positive 100%. Less than 1% of the delisting returns - out of 7,393 delisting observations - are missing across the whole sample period. This is quite low, when compared to Shumway (1997), and Shumway and Warther (2002), which document about 90% missing data for AMEX-NYSE, and almost all data missing for NASDAQ, or CRSP(2001) which documented the availability of about 73% delisting returns in the 500 series. It seems that CRSP coverage of delisting returns is now almost complete.

The equal-weighted and value-weighted average delisting returns are respectively -25%, and -33.6%, for the whole sample period. The average delisting returns for the whole sample are consistent with (Shumway 1997) statement, who reports an average

\textsuperscript{19}Before 1987, all performance-related and stock-exchange-related delistings were coded 5. After 1987, CRSP started a more refined breakdown. The original code 5 delistings were initially given 500, and are considered to be mainly performance-related delistings (there is only a small number of exchange-related delistings).

\textsuperscript{20}The 572 delisting code (liquidation at company request), is now discontinued and is replaced by the 400 delisting series. The average delisting returns on the 400 series is slightly positive, which may suggest that it does not really reflect negative company performance.
delisting return of -29.9%, for the 1962-1993 sample, for AMEX-NYSE stocks. Interestingly the delisting return $\Gamma(t)$ seems to exhibit significant time-variation and is often larger in magnitude during market downturns.
Appendix: Firm Level Data and Variables

This appendix describes in detail how our the variables used in the analysis are constructed. All variables codes are for the COMPUSTAT annual file.

- **Relative size**
  
  \[ RSIZE_{it} = \log(SIZE_{it}/TOTVAL_t \times 1000) \]

  where \( TOTVAL_t \) is total dollar value of CRSP’s value-weighted portfolio VWRETD and \( SIZE_{it} = PRC_{it} \times SHROUT_{it}/1000 \)

- **Leverage**
  
  \[ TLMTA_{it} = LT_{it}/(SIZE_{it} + LT_{it}) \]

- **Relative cash holdings**
  
  \[ CASHMTA_{it} = CHE_{it}/(SIZE_{it} + LT_{it}) \]

- **Market to book ratio**
  
  \[ MB_{it} = SIZE_{it}/ADJBE_{it} \]

- **Adjusted book equity (observation removed if negative)**
  
  \[ ADJBE_{it} = BE_{it} + 0.1 \times (SIZE_{it} - BE_{it}) \]

- **Stock price**
  
  \[ PRICE_{it} = \log(\min\{PRC_{it}, 15\}) \]

- **Excess returns**
  
  \[ EXRETAVG_{it} = (1 - \psi)/(1 - \psi^{12}) \times (EXRET_{it} + .. + \psi^{11}EXRET_{it-11}) \]

  where

  \[ EXRET_{it} = \log(1 + R_{it}) - \log(1 + VWRETD_{it}) \]

  and \( VWRETD \) is CRSP’s value-weighted total return. Because of the need for an uninterrupted series any missing variables are set equal to their cross-sectional means.
• Return on assets, or profitability

\[ NIMTAAVG_{it} = \frac{(1 - \psi^{3})}{(1 - \psi^{12})} \times (NIMTA_{it,t-2} + \psi^{3} NIMTA_{it-3,t-5} + \psi^{6} NIMTA_{it-6,t-8} + \psi^{9} NIMTA_{it-9,t-11}) \]

where we use \( \psi = 2^{-1/3} \) and

\[ NIMTA_{it} = NI_{it}/(SIZE_{it} + LT_{it}) \]

\[ NIMTA_{it-x,t-x-2} = (NIMTA_{it-x} + NIMTA_{it-x-1} + NIMTA_{it-x-2})/3 \]

Because of the need for an uninterrupted series any missing variables are set equal to their cross-sectional means.

• Return volatility

\[ SIGMA_{it} = \sqrt{\frac{252}{N-1} \sum R_{it}^{2}} \]

where the summation is of daily returns over the past three months and missing SIGMA observations (when \( N < 5 \)) are replaced with the cross-sectional mean.

Each of these variables is also winsorized at the fifth and ninety-fifth percentiles in every year. Furthermore, following Campbell, Hilscher, and Szilagyi (2008), all observations with missing size, profitability, leverage, or excess return data are dropped.
Table I: Summary Statistics

This table reports summary statistics for the core variables used in the logistic regressions. The data are monthly over the period 1950 to 2013.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>NIMTA</td>
<td>0.001</td>
<td>0.006</td>
<td>0.024</td>
<td>-0.187</td>
<td>0.043</td>
</tr>
<tr>
<td>TLMTA</td>
<td>0.434</td>
<td>0.405</td>
<td>0.276</td>
<td>0.015</td>
<td>0.968</td>
</tr>
<tr>
<td>EXRET</td>
<td>-0.010</td>
<td>-0.008</td>
<td>0.116</td>
<td>-0.445</td>
<td>0.338</td>
</tr>
<tr>
<td>RSIZE</td>
<td>-10.692</td>
<td>-10.871</td>
<td>1.954</td>
<td>-14.711</td>
<td>-4.842</td>
</tr>
<tr>
<td>SIGMA</td>
<td>0.529</td>
<td>0.444</td>
<td>0.339</td>
<td>0.106</td>
<td>1.924</td>
</tr>
<tr>
<td>CASHMTA</td>
<td>0.086</td>
<td>0.048</td>
<td>0.101</td>
<td>0.001</td>
<td>0.652</td>
</tr>
<tr>
<td>MB</td>
<td>2.067</td>
<td>1.547</td>
<td>1.979</td>
<td>0.244</td>
<td>102.7</td>
</tr>
<tr>
<td>PRICE</td>
<td>2.044</td>
<td>2.514</td>
<td>0.908</td>
<td>-1.386</td>
<td>2.708</td>
</tr>
</tbody>
</table>

Firm-month observations = 2,732,499
Table II: **Logistic Regression Estimates**

This table reports the estimated coefficients for the full sample period (data up to December 2013) for the logistic regression (23).

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Estimate</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>-9.927</td>
<td>(0.235)***</td>
</tr>
<tr>
<td>EXRETAVG</td>
<td>-7.766</td>
<td>(0.287)***</td>
</tr>
<tr>
<td>SIGMA</td>
<td>0.395</td>
<td>(0.042)***</td>
</tr>
<tr>
<td>MB</td>
<td>0.187</td>
<td>(0.009)***</td>
</tr>
<tr>
<td>NIMTAAVG</td>
<td>-13.085</td>
<td>(0.557)***</td>
</tr>
<tr>
<td>TLMTA</td>
<td>1.320</td>
<td>(0.060)***</td>
</tr>
<tr>
<td>CASHMTA</td>
<td>-1.370</td>
<td>(0.142)***</td>
</tr>
<tr>
<td>RSIZE</td>
<td>-0.441</td>
<td>(0.017)***</td>
</tr>
<tr>
<td>PRICE</td>
<td>-0.653</td>
<td>(0.021)***</td>
</tr>
</tbody>
</table>

Observations: 212,073
Delistings: 5,600
Pseudo-$R^2$: 0.40

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
This table reports summary statistics for the portfolios constructed using the estimated probabilities of default using the logistic regression (23). Excess returns are over CRSP’s value-weighted total return, VWRETD. This data covers monthly data from 1970 until 2013. Some denoted quantities are annualized.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>0005</th>
<th>0510</th>
<th>1020</th>
<th>2040</th>
<th>4060</th>
<th>6080</th>
<th>8090</th>
<th>9095</th>
<th>9500</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean annual $\hat{p}$</td>
<td>0.0004</td>
<td>0.0006</td>
<td>0.0009</td>
<td>0.0022</td>
<td>0.0061</td>
<td>0.0218</td>
<td>0.0613</td>
<td>0.1159</td>
<td>0.1999</td>
</tr>
<tr>
<td>Mean MB</td>
<td>2.341</td>
<td>2.450</td>
<td>2.414</td>
<td>2.313</td>
<td>2.382</td>
<td>2.638</td>
<td>2.993</td>
<td>3.337</td>
<td>4.035</td>
</tr>
<tr>
<td>Mean annual excess return</td>
<td>0.80</td>
<td>-0.04</td>
<td>0.56</td>
<td>0.62</td>
<td>-0.14</td>
<td>-0.71</td>
<td>-2.11</td>
<td>-2.93</td>
<td>-6.28</td>
</tr>
<tr>
<td>Portfolio skewness</td>
<td>0.148</td>
<td>0.221</td>
<td>-0.206</td>
<td>-0.390</td>
<td>0.802</td>
<td>1.512</td>
<td>1.877</td>
<td>1.985</td>
<td>2.574</td>
</tr>
<tr>
<td>Portfolio std. dev.</td>
<td>0.015</td>
<td>0.013</td>
<td>0.015</td>
<td>0.023</td>
<td>0.031</td>
<td>0.045</td>
<td>0.062</td>
<td>0.080</td>
<td>0.099</td>
</tr>
</tbody>
</table>
Table IV: Actual and Estimated Delisting Frequencies

This table reports $R^2$ associated with regressing ex-post default frequencies on the average estimated probabilities of default for nine portfolios, indexed by subscript $p$:

$$p_{pt} = b_p \hat{P}_{pt-1} + \epsilon_{pt}.$$ 

Each portfolio is constructed using the estimated default probabilities using the logistic regression (23). Logit regressions coefficients are calculated in December and applied over the entire following year. The predicted probability estimate over the entire following calendar year is paired with the year’s corresponding realized default frequency. This annual data is from 1970 until 2013.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>( \hat{b}_j )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0005</td>
<td>0.70</td>
<td>0.07</td>
</tr>
<tr>
<td>0510</td>
<td>0.46</td>
<td>0.00</td>
</tr>
<tr>
<td>1020</td>
<td>0.43</td>
<td>0.09</td>
</tr>
<tr>
<td>2040</td>
<td>0.82</td>
<td>0.54</td>
</tr>
<tr>
<td>4060</td>
<td>0.90</td>
<td>0.63</td>
</tr>
<tr>
<td>6080</td>
<td>0.84</td>
<td>0.87</td>
</tr>
<tr>
<td>8090</td>
<td>0.89</td>
<td>0.88</td>
</tr>
<tr>
<td>9095</td>
<td>0.92</td>
<td>0.89</td>
</tr>
<tr>
<td>9500</td>
<td>1.01</td>
<td>0.91</td>
</tr>
</tbody>
</table>
Table V: Systematic Components of Delisting Probabilities

This table reports the results of regressing the average estimated probabilities of default for nine portfolios, indexed by \( p \), on the Carhart (1997) four risk factors:

\[
\hat{p}_{pt} = a_p + b_p F_t + \epsilon_{pt}.
\]

Each portfolio is constructed using the estimated default probabilities using the logistic regression (23). Sample period is from 1970 to 2013 at a monthly frequency. Standard errors are OLS.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Constant</th>
<th>MKT</th>
<th>SMB</th>
<th>HML</th>
<th>MOM</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0005</td>
<td>0.00***</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>0510</td>
<td>0.00***</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>1020</td>
<td>0.00***</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>2040</td>
<td>0.00***</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>4060</td>
<td>0.00***</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>6080</td>
<td>0.00***</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>8090</td>
<td>0.01***</td>
<td>-0.01</td>
<td>-0.02</td>
<td>-0.02</td>
<td>-0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>9095</td>
<td>0.01***</td>
<td>-0.01</td>
<td>0.00</td>
<td>-0.02</td>
<td>-0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>9500</td>
<td>0.02***</td>
<td>-0.01</td>
<td>0.03</td>
<td>0.00</td>
<td>-0.03</td>
<td>0.01</td>
</tr>
</tbody>
</table>

*** \( p < 0.01 \), ** \( p < 0.05 \), * \( p < 0.1 \)
Table VI: Excess Return Simulation Results

This table reports the results of estimating a linear regression models on a constant, the excess market return, the Fama-French 3-factor model, and the Carhart 4-factor model on our simulated portfolios when the delisting probabilities are constant and equal to their time series averages for each portfolio. Alphas are annualized and in percent. Panel A reports the empirical estimates from (29). Panel B lists estimates of simulated portfolio returns that are adjusted according to (32). Standard errors are OLS. True alphas are zero across all portfolios.

### PANEL A

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Mean excess return</th>
<th>CAPM alpha</th>
<th>3-factor alpha</th>
<th>4-factor alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.19</td>
<td>0.40</td>
<td>0.97</td>
<td>-0.71</td>
</tr>
<tr>
<td>2</td>
<td>-0.45</td>
<td>-0.10</td>
<td>0.13</td>
<td>0.40</td>
</tr>
<tr>
<td>3</td>
<td>0.18</td>
<td>-0.33</td>
<td>-0.96</td>
<td>0.50</td>
</tr>
<tr>
<td>4</td>
<td>1.15</td>
<td>0.24</td>
<td>-0.86</td>
<td>0.39</td>
</tr>
<tr>
<td>5</td>
<td>1.86</td>
<td>0.33</td>
<td>-1.73**</td>
<td>0.39</td>
</tr>
<tr>
<td>6</td>
<td>-0.32</td>
<td>-2.40</td>
<td>-5.06***</td>
<td>-1.61***</td>
</tr>
<tr>
<td>7</td>
<td>-1.69</td>
<td>-4.36*</td>
<td>-7.05***</td>
<td>-2.73***</td>
</tr>
<tr>
<td>8</td>
<td>-4.50</td>
<td>-7.47**</td>
<td>-9.96***</td>
<td>-3.85***</td>
</tr>
<tr>
<td>9</td>
<td>-5.68</td>
<td>-8.82***</td>
<td>-12.11***</td>
<td>-6.93***</td>
</tr>
</tbody>
</table>

### PANEL B

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Mean excess return</th>
<th>CAPM alpha</th>
<th>3-factor alpha</th>
<th>4-factor alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.18</td>
<td>0.41</td>
<td>0.99</td>
<td>-0.69</td>
</tr>
<tr>
<td>2</td>
<td>-0.44</td>
<td>-0.09</td>
<td>0.14</td>
<td>0.42</td>
</tr>
<tr>
<td>3</td>
<td>0.21</td>
<td>-0.30</td>
<td>-0.93</td>
<td>0.52</td>
</tr>
<tr>
<td>4</td>
<td>1.22</td>
<td>0.30</td>
<td>-0.80</td>
<td>0.46</td>
</tr>
<tr>
<td>5</td>
<td>2.05</td>
<td>0.52</td>
<td>-1.55**</td>
<td>0.58</td>
</tr>
<tr>
<td>6</td>
<td>0.34</td>
<td>-1.74</td>
<td>-4.40***</td>
<td>-0.95</td>
</tr>
<tr>
<td>7</td>
<td>0.20</td>
<td>-2.47</td>
<td>-5.15***</td>
<td>-0.83</td>
</tr>
<tr>
<td>8</td>
<td>-0.83</td>
<td>-3.79</td>
<td>-6.29***</td>
<td>-0.18</td>
</tr>
<tr>
<td>9</td>
<td>0.95</td>
<td>-2.19</td>
<td>-5.48***</td>
<td>-0.30</td>
</tr>
</tbody>
</table>

*** p < 0.01, ** p < 0.05, * p < 0.1
Table VII: Excess Returns Across Delisting Portfolios

This table reports the average excess returns over the market portfolio as well as the excess return over three different empirical models: the CAPM, the three-factor Fama-French (1992) regression, and a four-factor Carhart (1997) regression. Panel A uses raw portfolio returns while Panel B adjusts portfolio returns for delisting events. Each portfolio is constructed using the estimated default probabilities using the logistic regression (23). Sample period runs monthly from 1970 until 2013.

### PANEL A

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Mean excess return</th>
<th>CAPM alpha</th>
<th>3-factor alpha</th>
<th>4-factor alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>0005</td>
<td>0.80</td>
<td>1.60**</td>
<td>2.41***</td>
<td>0.46</td>
</tr>
<tr>
<td>0510</td>
<td>-0.04</td>
<td>0.38</td>
<td>0.64</td>
<td>0.81</td>
</tr>
<tr>
<td>1020</td>
<td>0.56</td>
<td>0.09</td>
<td>-0.54</td>
<td>0.91</td>
</tr>
<tr>
<td>2040</td>
<td>0.62</td>
<td>-0.52</td>
<td>-1.46</td>
<td>0.28</td>
</tr>
<tr>
<td>4060</td>
<td>-0.14</td>
<td>-1.90</td>
<td>-3.83***</td>
<td>-1.55*</td>
</tr>
<tr>
<td>6080</td>
<td>-0.71</td>
<td>-3.22</td>
<td>-5.85***</td>
<td>-2.57**</td>
</tr>
<tr>
<td>8090</td>
<td>-2.11</td>
<td>-5.22*</td>
<td>-7.91***</td>
<td>-3.70*</td>
</tr>
<tr>
<td>9095</td>
<td>-2.93</td>
<td>-6.62</td>
<td>-9.15***</td>
<td>-3.11</td>
</tr>
<tr>
<td>9500</td>
<td>-6.28</td>
<td>-9.87*</td>
<td>-13.47***</td>
<td>-8.89**</td>
</tr>
</tbody>
</table>

### PANEL B

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Mean excess return</th>
<th>CAPM alpha</th>
<th>3-factor alpha</th>
<th>4-factor alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>0005</td>
<td>0.81</td>
<td>1.62**</td>
<td>2.42***</td>
<td>0.47</td>
</tr>
<tr>
<td>0510</td>
<td>-0.02</td>
<td>0.40</td>
<td>0.66</td>
<td>0.83</td>
</tr>
<tr>
<td>1020</td>
<td>0.59</td>
<td>0.12</td>
<td>-0.51</td>
<td>0.94</td>
</tr>
<tr>
<td>2040</td>
<td>0.70</td>
<td>-0.45</td>
<td>-1.39</td>
<td>0.35</td>
</tr>
<tr>
<td>4060</td>
<td>0.07</td>
<td>-1.68</td>
<td>-3.62***</td>
<td>-1.34</td>
</tr>
<tr>
<td>6080</td>
<td>0.08</td>
<td>-2.45</td>
<td>-5.07***</td>
<td>-1.77</td>
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<tr>
<td>8090</td>
<td>0.30</td>
<td>-2.84</td>
<td>-5.50**</td>
<td>-1.21</td>
</tr>
<tr>
<td>9095</td>
<td>2.10</td>
<td>-1.64</td>
<td>-4.15</td>
<td>2.07</td>
</tr>
<tr>
<td>9500</td>
<td>3.43</td>
<td>-0.24</td>
<td>-3.79</td>
<td>1.12</td>
</tr>
</tbody>
</table>

*** p < 0.01, ** p < 0.05, * p < 0.1
Table VIII: **Factor Loadings Simulation Results**

This table reports the results of estimating a our simulated portfolio returns on a constant, the excess market return, the Fama-French 3-factor model and the 4-factor model when the delisting probabilities are constant and equal to their empirical time series averages for each portfolio. Panel A reports the empirical estimates from (29). Panel B lists estimates of simulated portfolio returns that are adjusted according to (32). Standard errors are OLS. True betas are taken to be our estimates in the data over the monthly sample 1970-2013.

**PANEL A**

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>MKT</th>
<th>SMB</th>
<th>HML</th>
<th>MOM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.08</td>
<td>-0.16</td>
<td>-0.05</td>
<td>0.14</td>
</tr>
<tr>
<td>2</td>
<td>-0.03</td>
<td>-0.15</td>
<td>-0.03</td>
<td>-0.02</td>
</tr>
<tr>
<td>3</td>
<td>0.08</td>
<td>0.00</td>
<td>0.06</td>
<td>-0.15</td>
</tr>
<tr>
<td>4</td>
<td>0.08</td>
<td>0.46</td>
<td>0.01</td>
<td>-0.13</td>
</tr>
<tr>
<td>5</td>
<td>0.10</td>
<td>0.75</td>
<td>0.10</td>
<td>-0.18</td>
</tr>
<tr>
<td>6</td>
<td>0.15</td>
<td>1.09</td>
<td>0.12</td>
<td>-0.32</td>
</tr>
<tr>
<td>7</td>
<td>0.14</td>
<td>1.41</td>
<td>0.01</td>
<td>-0.42</td>
</tr>
<tr>
<td>8</td>
<td>0.17</td>
<td>1.60</td>
<td>-0.07</td>
<td>-0.54</td>
</tr>
<tr>
<td>9</td>
<td>0.14</td>
<td>1.92</td>
<td>0.02</td>
<td>-0.46</td>
</tr>
</tbody>
</table>

**PANEL B**

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>MKT</th>
<th>SMB</th>
<th>HML</th>
<th>MOM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.08</td>
<td>-0.16</td>
<td>-0.05</td>
<td>0.14</td>
</tr>
<tr>
<td>2</td>
<td>-0.03</td>
<td>-0.15</td>
<td>-0.03</td>
<td>-0.02</td>
</tr>
<tr>
<td>3</td>
<td>0.08</td>
<td>0.00</td>
<td>0.06</td>
<td>-0.15</td>
</tr>
<tr>
<td>4</td>
<td>0.08</td>
<td>0.46</td>
<td>0.01</td>
<td>-0.13</td>
</tr>
<tr>
<td>5</td>
<td>0.10</td>
<td>0.75</td>
<td>0.10</td>
<td>-0.18</td>
</tr>
<tr>
<td>6</td>
<td>0.15</td>
<td>1.09</td>
<td>0.12</td>
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<tr>
<td>7</td>
<td>0.14</td>
<td>1.42</td>
<td>0.01</td>
<td>-0.42</td>
</tr>
<tr>
<td>8</td>
<td>0.17</td>
<td>1.61</td>
<td>-0.07</td>
<td>-0.54</td>
</tr>
<tr>
<td>9</td>
<td>0.14</td>
<td>1.95</td>
<td>0.02</td>
<td>-0.47</td>
</tr>
</tbody>
</table>
Table IX: **Factor Loadings Across Delisting Portfolios**

This table reports the loading on the market, size, book-to-market, and momentum factors for the excess returns over the market portfolio for each delisting portfolio. Panel A uses raw portfolio returns while Panel B adjusts portfolio returns for delisting events. Each portfolio is constructed using the estimated default probabilities using the logistic regression (23). Sample period runs monthly from 1970 to 2013. Standard errors are OLS.

**PANEL A**

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>MKT</th>
<th>SMB</th>
<th>HML</th>
<th>MOM</th>
</tr>
</thead>
<tbody>
<tr>
<td>0005</td>
<td>-0.08</td>
<td>-0.15</td>
<td>-0.05</td>
<td>0.17</td>
</tr>
<tr>
<td>0510</td>
<td>-0.03</td>
<td>-0.18</td>
<td>-0.01</td>
<td>-0.02</td>
</tr>
<tr>
<td>1020</td>
<td>0.07</td>
<td>-0.01</td>
<td>0.07</td>
<td>-0.13</td>
</tr>
<tr>
<td>2040</td>
<td>0.09</td>
<td>0.37</td>
<td>0.03</td>
<td>-0.16</td>
</tr>
<tr>
<td>4060</td>
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<td>0.74</td>
<td>0.11</td>
<td>-0.20</td>
</tr>
<tr>
<td>6080</td>
<td>0.16</td>
<td>1.11</td>
<td>0.12</td>
<td>-0.29</td>
</tr>
<tr>
<td>8090</td>
<td>0.17</td>
<td>1.41</td>
<td>0.03</td>
<td>-0.38</td>
</tr>
<tr>
<td>9095</td>
<td>0.18</td>
<td>1.56</td>
<td>-0.08</td>
<td>-0.54</td>
</tr>
<tr>
<td>9500</td>
<td>0.14</td>
<td>1.93</td>
<td>0.07</td>
<td>-0.41</td>
</tr>
</tbody>
</table>

**PANEL B**

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>MKT</th>
<th>SMB</th>
<th>HML</th>
<th>MOM</th>
</tr>
</thead>
<tbody>
<tr>
<td>0005</td>
<td>-0.08</td>
<td>-0.15</td>
<td>-0.05</td>
<td>0.17</td>
</tr>
<tr>
<td>0510</td>
<td>-0.03</td>
<td>-0.18</td>
<td>-0.01</td>
<td>-0.02</td>
</tr>
<tr>
<td>1020</td>
<td>0.07</td>
<td>-0.01</td>
<td>0.07</td>
<td>-0.13</td>
</tr>
<tr>
<td>2040</td>
<td>0.09</td>
<td>0.37</td>
<td>0.03</td>
<td>-0.16</td>
</tr>
<tr>
<td>4060</td>
<td>0.12</td>
<td>0.74</td>
<td>0.11</td>
<td>-0.20</td>
</tr>
<tr>
<td>6080</td>
<td>0.16</td>
<td>1.11</td>
<td>0.12</td>
<td>-0.29</td>
</tr>
<tr>
<td>8090</td>
<td>0.17</td>
<td>1.41</td>
<td>0.03</td>
<td>-0.38</td>
</tr>
<tr>
<td>9095</td>
<td>0.18</td>
<td>1.56</td>
<td>-0.08</td>
<td>-0.54</td>
</tr>
<tr>
<td>9500</td>
<td>0.14</td>
<td>2.01</td>
<td>0.06</td>
<td>-0.45</td>
</tr>
</tbody>
</table>
Table X: Price of Distress Risk Simulation Results

This table reports estimates of intercepts from regressions of long-short portfolios of three different percentile groups—05-95, 10-90, and 20-80, where the first percentile lists the long portfolio; the second, the short portfolio—onto a constant, the market return, the Fama-French (1992) three-factor model, and the Carhart (1997) four-factor model. Returns are equal weighted across portfolios when a long or short portfolio spans more than one of our nine simulated portfolios. Portfolio returns are constructed with simulated data when the delisting probabilities are constant and equal to their time series averages for each portfolio. Factor returns are taken from the Ken French’s Data Library and cover the monthly period 1970 to 2013. All Panel A uses raw portfolio returns and estimates for each portfolio \( p = 1, 2, \ldots, 9 \)

\[
    r_{Lt} - r_{St} = \alpha_p + \beta_p F_t + \epsilon_p t.
\]

Panel B adjusts portfolio returns using the correction in (33) and estimates

\[
    r_{Lt} - r_{St} + (\Gamma_t + r_{ft}) \times (\hat{p}_{Lt} - \hat{p}_{St}) = \alpha_p + \beta_p F_t (\hat{p}_{St} - \hat{p}_{Lt}) + \epsilon_p t,
\]

where the subscript \( L \) denotes the bought portfolio and \( S \) denotes the shorted portfolio. Standard errors are OLS.

<table>
<thead>
<tr>
<th></th>
<th>LS2080</th>
<th>LS1090</th>
<th>LS0595</th>
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<tbody>
<tr>
<td>MER</td>
<td>3.38</td>
<td>4.77</td>
<td>5.20</td>
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<tr>
<td>CAPM</td>
<td>6.49**</td>
<td>8.35**</td>
<td>9.03**</td>
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<tr>
<td>3-factor</td>
<td>9.54***</td>
<td>11.86***</td>
<td>13.31***</td>
</tr>
<tr>
<td>4-factor</td>
<td>4.23***</td>
<td>5.20***</td>
<td>6.06***</td>
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</table>

<table>
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<td>4-factor</td>
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<td>-0.56</td>
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</tbody>
</table>

*** \( p < 0.01 \), ** \( p < 0.05 \), * \( p < 0.1 \)
Table XI: Estimates of the Market Price of Distress Risk

This table reports estimates of intercepts from regressions of long-short portfolios of three different percentile groups—05-95, 10-90, and 20-80, where the first percentile lists the long portfolio; the second, the short portfolio—onto a constant, the market return, the Fama-French (1992) three-factor model, and the Carhart (1997) four-factor model. Panel A uses raw portfolio returns and estimates for each portfolio \( p = 1, 2, \ldots, 9 \)

\[
r_{Lt} - r_{St} = \alpha_p + \beta_p'F_t + \epsilon_{pt}.
\]

Panel B adjusts portfolio returns using the correction in (33) and estimates

\[
r_{Lt} - r_{St} + (\Gamma_t + r_{ft})(\hat{p}_{Lt} - \hat{p}_{St}) = \alpha_p + \beta_p'(\hat{p}_{St} - \hat{p}_{Lt}) + \epsilon_{pt},
\]

where the subscript \( L \) denotes the bought portfolio and \( S \) denotes the shorted portfolio. Each portfolio is constructed using the estimated default probabilities using the logistic regression (23). Sample period runs monthly from 1970 to 2013. Standard errors are OLS.

**PANEL A**

<table>
<thead>
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<th>LS0595</th>
</tr>
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<td>7.08</td>
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<td>8.86*</td>
<td>11.48**</td>
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<td>3-factor</td>
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<td>12.33***</td>
<td>15.88***</td>
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<tr>
<td>4-factor</td>
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<td>5.70*</td>
<td>9.35**</td>
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</tbody>
</table>

**PANEL B**

<table>
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<th>LS0595</th>
</tr>
</thead>
<tbody>
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<td>-2.62</td>
</tr>
<tr>
<td>CAPM</td>
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<tr>
<td>4-factor</td>
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<td>0.07</td>
<td>1.57</td>
</tr>
</tbody>
</table>

*** \( p < 0.01 \), ** \( p < 0.05 \), * \( p < 0.1 \)
This figure shows the observed value-weighted delisting returns by year over the period 1970-2013.
Figure 2: Estimated Probabilities for the Logistic Model

This figure shows the estimated delisting probabilities, $\hat{p}_{pt}$, and the ex-post delisting frequencies, $p_{pt}$, for the four high-risk portfolios, indexed by subscript $p$, from the benchmark logistic model in equation (23).