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On the Conditional Risk and Performance of Financially Distressed Stocks

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Several recent articles find that stocks with high probabilities of bankruptcy or default earn anomalously low returns and negative unconditional capital asset pricing model (CAPM) alphas in the post-1980 period. I show that the conditional CAPM resolves the performance difference between high- and low-distress stocks. In particular, financially distressed stocks have relatively low exposure to market risk during bad economic times. I help to explain these findings through a theoretical model in which a levered firm's equity beta is negatively related to uncertainty about the unobserved value of its underlying assets.

Key words: conditional CAPM; asset-pricing anomalies; distress risk; default risk; information risk
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1. Introduction

In a recent article, Campbell et al. (2008) show that firms with a high probability of bankruptcy or default earn lower average returns than those with a low probability of financial distress in the post-1980 period.[1] Furthermore, this poor performance of distressed stocks is not explained by standard asset-pricing models, including the unconditional capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) and the three-factor model of Fama and French (1993). Portfolios of distressed stocks have high market betas, load heavily on the size and value factors, and have significantly negative unconditional alphas. These empirical findings have received considerable attention in the finance literature for at least two reasons. First, they contradict the notion that many cross-sectional anomalies are linked to a *premium* required by investors for exposure to nondiversifiable distress risk (e.g., Fama and French 1996). Second, they imply financial distress should be included in the growing list of characteristic-based CAPM anomalies.

This paper shows these results are consistent with an intuitive, risk-based explanation. As indicated above, prior studies documenting the financial distress anomaly only control for risk in an unconditional framework and do not consider the potential for time variation in factor loadings or risk premiums. Grant (1977), Jagannathan and Wang (1996), and Boguth et al. (2011), among others, demonstrate that stocks can exhibit large pricing errors relative to unconditional asset-pricing models even when a conditional version of the CAPM holds perfectly. In particular, a stock's conditional alpha might be zero, when its unconditional alpha is not, if its beta changes through time and is correlated with the equity premium or market volatility. Building on these arguments, I show empirically that the poor unconditional performance for distressed stocks is consistent with the conditional CAPM.

I conduct the analysis in this paper in three steps. First, I revisit the empirical evidence on the financial distress anomaly. Using both the Campbell et al. (2008) failure probability (hereafter, *CHS*) and Ohlson (1980) *O*-score to proxy for distress risk, I find portfolios of distressed stocks have low average returns. Moreover, a trading strategy that takes a long position in the quintile of stocks with highest distress risk and a short position in the quintile with lowest distress risk earns a significantly negative unconditional alpha regardless of the proxy used for financial distress.

[1] See Dichev (1998) and Griffin and Lemmon (2002) for additional evidence. Dichev (1998) uses Altman's (1968) *Z*-score and Ohlson's (1980) *O*-score to identify firms with a high likelihood of bankruptcy. He finds that portfolios of distressed stocks earn significantly lower than average returns. Griffin and Lemmon (2002) show that Dichev's (1998) results are driven by the exceptionally poor performance of stocks with high bankruptcy risk and low book-to-market ratios. More recently, Campbell et al. (2008) estimate a dynamic panel model that includes both market and accounting data to measure the probability with which a firm enters bankruptcy, is delisted for financial reasons, or defaults over a given period. They then sort firms into portfolios based on this failure measure and find a negative relation between the probability of financial distress and average returns.

These findings are consistent with the existing evidence in the literature. I further show, however, that after allowing for time variation in market risk, there is no significant difference in the CAPM alphas for high- and low-distress stocks. The results are robust across proxies for distress risk and several alternative empirical approaches for estimating the conditional CAPM.

Second, I provide additional insight on these results by considering a decomposition of unconditional alpha. As discussed by Grant (1977), Jagannathan and Wang (1996), and Boguth et al. (2011), the conditional CAPM can only explain cross-sectional anomalies if long–short portfolio betas covary with the equity premium ("market timing") or market volatility ("volatility timing"). More formally, if the conditional CAPM holds, we should observe an unconditional CAPM alpha for a given asset of $\alpha_i^u \approx \mathrm{cov}(\beta_{i,t}, \gamma_t) - (\gamma/\sigma_m^2) \cdot \mathrm{cov}(\beta_{i,t}, \sigma_t^2)$, where $\beta_{i,t}$ is the asset's conditional beta, γ_t is the conditional market risk premium, σ_t^2 is the conditional variance of the market risk premium, γ is the unconditional market risk premium, and σ_m^2 is the unconditional variance of the market risk premium. I find that when examining the financial distress anomaly, long–short portfolio betas exhibit significant negative covariance with the equity premium and significant positive covariance with market volatility. As such, conditional betas tend to adjust over time in a manner that can explain the negative unconditional alphas for distressed stocks.

The negative relation between equity betas for distressed firms and the equity premium turns out to be key to the economic story in this paper. The asset-pricing literature generally argues that the market risk premium is countercyclical.[2] The above result therefore implies that distressed stocks must have relatively low systematic risk during bad economic times, when the price of risk is high. Although these findings may initially seem counterintuitive, they end up having a simple explanation.

Third, I build on the model of Johnson (2004) to explain the observed variation in market risk for distressed stocks. The analysis highlights the importance of "information risk," that is, investor uncertainty about the underlying value of a firm's assets, in determining equity betas and expected returns. In the model, asset values are unobservable, and investors receive noisy signals about the level of fundamentals. Within this theoretical environment, I show that increases in uncertainty about asset values lead to lower market betas and lower expected returns. The asset-pricing framework is similar to the one developed by Duffie and Lando (2001), in which incomplete information on a firm's asset value leads to higher risk on corporate debt. If equity is viewed as the firm's asset value plus a short position in the firm's debt, then such an increase in information uncertainty also leads to higher equity prices and lower required stock returns. These effects are magnified in firms with high leverage. Given that distressed firms also tend to be highly levered, the model suggests that increases in investor uncertainty about fundamentals during bad economic times can potentially account for the observed negative correlation between betas for distressed firms and the market risk premium.

I formally test the implications of the model in the context of the financial distress anomaly using an instrumental variables framework. Following Johnson (2004), I use dispersion in analysts' earnings estimates as a measure of unpriced information risk. I hypothesize that (i) portfolio betas for stocks with a high probability of failure are negatively related to measures of investor uncertainty in the time series, and (ii) portfolio betas for stocks with a low probability of failure are unrelated to measures of investor uncertainty. The empirical evidence is largely consistent with the model's predictions and successfully reconciles the potentially counterintuitive fact that market risk for distressed stocks declines in bad economic times.

This paper contributes to the literature attempting to reconcile the financial distress anomaly. Whereas Griffin and Lemmon (2002) interpreted the low returns on distressed stocks as evidence of market mispricing, recent papers have proposed rational explanations. Chava and Purnanandam (2010) argue that the poor performance of firms with high-distress risk in the post-1980 period is simply the result of bad luck. They show the evidence of underperformance weakens when they extend the sample period back to 1953. George and Hwang (2010) propose a model in which firms that have high exposures to systematic risk and high-distress costs choose lower levels of financial leverage as a safeguard and thus also have lower default probabilities. This choice results in a cross section of expected returns that is negatively related to leverage and default probabilities.[3] Garlappi and Yan (2011) also propose an equity valuation model that incorporates financial leverage and potential shareholder recovery upon the resolution of financial distress. In this model, the possibility of debt renegotiation drives a negative relation between leverage and equity betas in firms with high default

[2] See Fama and French (1989), Constantinides and Duffie (1996), Campbell and Cochrane (1999), Petkova and Zhang (2005), and Rapach et al. (2010).

[3] See Johnson et al. (2011) for a comment on George and Hwang (2010) and additional discussion of the impact of endogenous debt choice on expected stock returns.

probabilities. One advantage of my approach is its simplicity. I show that the distress effect is completely consistent with the CAPM once we allow for sufficient time variation in market risk and propose a mechanism to account for the documented changes in equity betas. This paper is also the only work that simultaneously explains the low raw returns for distressed stocks, the negative and significant difference in unconditional CAPM alphas for distressed and nondistressed stocks, and the corresponding insignificant difference in abnormal returns relative to the conditional CAPM.[4]

This paper is organized as follows. Section 2 introduces the conditional CAPM and outlines the empirical approach. Section 3 presents a theoretical valuation model and motivates information risk as a useful instrument for conditional beta. Section 4 describes the data. Section 5 presents empirical results on the performance of distress-sorted portfolios relative to the conditional CAPM. Section 6 concludes.

2. The Conditional CAPM

Section 2.1 briefly introduces the conditional CAPM and presents a general formula for the unconditional CAPM pricing error when the conditional CAPM holds. Section 2.2 outlines the empirical methods for testing the conditional CAPM on distress-sorted portfolios.

2.1. Key Features of the Conditional CAPM

The unconditional CAPM is given by $\mathrm{E}[r_{i,t}] = \beta_i^u \gamma$, where $r_{i,t}$ is the excess return on asset i in period t, β_i^u is the asset's unconditional beta, and γ is the unconditional market risk premium. The unconditional alpha for asset i is then $\alpha_i^u = \mathrm{E}[r_{i,t}] - \beta_i^u \gamma$. The conditional version of the CAPM allows betas and the market risk premium to vary over time. Thus, expected excess returns in period t depend on information available at the end of period $t-1$: $\mathrm{E}_{t-1}[r_{i,t}] = \beta_{i,t}\gamma_t$, where $\beta_{i,t}$ is the conditional beta for asset i, and $\gamma_t = \mathrm{E}_{t-1}[r_{m,t}]$ is the conditional market risk premium.

In this paper, we are primarily concerned with explaining negative unconditional alphas for zero-cost portfolios that are long stocks with high bankruptcy risk and short stocks with low bankruptcy risk. Thus, we would like an expression for the unconditional CAPM alpha for asset i assuming the conditional version of the model holds. Such a relation is well known from the prior literature (e.g., Grant 1977, Jagannathan and Wang 1996, Lewellen and Nagel 2006):

$$\alpha_i^u = \gamma(\mathrm{E}[\beta_{i,t}] - \beta_i^u) + \mathrm{cov}(\beta_{i,t}, \gamma_t). \tag{1}$$

[4] Other relevant papers include Vassalou and Xing (2004), Garlappi et al. (2008), Avramov et al. (2009, 2010), and Da and Gao (2010).

Equation (1) can be further simplified by deriving an expression for β_i^u and substituting to obtain

$$\alpha_i^u = \left[1 - \frac{\gamma^2}{\sigma_m^2}\right]\mathrm{cov}(\beta_{i,t}, \gamma_t) - \frac{\gamma}{\sigma_m^2}\mathrm{cov}\big[\beta_{i,t}, (\gamma_t - \gamma)^2\big] - \frac{\gamma}{\sigma_m^2}\mathrm{cov}(\beta_{i,t}, \sigma_t^2), \tag{2}$$

where σ_t^2 is the conditional variance of the market risk premium, and σ_m^2 is the unconditional variance of the market risk premium. Lewellen and Nagel (2006) show that, for reasonable monthly parameter values, the squared Sharpe ratio for the market, γ^2/σ_m^2, and the second covariance term in Equation (2) are negligible. Boguth et al. (2011) also demonstrate the importance of considering the third covariance term in empirical applications. Thus, we can approximate the unconditional CAPM alpha for asset i as

$$\alpha_i^u \approx \mathrm{cov}(\beta_{i,t}, \gamma_t) - \frac{\gamma}{\sigma_m^2}\mathrm{cov}(\beta_{i,t}, \sigma_t^2). \tag{3}$$

Equation (3) suggests the observed negative unconditional alphas for long–short distress portfolios are consistent with the conditional CAPM if conditional portfolio betas covary sufficiently negatively with the market risk premium ("market timing") and/or positively with market volatility ("volatility timing").

The first covariance term in Equation (3) further implies that, all else equal, stocks or portfolios that have higher betas in times when the price of risk is high will have an upward bias in unconditional alpha. Much of the existing empirical literature on the conditional CAPM has focused on this market-timing effect. In a recent paper, however, Boguth et al. (2011) show the volatility-timing effect has an even larger potential magnitude. They further confirm both analytically and in their empirical application on the momentum anomaly that the volatility-timing effect can have a substantial impact on portfolio performance measures.

2.2. Empirical Approach

I directly test the conditional CAPM on distress-sorted stock portfolios using several alternative estimation approaches. This section outlines the empirical methods and discusses the advantages and disadvantages of each approach.

2.2.1. Proxy Methods. The first estimation approach is the short-window regression method outlined by Lewellen and Nagel (2006). These tests directly estimate conditional portfolio alphas and betas using a sequence of time-series CAPM regressions. The tests use realized portfolio betas that are estimated contemporaneously to the conditional alphas to proxy for conditional beta. Specifically, I estimate a separate CAPM regression each month, quarter, or half year using daily return data to obtain a time series of nonoverlapping conditional portfolio alphas that spans the entire sample period. The regression model is

$$r_{i,t} = \alpha_i + \beta_{i,0} r_{m,t} + \beta_{i,1} r_{m,t-1} + \beta_{i,2}[(r_{m,t-2} + r_{m,t-3} + r_{m,t-4})/3] + \epsilon_{i,t}, \quad (4)$$

where $r_{i,t}$ is the excess return on portfolio i, and $r_{m,t}$ is the excess market return on day t. The portfolio beta estimate is

$$\hat{\beta}_i^{cp} = \hat{\beta}_{i,0} + \hat{\beta}_{i,1} + \hat{\beta}_{i,2}. \quad (5)$$

The regressions include lags of the market return to control for nonsynchronous returns, and the slopes on lags two through four are constrained to be equal. The Lewellen and Nagel (2006) test of the conditional CAPM for portfolio i examines whether the average of the conditional alphas is significantly different from zero. I also consider whether the time-series variation in conditional portfolio betas is consistent with the relation in Equation (3); that is, I test if the estimated portfolio betas covary with the market risk premium or with market volatility in a manner that might explain the large negative unconditional alphas for high-distress portfolios.

For robustness, I use three different window lengths (i.e., monthly, quarterly, and semiannual). This method requires that CAPM regression parameters do not vary too much within each estimation window. The shorter the window length, the more confident we can be that portfolio betas are relatively stable. There is a trade-off, however, as shorter window lengths can result in less precise parameter estimates.

More traditional time-series tests of the conditional CAPM model conditional betas and/or the market risk premium as functions of state variables. These methods require the econometrician to take a stance on an appropriate set of conditioning variables. This decision can be problematic because investors' information sets are inherently unobservable. As an example, Cooper and Gubellini (2011) show the choice of state variables can critically affect inferences about the conditional CAPM. The primary advantage of Lewellen and Nagel's (2006) approach is that the econometrician does not have to choose any conditioning variables.

Recent papers, however, pose challenges to the Lewellen and Nagel (2006) method. Most notably, Boguth et al. (2011) point out that using contemporaneous estimates of portfolio betas when estimating conditional alphas can be problematic. Given that these betas are not in the investor information set, the econometrician is essentially "overconditioning." Boguth et al. (2011) show this approach can lead to large biases in reported alphas when an asset's payoffs are nonlinear in market returns. One proposed method to address overconditioning is the lagged portfolio risk adjustment approach.

Let $j = 1, \ldots, J$ index the short-window regression intervals in the Lewellen and Nagel (2006) approach (e.g., months, quarters, or half years), where J is the total number of intervals. The vector of Lewellen and Nagel (2006) factor loadings for portfolio i in interval j is $\hat{B}_{i,j} = [\hat{\beta}_{i,0,j}\ \hat{\beta}_{i,1,j}\ \hat{\beta}_{i,2,j}]'$. The lagged portfolio estimate of alpha is then given by

$$\hat{\alpha}_i^{lp} = \frac{1}{T} \sum_{j=1}^{J} \sum_{t \in j} (r_{i,t} - \hat{B}'_{i,j-1} R_{m,t}), \quad (6)$$

where $R_{m,t} = [r_{m,t}\ \ r_{m,t-1}\ \ (r_{m,t-2} + r_{m,t-3} + r_{m,t-4})/3]'$, and T is the total number of days in the estimation sample. In short, the lagged portfolio approach simply estimates conditional portfolio alphas in interval j using estimates of beta from interval $j-1$. These factor loadings are available to investors at the start of interval j and, as such, this approach alleviates the potential bias in estimated alphas.

2.2.2. Instrumental Variables Methods. The approach primarily advocated by Boguth et al. (2011) to address potential problems with overconditioning is to estimate the conditional CAPM using lagged conditioning variables. This framework follows Ferson and Schadt (1996), Ferson and Harvey (1999), and others and is the traditional empirical approach for implementing the conditional CAPM. In this spirit, I estimate the conditional CAPM on daily portfolio return data using a two-stage instrumental variables method.

In the first stage, contemporaneous (monthly) portfolio betas are regressed on lagged instruments:

$$\beta_{i,\tau}^{cp} = \gamma_{i,0} + \gamma'_{i,1} Z_{i,\tau-1} + \epsilon_{i,\tau}, \quad (7)$$

where τ indexes months, and $Z_{i,\tau-1}$ is a $k \times 1$ vector of instruments. The second-stage return regression restricts the conditional beta to be linear in the fitted beta from the first stage and is given by

$$r_{i,t} = \alpha_i^{IV} + \phi'_{i,0} R_{m,t} + \phi'_{i,1} \hat{\beta}_{i,\tau}^{cp} R_{m,t} + u_{i,t}. \quad (8)$$

The most commonly used instruments in the first-stage regression are predictors of the equity premium, including the log dividend-to-price ratio (*DP*), the default premium (*DEF*), the term premium (*TS*), and the short-term interest rate (*TB*). Boguth et al. (2011) also suggested that lagged market returns, lagged market volatility, and betas from prior estimation windows are valuable instruments for portfolio betas. In addition, the following section provides theoretical motivation for using portfolio-level information risk to explain the time-series patterns in betas for distress-sorted portfolios.[5]

3. A Model for Equity Betas

This section builds on the theory in Johnson (2004) to derive a potentially interesting instrument for equity beta and provide some economic content to the empirical results. In the model, a firm's asset value is unobservable, and investors receive noisy signals about the level of fundamentals. The parameter governing the quality of these signals is analogous to dispersion in analysts' earnings forecasts. The model relies on the theory of unobserved state variables and the pricing of levered claims along the lines of Merton (1974). Johnson (2004) applies this model to analyze the cross-sectional relation between forecast dispersion and expected returns. I extend the theory to explicitly consider a CAPM economy and the relation between information risk and equity betas.

The model considers a single firm whose asset value, V_t, follows an unobservable geometric Brownian motion

$$\frac{dV_t}{V_t} = \epsilon dt + \sigma_V dW_t^V, \tag{9}$$

where ϵ is the known expected instantaneous rate of return on assets, σ_V is the instantaneous volatility, and W_t^V is a standard Brownian motion. Investors do not observe the true level of fundamentals, but are able to aggregate the information contained in analysts' forecasts of the firm's earnings rate to make inferences about V_t; that is, investors receive a signal, U_t, of the true value process corrupted by a stationary noise process:

$$U_t = V_t e^{\eta_t}. \tag{10}$$

Taking logs, $dv_t = \bar{\epsilon} dt + \sigma_V dW_t^V$, and $du_t = dv_t + d\eta_t$, where $\bar{\epsilon} \equiv \epsilon - (1/2)\sigma_V^2$. The noise process, η_t, is assumed to follow an Ornstein–Uhlenbeck process:

$$d\eta_t = -\kappa \eta_t dt + \sigma_\eta dW_t^\eta, \tag{11}$$

where the parameters κ and σ_η determine the information quality of the signal, U_t.

In the model, the rate of return on assets also has a known systematic component, and investors are able to use information on the aggregate state of the economy to make inferences about V_t; that is, the earnings process in Equation (9) has a known correlation with the stochastic discount factor. I specify the following discount factor process that is consistent with the CAPM:

$$\frac{d\Lambda_t}{\Lambda_t} = -r dt - \sigma_M dW_t^M, \tag{12}$$

where r is the risk-free rate, and σ_M is market volatility. Finally, it is assumed that the variances and covariances of the processes specified above are known, and the signal noise, dW_t^η, is uncorrelated with both dW_t^V and dW_t^M. The model solution follows the approach in Johnson (2004).

In summary, investors observe the processes U_t and Λ_t and use this information to update their beliefs about the unobserved state variable V_t. Let $m_t \equiv \mathrm{E}_t[v_t]$ and $\omega_t \equiv \mathrm{E}_t[(v_t - m_t)^2]$. Applying results on optimal nonlinear filtering, m_t follows the stochastic process

$$dm_t = \bar{\epsilon} dt + \tilde{h}_t d\tilde{W}_t, \tag{13}$$

where $\tilde{W}_t$ is a Brownian motion, and $\tilde{h}_t$ converges to σ_V in the steady state. The posterior variance, ω_t, also converges to a steady-state value, ω, given by

$$\omega = \frac{\sigma_V^2}{\kappa}(1 - \rho_{VM}^2)\left[\sqrt{1 + \frac{\sigma_\eta^2}{\sigma_V^2(1 - \rho_{VM}^2)}} - 1\right], \tag{14}$$

where ρ_{VM} is the correlation between dW_t^V and dW_t^M. Assuming $\tilde{h}_t$ and ω_t have reached their steady-state values, the conditional distribution at time t about future values v_T is

$$N(m_t + \bar{\epsilon}\tau, \omega + \sigma_V^2 \tau), \tag{15}$$

where $\tau \equiv T - t$. Thus, uncertainty about future asset values depends on both the true volatility of fundamentals and on the level of parameter uncertainty. Parameter uncertainty, in turn, is a function of the volatility of the noise process, σ_η, and the mean reversion parameter, κ. The primary focus of the model, however, is the impact of σ_η on asset prices and expected returns. Intuitively, we should see substantial heterogeneity both across firms and over time in terms of investor familiarity, predictability of operations, and information transparency. The empirical proxy for this uncertainty about fundamentals is dispersion in analysts' forecasts.

The asset-pricing results assume that the value of the firm is paid out to equityholders at some future time T. For a levered firm with face value of debt K, equity is valued as a call option on the value of the firm along the lines of Merton (1974). One can readily derive closed-form solutions for the dynamics of equity prices and expected returns. The primary quantities of interest for this paper, however, are

[5] Following Boguth et al. (2011), I also estimate the following one-stage instrumental variables regression: $r_{i,t} = \alpha_i^{IV} + b_{i,0}' R_{m,t} + (b_{i,1} Z_{i,\tau-1})' R_{m,t} + e_{i,t}$. As in their paper, the resulting estimates of alpha are virtually indistinguishable for the one-stage and two-stage approaches. I therefore only present the two-stage results.

equity betas. The beta for an unlevered claim to the value of the firm's assets can be solved for as

$$\beta_S = \frac{\rho_{VM}\sigma_V}{\sigma_M}. \tag{16}$$

Note that for an unlevered firm, the parameter risk term, ω, has absolutely no effect on either equity beta or expected returns. Parameter risk, however, does have a pronounced impact on the beta for a levered claim:

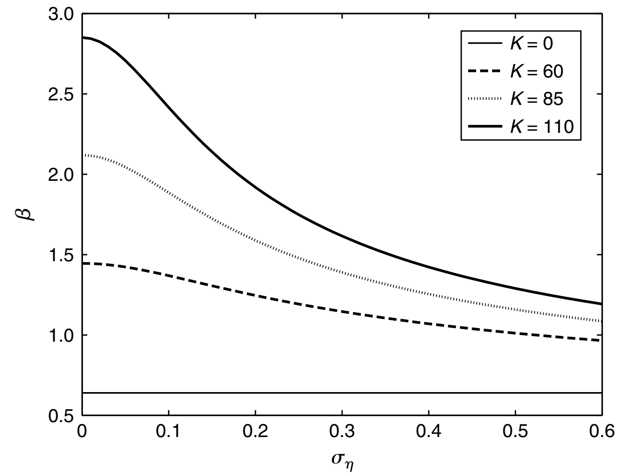
$$\begin{aligned}\beta_P &= \beta_S \frac{S_t}{P_t}\Phi(d_1)\\ &= \beta_S \frac{S_t}{P_t}\Phi\left(\frac{\log(S_t/K) + r\tau + (\omega+\sigma_V^2\tau)/2}{\sqrt{\omega+\sigma_V^2\tau}}\right),\end{aligned} \tag{17}$$

where $S_t = e^{-r\tau}e^{m_t+(1/2)\omega}e^{(\epsilon-\rho_{VM}\sigma_V\sigma_M)\tau}$ is the price of an unlevered claim to the firm, $P_t = S_t\Phi(d_1) - e^{-r\tau}K\Phi(d_2)$ is the price of equity for a levered firm, $\Phi(\cdot)$ is the normal cumulative distribution function, $d_1 = [\log(S_t/K) + r\tau + (\omega+\sigma_V^2\tau)/2]/\sqrt{\omega+\sigma_V^2\tau}$, and $d_2 = [\log(S_t/K) + r\tau - (\omega+\sigma_V^2\tau)/2]/\sqrt{\omega+\sigma_V^2\tau}$.

The relevant result for this paper is that β_P is decreasing in ω (and also σ_η). Intuitively, an increase in parameter risk raises investor uncertainty about the future value of the firm, V_T, that is to be paid out to investors at time T. Because parameter risk is unpriced, there is no impact on the asset beta for an unlevered claim. However, because equity is a call option on the asset value of the firm, any such increase in uncertainty that does not simultaneously impact the unlevered beta, β_S, will lead to a lower β_P. Thus, for a levered firm an increase in parameter risk increases the option value of the claim and lowers the covariance between equity payoffs and the stochastic discount factor. The pricing mechanism here is closely related to that in Duffie and Lando (2001). In their model, investors receive noisy accounting reports of asset value, and this incomplete information leads to higher credit spreads on corporate debt. Although their emphasis is on the required returns on debt, put–call parity implies that incomplete information also decreases required returns on equity.

The effects are displayed graphically in Figure 1. I plot the theoretical relation between the volatility of the noise process, σ_η, and equity beta for various levels of firm leverage. In constructing the plots, I follow the discussion in Johnson (2004) in selecting reasonable model parameter values.[6] In particular, Johnson (2004) argues that the range of σ_η displayed in Figure 1 is a realistic representation of investor uncertainty observed in the Institutional Brokers Estimate System (IBES) data. The plots are intended to show qualitative patterns that are robust across a wide range of parameter choices.

Figure 1 **Theoretical Relation Between Information Risk and Equity Beta**



Notes. This figure shows equity beta as a function of the volatility of the noise process (σ_η) and the face value of debt (K) based on the model outlined in §3. Values for other model parameters are provided in the text.

Figure 1 shows that when the firm has no debt (i.e., $K = 0$), there is no relation between parameter risk and equity beta. For firms with leverage (i.e., $K > 0$), we see that equity beta decreases monotonically with parameter risk. These effects are significantly magnified as leverage increases. The simple theoretical relations in Figure 1 form the basis for the economic argument in this paper. Given that financially distressed stocks tend to be highly levered, the theory suggests that information risk could be a valuable instrument for capturing time-series trends in systematic risk for these stocks. I return to this issue empirically in §5.

4. Data

Section 4.1 discusses the proxies for distress risk used in the paper, §4.2 describes the sample period and portfolio construction, and §4.3 lists the instrumental variables used in the empirical analysis.

4.1. Measures of Financial Distress

To ensure the results are robust to alternative proxies for distress risk, I consider two separate measures. The first proxy for distress is the Campbell et al. (2008) failure probability (*CHS*).[7] Using a dynamic

[6] The plots correspond to the following parameter choices: conditional expectation $m_t = \log(100)$, instantaneous return on assets $\epsilon = 0.05$, risk-free rate $r = 0.04$, volatility of fundamentals $\sigma_V = 0.20$, market volatility $\sigma_M = 0.25$, correlation $\rho_{VM} = 0.8$, mean-reversion parameter in noise process $\kappa = 0.1$, and cash-flow horizon $\tau = 3$.

[7] This proxy for financial distress is given by

$$\begin{aligned}CHS = &-9.164 - 20.264(NIMTAAVG) + 1.416(TLMTA)\\ &-7.129(EXRETAVG) + 1.411(SIGMA) - 0.045(RSIZE)\\ &-2.132(CASHMTA) + 0.075(MB) - 0.058(PRICE),\end{aligned}$$

where *NIMTAAVG* is a geometrically declining average of past measures of firm-level profitability, *TLMTA* is the ratio of total panel specification, Campbell et al. (2008) model the probability with which a firm files for bankruptcy, is delisted from an exchange for financial reasons, or receives a *D* rating from a leading credit rating agency over the next 12 months as a function of firm-specific covariates. Using their model, Campbell et al. (2008) document a significantly negative association between distress risk and abnormal stock returns.

The *CHS* measure represents the state of the art in reduced-form bankruptcy forecast accuracy and is thus a logical choice for characterizing financial distress. *CHS* also has several advantages over potential alternatives. Notably, Shumway (2001) shows that several widely used static bankruptcy prediction models, including those of Altman (1968), Ohlson (1980), and Zmijewski (1984), introduce a selection bias because they are estimated with only one observation for each sample firm. In contrast, *CHS* is estimated from a panel that classifies each firm month as a separate observation. Other advantages of *CHS* are the inclusion of market-based predictor variables (e.g., Shumway 2001) and the use of Chava and Jarrow's (2004) proprietary bankruptcy data.

One disadvantage of *CHS* is that this distress measure is estimated from firm failures that cover the period 1963 to 2003. This sample period has some obvious overlap with the period considered in my paper. To alleviate any concerns about look-ahead bias, I also use Ohlson's (1980) bankruptcy measure, which becomes available in 1980.[8] Despite its vintage, the *O*-score remains a common proxy for financial distress in papers relating distress risk to equity returns, as well as in the general finance literature.[9]

In constructing the proxies for financial distress, I merge the Center for Research in Security Prices (CRSP) daily file, CRSP monthly file, and Compustat quarterly file. I lag all accounting data by four months to ensure it is available to investors at the time of portfolio formation. If an accounting variable for a given firm is missing in the Compustat file, I replace the missing variable with the most recent observation for that firm. To alleviate the influence of outliers, I winsorize each of the explanatory variables in the *CHS* and *O*-score models at the 1st and 99th percentiles of their monthly cross-sectional distributions.

4.2. Sample Construction

Dichev (1998) and Campbell et al. (2008) document the financial distress anomaly in the post-1980 period. Given additional limitations on measures of forecast dispersion from the IBES database, I restrict the sample period in this paper to January 1983 through December 2009. The sample includes all New York Stock Exchange, American Stock Exchange, and NASDAQ ordinary common stocks with (i) return data available on the CRSP daily file and (ii) data available to compute either *CHS* or *O*-score. Ohlson's (1980) *O*-score was developed explicitly for industrial companies, so I exclude financial firms (Standard Industrial Classification codes between 6000 and 6999) from the sample.

The empirical tests use daily returns on distress-sorted portfolios. For each year at the beginning of January, I sort firms into five groups based on either *CHS* or *O*-score. The value-weighted portfolios are held for 12 months and then rebalanced. In many cases, I focus on the performance of a long–short hedge portfolio that takes a long position in the top quintile and a short position in the bottom quintile of stocks based on a particular measure of distress risk. Following Campbell et al. (2008), I exclude stocks with a share price below one dollar at the portfolio formation date. For cases in which a firm is delisted from an exchange during a given month, I replace any missing returns with the delisting returns provided by CRSP.[10] Data on the daily market return and risk-free rate are from Kenneth French's website.[11]

4.3. Instrumental Variables

The instrumental variables methods outlined in §2.2.2 require data on a variety of state variables. Each of the

liabilities to the market value of total assets, *EXRETAVG* is a geometrically declining average of log monthly excess returns relative to the S&P 500 index, *SIGMA* is the standard deviation of daily stock returns over the previous three months, *RSIZE* is the log ratio of market capitalization to the market value of the S&P 500 index, *CASHMTA* is the ratio of cash to the market value of total assets, *MB* is the market-to-book ratio, and *PRICE* is the log price per share truncated from above at $15. See Campbell et al. (2008) for additional details on variable definitions. *CHS* is the third model from Table IV in their paper.

[8] Ohlson's (1980) bankruptcy measure is given by

$$\begin{aligned} O\text{-score} &= -1.32 - 0.407(SIZE) + 6.03(TLTA) - 1.43(WCTA) \\ &\quad + 0.076(CLCA) - 1.72(OENEG) - 2.37(NITA) \\ &\quad - 1.83(FUTL) + 0.285(INTWO) - 0.521(CHIN), \end{aligned}$$

where *SIZE* is the log of the ratio of total assets to the gross national product price-level index, *TLTA* is the ratio of total liabilities to total assets, *WCTA* is the ratio of working capital to total assets, *CLCA* is the ratio of current liabilities to current assets, *OENEG* is a dummy variable equal to one if total liabilities exceeds total assets and zero otherwise, *NITA* is the ratio of net income to total assets, *FUTL* is the ratio of funds from operations to total liabilities, *INTWO* is a dummy variable equal to one if net income was negative for the past two years and zero otherwise, and *CHIN* is a measure of the change in net income. See Ohlson (1980) for exact variable definitions. The *O*-score is the first model from Table IV in his paper.

[9] See Dichev (1998), Griffin and Lemmon (2002), Fama and French (2006), Chava and Purnanandam (2010), and Chen et al. (2010).

[10] See Shumway (1997) for a discussion of delisting bias.

[11] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. I thank Kenneth French for making these data available.

variables described below is available at a monthly frequency from January 1983 to December 2009. I use four traditional instruments: the dividend-to-price ratio (*DP*), default premium (*DEF*), term spread (*TS*), and short-term interest rate (*TB*). The dividend-to-price ratio is the difference between the log of the sum of dividends accruing to the CRSP value-weighted market portfolio over the previous 12 months and the log of the current index level. The default premium is the yield spread between Moody's Baa and Aaa corporate bonds. The term spread is the yield spread between the 10-year Treasury constant maturity and Treasury bills (*TB*). The short-term interest rate is the yield on the three-month Treasury bill. All bond yields are from the Federal Reserve Bank of St. Louis website.[12]

Boguth et al. (2011) also suggest that lagged portfolio betas from prior estimation windows and prior window market returns and volatilities are useful instruments for conditional betas. I construct lagged portfolio betas from the previous three months ($\hat{\beta}^{lp3}$) on a rolling basis following Equations (4) and (5). I also compute the excess market return over the prior three months (*RM*) and the realized volatility of daily excess market returns over the prior three months (*VOL*).

Finally, the analysis in §3 suggests portfolio-level measures of investor uncertainty and leverage as useful instruments for portfolio betas. Following Johnson (2004), I use dispersion in analysts' earnings forecasts as a proxy for investor uncertainty. I first compute forecast dispersion for each firm from the IBES database as the month-end standard deviation of current-fiscal-year earnings estimates across analysts tracked by IBES divided by the absolute value of the mean forecast. The dispersion measures are constructed from the unadjusted detailed history file using only the most recent forecast made by a particular analyst. I also eliminate forecasts that are over six months old or are related to fiscal periods that have already ended and winsorize the dispersion measures at the 1st and 99th percentiles of their monthly cross-sectional distributions. I measure leverage for each sample firm as the ratio of total liabilities to the market value of total assets, where the market value of assets is the book value of debt plus the market value of equity.

Johnson (2004) discusses in detail the motivation for using dispersion as a proxy for nonsystematic risk related to investor uncertainty about the underlying value of a firm's assets. He specifically cites the common practice in the social sciences to use disagreement across a survey of respondents as a measure of uncertainty in the underlying environment.[13] The empirical specification outlined in §2.2.2 requires us to convert the firm-level proxies for information risk and leverage into corresponding portfolio-level measures. For each distress-sorted portfolio, I compute dispersion (*DIS*) for a given month as the value-weighted average forecast dispersion across all stocks in the specified portfolio with a valid measure for dispersion. Similarly, portfolio leverage (*LEV*) is the median value of leverage across firms in the given portfolio.

5. Results

This section revisits the prior evidence on the financial distress anomaly and then evaluates the performance of distress-sorted portfolios relative to the conditional CAPM. As a starting point, Table 1 presents summary statistics for the portfolios sorted on either *CHS* or *O*-score from January 1983 to December 2009.

Panel A shows distributional statistics for each portfolio. I report average returns and standard deviations in percentage per month (i.e., the daily average returns are multiplied by 21 and the daily standard deviations are multiplied by $\sqrt{21}$). Using either proxy for distress, there is an inverse relation between average portfolio returns and distress risk. A zero-cost portfolio that takes a long position in the high-distress quintile and a short position in the low-distress quintile earns an average return of −0.30% per month for the *CHS* sample and −0.32% per month for the *O*-score sample. Each of the high-distress strategies also has relatively high volatility. Panel A additionally reveals that all of the distress-sorted portfolios show substantial excess kurtosis in daily returns, but not surprisingly there is considerably less kurtosis in the any of the monthly return series.

Panel B of Table 1 reports autocorrelations in monthly returns for each quintile portfolio. Both of the high-distress strategies show slight positive autocorrelation at one lag. Finally, panel C shows down-market betas (β^-), up-market betas (β^+), and beta asymmetry for each portfolio. These betas are estimated following Equations (4) and (5), but the down-market (up-market) betas use only below-average

[12] See http://research.stlouisfed.org/fred2/.

[13] Barron et al. (2009) provide additional support for the argument that dispersion levels reflect idiosyncratic uncertainty that increases the option value of the firm. Their results directly contradict other potential interpretations, including the notion that forecast dispersion proxies for information asymmetry or disagreement among investors (e.g., Diether et al. 2002). Similarly, Güntay and Hackbarth (2010) examine the relation between dispersion of analysts' earnings forecasts and corporate bond credit spreads and conclude that dispersion primarily reflects future cash-flow uncertainty.

Table 1 Summary Statistics for Distress-Sorted Portfolios, 1983–2009

	CHS portfolios						*O*-score portfolios					
Portfolio	*L*	2	3	4	*H*	*H* − *L*	*L*	2	3	4	*H*	*H* − *L*
					Panel A: Distributional statistics							
Average return	1.11	1.02	1.01	0.91	0.82	−0.30	1.03	1.11	1.02	1.09	0.71	−0.32
Standard deviation	4.85	4.78	5.56	7.18	8.24	6.22	5.67	4.81	4.66	5.49	6.97	4.15
Skewness	−0.69	−0.54	−0.37	0.01	0.08	0.62	−0.31	−0.80	−0.56	−0.42	−0.28	−0.22
Kurtosis, daily	25.08	19.64	12.18	13.08	12.54	27.01	14.37	23.85	19.76	10.44	9.00	7.27
Kurtosis, monthly	2.22	2.63	2.86	2.74	4.92	9.79	1.54	2.21	3.57	2.61	2.50	4.66
					Panel B: Autocorrelations for monthly returns							
Lag 1	0.03	0.07	0.07	0.09	0.15	0.10	0.03	0.05	0.12	0.13	0.13	0.05
Lag 2	0.02	−0.01	−0.07	−0.13	−0.13	−0.13	−0.04	−0.06	−0.06	−0.03	−0.07	−0.04
Lag 3	−0.02	−0.01	0.03	0.01	0.02	0.03	0.01	0.00	−0.01	0.00	−0.06	−0.13
					Panel C: Asymmetric betas							
β^-	0.89	0.90	1.03	1.34	1.44	0.54	1.02	0.88	0.92	1.10	1.44	0.42
β^+	0.95	0.92	1.09	1.26	1.26	0.31	1.13	0.94	0.90	1.05	1.13	0.00
$\Delta\beta \equiv \beta^- - \beta^+$	−0.06	−0.02	−0.06	0.08	0.17	0.23	−0.11	−0.05	0.01	0.05	0.31	0.42

Notes. This table presents summary statistics for portfolios sorted on financial distress. *CHS* is Campbell et al. (2008) failure probability. *O*-score is Ohlson's (1980) bankruptcy probability. Each year at the beginning of January, stocks are sorted into quintile portfolios based on their distress probabilities. The portfolios are value weighted and rebalanced annually. "*H*" is the high-distress quintile, "*L*" is the low-distress quintile, and "*H* − *L*" is their difference. Panel A reports the average return, standard deviation, skewness, and excess kurtosis for each portfolio using daily return data. The average returns and standard deviations are expressed as percentage per month (i.e., the daily average returns are multiplied by 21, and the daily standard deviations are multiplied by $\sqrt{21}$). Panel A also reports excess kurtosis for monthly portfolio returns, which are computed by compounding daily portfolio returns. Panel B presents autocorrelations for monthly portfolio returns. Panel C reports down-market betas (β^-), up-market betas (β^+), and beta asymmetry; β^+ and β^- are computed in each calendar year and then averaged. The CAPM regressions use daily returns and correct for nonsynchronous trading as discussed in the text.

(above-average) observations of the market risk premium. Values of β^+ and β^- are computed in each calendar year and then averaged. Both of the long–short distress portfolios show evidence of positive beta asymmetry. Boguth et al. (2011) show via a simulation exercise that strategies exhibiting such positive asymmetry are likely to have positively biased conditional performance measures under the Lewellen and Nagel (2006) approach that relies on contemporaneously estimated realized betas. Thus, the figures in panel C should help us to understand the differences in results across alternative estimation approaches for the conditional CAPM.

5.1. Conditional CAPM Alphas: Proxy Methods

Panel A of Table 2 shows the financial distress anomaly relative to the unconditional CAPM.[14] Unconditional portfolio betas are monotonically increasing in distress risk for the *CHS* portfolios. Thus, the poor performance of distressed stocks shown in Table 1 appears even worse after adjusting for risk in an unconditional framework. The long–short *CHS* portfolio has an unconditional alpha of −0.73% per month (−8.76% per year), which is statistically significant at the 5% level (*t*-statistic of −2.24).

For the *O*-score portfolios, the relation between beta and financial distress is not strictly monotonic, but the long–short portfolio does have a positive unconditional beta. The unconditional alpha for this portfolio is −0.56% per month (−6.72% per year), which is also significant at the 5% level (*t*-statistic of −2.50). Thus, the financial distress anomaly is not sensitive to the proxy for distress risk. Campbell et al. (2008) show that portfolios of distressed stocks also have significant underperformance relative to other unconditional factor models, including the three-factor model of Fama and French (1993) and the four-factor model of Carhart (1997). I confirm these results in my sample (not tabulated).

Panel B of Table 2 shows the results for the conditional CAPM using contemporaneously estimated portfolio betas. As described above, I estimate a separate CAPM regression each month (*M*), quarter (*Q*), or half year (*SA*) to obtain a series of conditional alphas for each portfolio. Panel B reports the averages of these conditional alpha estimates. I test for statistical significance by using the time-series variability of the conditional alpha estimates to compute standard errors. None of the average alphas for the long–short portfolios is significantly different from zero at the 5% level. The average conditional alpha for the *CHS* hedge portfolio ranges from −0.38% to −0.17% per month, depending on the rolling estimation window length (*t*-statistics are between −1.07 and −0.55). Each of these estimates is noticeably smaller in magnitude than the −0.73% unconditional alpha reported in panel A. The results for the long–short *O*-score

[14] The unconditional CAPM regressions are also estimated following Equations (4) and (5).

Table 2 Unconditional CAPM Regressions and Average Conditional Alphas, 1983–2009

	CHS portfolios						*O*-score portfolios					
Portfolio	*L*	2	3	4	*H*	*H* − *L*	*L*	2	3	4	*H*	*H* − *L*
	Panel A: Unconditional CAPM regressions											
$\hat{\alpha}^u$	0.24	0.13	0.00	−0.29	−0.49	−0.73	0.05	0.21	0.10	0.07	−0.50	−0.56
	(2.71)	(1.83)	(0.00)	(−1.54)	(−1.78)	(−2.24)	(0.56)	(2.93)	(1.25)	(0.60)	(−2.35)	(−2.50)
$\hat{\beta}^u$	0.85	0.87	1.07	1.41	1.59	0.74	1.02	0.88	0.92	1.09	1.43	0.41
	(98.2)	(121.1)	(114.0)	(76.7)	(58.4)	(23.1)	(105.6)	(123.0)	(116.8)	(97.9)	(67.4)	(18.7)
	Panel B: Average conditional CAPM alphas, contemporaneous portfolio approach											
$\hat{\alpha}^{cp}(M)$	0.22	0.04	0.01	−0.17	−0.13	−0.35	−0.14	0.13	0.26	0.24	0.02	0.16
	(2.47)	(0.47)	(0.05)	(−0.77)	(−0.40)	(−0.92)	(−1.26)	(1.54)	(2.69)	(2.06)	(0.08)	(0.59)
$\hat{\alpha}^{cp}(Q)$	0.17	0.09	0.04	−0.19	−0.21	−0.38	−0.06	0.13	0.21	0.24	−0.23	−0.17
	(2.38)	(1.49)	(0.51)	(−1.12)	(−0.64)	(−1.07)	(−0.66)	(2.02)	(2.23)	(2.45)	(−0.95)	(−0.71)
$\hat{\alpha}^{cp}(SA)$	0.15	0.09	0.05	−0.03	−0.02	−0.17	0.01	0.17	0.18	0.20	−0.19	−0.20
	(2.55)	(1.48)	(0.51)	(−0.19)	(−0.06)	(−0.55)	(0.10)	(2.70)	(2.03)	(1.80)	(−0.91)	(−0.99)
	Panel C: Average conditional CAPM alphas, lagged portfolio approach											
$\hat{\alpha}^{lp}(M)$	0.05	0.06	0.14	0.04	0.12	0.07	0.03	0.14	0.19	0.18	−0.20	−0.22
	(0.58)	(0.76)	(1.44)	(0.21)	(0.44)	(0.23)	(0.27)	(1.82)	(2.41)	(1.46)	(−0.91)	(−0.97)
$\hat{\alpha}^{lp}(Q)$	0.16	0.09	−0.01	−0.09	0.02	−0.14	0.07	0.18	0.09	0.08	−0.20	−0.27
	(1.83)	(1.25)	(−0.06)	(−0.48)	(0.07)	(−0.45)	(0.75)	(2.50)	(1.19)	(0.66)	(−0.94)	(−1.22)
$\hat{\alpha}^{lp}(SA)$	0.18	0.08	−0.02	−0.20	−0.18	−0.35	0.03	0.18	0.09	0.06	−0.22	−0.25
	(2.02)	(1.08)	(−0.21)	(−1.10)	(−0.65)	(−1.11)	(0.31)	(2.56)	(1.16)	(0.52)	(−1.05)	(−1.12)

Notes. This table presents unconditional CAPM regression coefficients (panel A) and average conditional CAPM regression alphas (panels B and C) for portfolios sorted on financial distress. *CHS* is Campbell et al. (2008) failure probability. *O*-score is Ohlson's (1980) bankruptcy probability. Each year at the beginning of January, stocks are sorted into quintile portfolios based on their distress probabilities. The portfolios are value weighted and rebalanced annually. The regressions use daily returns and correct for nonsynchronous trading as discussed in the text. Alphas are expressed as percentage per month (i.e., the daily alpha estimates are multiplied by 21). The conditional alphas used to construct the averages in panel B (contemporaneous portfolio approach) are estimated monthly (*M*), quarterly (*Q*), and semiannually (*SA*) using daily returns. The lagged portfolio alphas in panel C are averages of daily portfolio abnormal returns. Abnormal returns in a given interval (i.e., month, quarter, or half year) are computed using beta estimates from the prior interval as described in the text. The numbers in parentheses are *t*-statistics. "*H*" is the high-distress quintile, "*L*" is the low-distress quintile, and "*H* − *L*" is their difference.

portfolio are even more striking. The average conditional alphas range from −0.20% to 0.16% per month (*t*-statistics between −0.99 and 0.59) and are considerably larger than the −0.56% unconditional estimate in panel A.

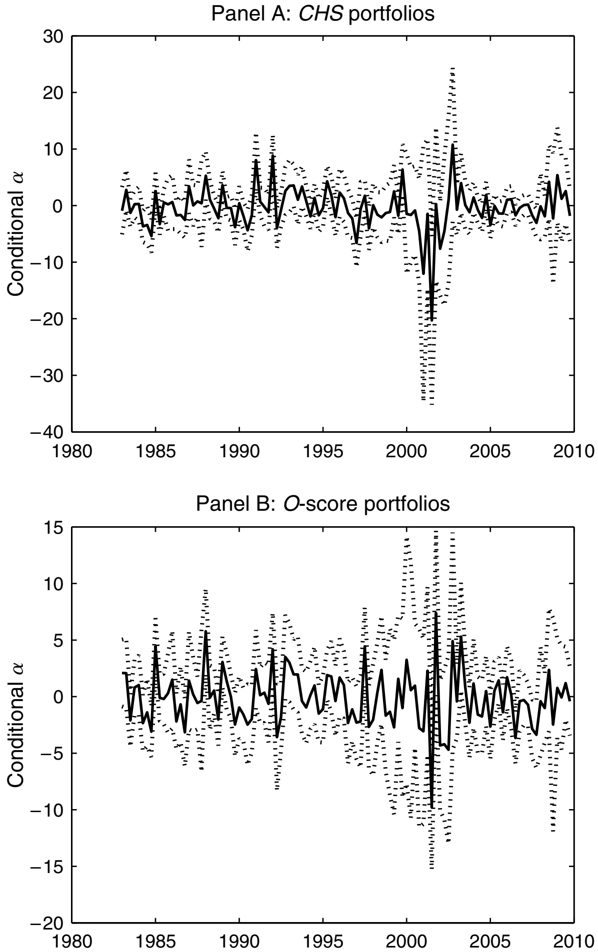
Figure 2 shows the time series of conditional (quarterly) alpha estimates for the long–short distress portfolios. The estimates are noisy, but seem to fluctuate around zero without any obvious time-series trends.

Panel C of Table 2 reports estimates of average conditional alphas for the *CHS* and *O*-score portfolios using the lagged portfolio method described in §2.2.1. As noted above, Boguth et al. (2011) recommend the lagged portfolio approach as an alternative to the Lewellen and Nagel (2006) contemporaneous portfolio method, which suffers from a potential overconditioning bias. The results are again provided for monthly, quarterly, and semiannual periods. The average lagged portfolio alpha for the long–short *CHS* portfolio ranges from −0.35% to 0.07% per month depending on the rolling estimation window length. None of these estimates is statistically significant at the 5% level. Moreover, the lagged portfolio alphas are similar in magnitude to the Lewellen and Nagel (2006) alphas in panel B, suggesting that any overconditioning bias is likely small.

Similarly, none of the alpha estimates in panel C for the long–short *O*-score portfolio is significantly different from zero. The monthly estimate of −0.22%, however, is considerably smaller than the corresponding contemporaneous portfolio monthly alpha of 0.16%. This result suggests overconditioning could be an issue when the estimation windows are divided very finely. In contrast, the quarterly and semiannual alphas for the *O*-score portfolio are relatively similar across the two approaches.[15]

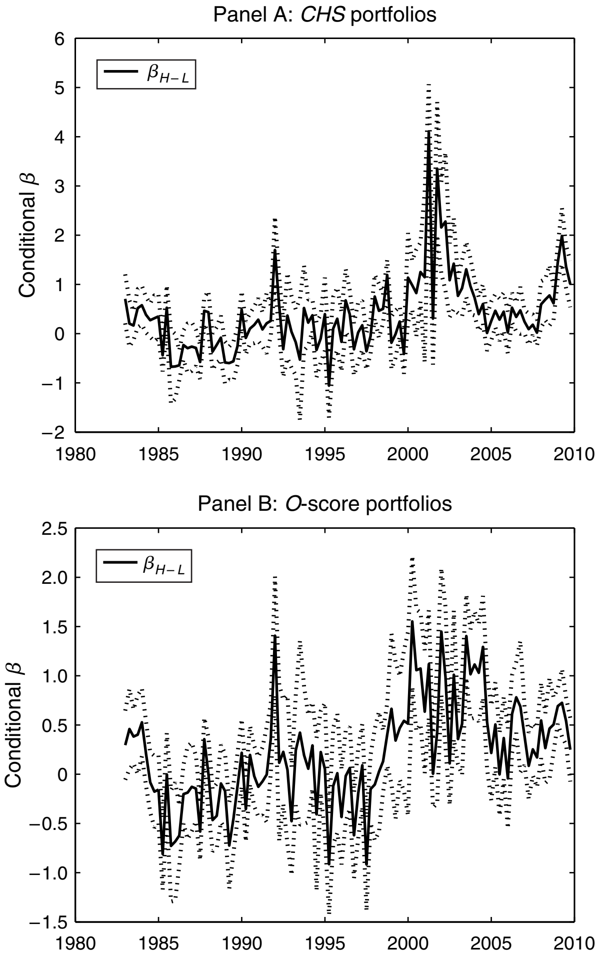
[15] In untabulated results, I also examine whether the results in panels B and C of Table 2 are robust to a conditional version of the Fama and French (1993) three-factor model. The empirical tests include one lag of each factor return, and I consider results for quarterly and semiannual estimation windows using both the contemporaneous portfolio approach and lagged portfolio approach. Consistent with the findings of Campbell et al. (2008), both long–short portfolios have unconditional three-factor alphas that are negative and significant (−0.70% for the *CHS* portfolio and −0.56% for the *O*-score portfolio with *t*-statistics of −2.38 and −3.09, respectively). Conditioning has a pronounced impact on the three-factor alphas for the *CHS* portfolio. The conditional estimates range from −0.41% to −0.12% per month, and none is significantly different from zero at the 5% level. In contrast, the conditional three-factor model does not explain the financial distress effect for the *O*-score portfolios. Each of the long–short conditional alphas remains significant and close to the corresponding unconditional estimate.

Figure 2 Conditional Alphas, 1983–2009



Notes. This figure presents conditional CAPM regression alphas (in percentage per month) for portfolios sorted on financial distress. Panel A plots the conditional alphas for the hedge portfolio that takes a long position in the top quintile and a short position in the bottom quintile of firms sorted based on the Campbell et al. (2008) failure probability. Panel B plots the conditional alphas for the hedge portfolio that takes a long position in the top quintile and a short position in the bottom quintile of firms sorted based on Ohlson's (1980) bankruptcy probability. The alphas are estimated quarterly using daily returns. The dotted lines indicate a two-standard-error confidence interval.

Figure 3 Conditional Betas, 1983–2009



Notes. This figure presents conditional CAPM regression betas for portfolios sorted based on the Campbell et al. (2008) failure probability (panel A) and Ohlson's (1980) *O*-score (panel B). The betas are estimated quarterly using daily returns. Each panel shows the conditional beta for the hedge portfolio that takes a long position in the top quintile and a short position in the bottom quintile of firms sorted on the given measure of financial distress. The dotted lines indicate a two-standard-error confidence interval.

The results in panels B and C of Table 2 suggest the conditional CAPM is able to explain the poor unconditional performance of financially distressed stocks. The next empirical task is to provide additional details on why using conditioning information raises the estimated alpha. As a starting point, Figure 3 presents plots of the conditional (quarterly) betas for the long–short portfolios. Panel A shows that the long–short *CHS* portfolio beta is remarkably volatile, ranging from a low of −1.06 in 1995 to a high of 4.09 in 2001. There are substantial periods of time in the late 1980s and mid-1990s in which the portfolio beta is less than zero, suggesting that high-distress stocks often have less market risk than low-distress stocks. Panel B of Figure 3 plots the conditional betas for the *O*-score portfolio. The plot is qualitatively similar to the one in panel A. The long–short beta has a low of −0.92 in 1997 and a high of 1.55 in 2000.

In the context of the conditional CAPM, however, the observed volatility in beta only matters if there is also some meaningful correlation with either the expected market return or market volatility. More formally, Equation (3) shows that the negative unconditional alphas reported in panel A of Table 2 for long–short distress portfolios are entirely consistent with the conditional CAPM if the portfolio betas covary sufficiently negatively with the market risk premium and/or positively with market volatility. These quantities, $\text{cov}(\beta_{i,t}, \gamma_t)$ and $\text{cov}(\beta_{i,t}, \sigma_t^2)$, can be estimated directly from the data. The results are reported in Table 3.

Panel A presents covariance estimates that rely on contemporaneously estimated betas for the long–short distress portfolios; that is, I estimate

Table 3 Decomposing Unconditional Alphas, 1983–2009

	CHS portfolios					*O*-score portfolios				
	$\mathrm{cov}(\beta_{i,t}, \gamma_t)$	−	$\frac{\gamma}{\sigma_m^2}\mathrm{cov}(\beta_{i,t}, \sigma_t^2)$	=	Total	$\mathrm{cov}(\beta_{i,t}, \gamma_t)$	−	$\frac{\gamma}{\sigma_m^2}\mathrm{cov}(\beta_{i,t}, \sigma_t^2)$	=	Total
	Panel A: Covariances using contemporaneous betas, $\hat{\beta}^{cp}$									
M	−0.31	−	0.16**	=	−0.47	−0.60**	−	0.12**	=	−0.72
Q	−0.20	−	0.18**	=	−0.38	−0.30**	−	0.12**	=	−0.42
SA	−0.42**	−	0.18**	=	−0.60	−0.29**	−	0.11**	=	−0.40
	Panel B: Covariances using lagged betas, $\hat{\beta}^{lp}$									
M	−0.53**	−	0.14**	=	−0.67	−0.31*	−	0.08*	=	−0.39
Q	−0.35**	−	0.13**	=	−0.48	−0.17	−	0.05	=	−0.22
SA	−0.21*	−	0.11*	=	−0.32	−0.24**	−	0.08*	=	−0.32

Notes. The table presents estimates of the market-timing effect and volatility-timing effect for portfolios sorted on financial distress. *CHS* is the Campbell et al. (2008) failure probability. *O*-score is Ohlson's (1980) bankruptcy probability. The estimates are for value-weighted hedge portfolios that take a long position in the highest quintile of stocks and a short position in the lowest quintile for each variable. The covariance estimates in panel A use estimated betas from short-window regressions that are contemporaneous with the excess market returns. The covariance estimates in panel B use lagged portfolio betas from the prior estimation window. The betas are estimated monthly, quarterly, and semiannually using daily returns. The market-timing effect is estimated as $\mathrm{cov}(\hat{\beta}_{i,t}, r_{m,t})$, where $r_{m,t}$ is the return on the CRSP value-weighted portfolio in excess of the risk-free rate. These covariances are reported in percent per month (i.e., the quarterly covariance estimate is divided by three, and the semiannual estimate is divided by six). The estimated volatility-timing effect is the quantity $(\hat{\gamma}/\hat{\sigma}_m^2)\mathrm{cov}(\hat{\beta}_{i,t}, \hat{\sigma}_t^2)$, where $\hat{\gamma}$ is the average market risk premium, $\hat{\sigma}_m^2$ is the unconditional variance of the market risk premium, and $\hat{\sigma}_t^2$ is the conditional variance of the market risk premium.

**, * In the market-timing column, the estimated covariance between the conditional portfolio beta and the excess market return is significantly less than zero at the 5% and 10% levels, respectively, using a one-tailed test. In the volatility-timing column, the estimated covariance between the conditional portfolio beta and market volatility is significantly greater than zero at the 5% and 10% levels, respectively, using a one-tailed test.

$\mathrm{cov}(\beta_{i,t}, \gamma_t)$ as $\mathrm{cov}(\hat{\beta}^{cp}_{i,t}, r_{m,t})$, where $\hat{\beta}^{cp}_{i,t}$ is the estimated conditional beta for portfolio i, and $r_{m,t}$ is the realized excess market return over the same estimation window as the beta. Similarly, I estimate $\mathrm{cov}(\beta_{i,t}, \sigma_t^2)$ as $\mathrm{cov}(\hat{\beta}^{cp}_{i,t}, \hat{\sigma}_t^2)$, where $\hat{\sigma}_t^2$ is the realized variance of the market risk premium, calculated from daily returns over the same estimation window as the conditional beta. I then multiply this covariance estimate by $\hat{\gamma}/\hat{\sigma}_m^2$ to approximate the volatility effect in Equation (3).[16]

The results in panel A show that the covariance between betas and the market risk premium can explain a large proportion of the negative unconditional alphas for long–short distress portfolios. The covariance estimates range from −0.42% to −0.20% per month for the *CHS* portfolio (although only one of the three is statistically significant at the 5% level) and from −0.60% to −0.29% for the *O*-score portfolio (all three are statistically significant). However, with the exception of the monthly window *O*-score estimate (−0.60%), none of the covariance estimates can fully explain the corresponding unconditional alpha reported in Table 2 (−0.73% for the *CHS* portfolio and −0.56% for the *O*-score portfolio). Moving to the covariances between conditional betas and market volatility reported in panel A, all of the estimates are positive and significant at the 5% level. The estimated effects on unconditional alphas range from −0.18% to −0.16% per month for the *CHS* portfolio and from −0.12% to −0.11% for the *O*-score portfolio. Thus, the positive covariance between conditional betas and market volatility also appears to explain a portion of the negative unconditional alphas for the long–short portfolios.

Summing the risk premium effect and the volatility effect in panel A, I find that the unconditional alpha should be between −0.60% and −0.38% per month for the long–short *CHS* portfolio and between −0.72% and −0.40% per month for the *O*-score portfolio (the numbers vary depending on the rolling estimation window length). Thus, the conditional betas for distressed stocks vary over time in a way that makes the unconditional CAPM alpha estimates of −0.73% for the *CHS* portfolio and −0.56% per month for the *O*-score portfolio seem quite reasonable.

For robustness, panel B of Table 3 repeats the analysis using lagged portfolio betas. I estimate $\mathrm{cov}(\beta_{i,t}, \gamma_t)$ as $\mathrm{cov}(\hat{\beta}^{lp}_{i,t}, r_{m,t})$ and $\mathrm{cov}(\beta_{i,t}, \sigma_t^2)$ as $\mathrm{cov}(\hat{\beta}^{lp}_{i,t}, \hat{\sigma}_t^2)$, where $\hat{\beta}^{lp}_{i,t}$ is the estimated conditional beta from the prior estimation window. The results in panel B using lagged betas are qualitatively similar to those in panel A. The combined risk premium and volatility effects for the *CHS* portfolio range from −0.67% to −0.32% per month. The covariance estimates for the *O*-score portfolio imply an unconditional CAPM alpha between −0.39% and −0.22% per month.

The results in Table 3 highlight two important points. First, they confirm the argument of Boguth et al. (2011) that the volatility-timing channel, which

[16] The quantities $\hat{\gamma}$ and $\hat{\sigma}_m^2$ are computed using the full sample of data from 1983 to 2009.

has been largely ignored in prior empirical applications, can have an economically meaningful impact on portfolio performance measures. Second, it also appears that much of the success of the conditional CAPM in explaining the financial distress anomaly is driven by the covariance of conditional betas with the market risk premium. Stocks with high measures of financial distress tend to have low market risk in states of the world in which the market risk premium is high. These findings may be counterintuitive under the assumption that a high market risk premium is associated with recessionary periods and relatively high investor risk aversion. The following subsection considers this issue in further detail.

5.2. Conditional CAPM Alphas: IV Methods

This subsection examines the performance of the distress-sorted portfolios using the instrumental variables methods outlined in §2.2.2. This empirical approach was recommended by Boguth et al. (2011) as a way to address overconditioning bias in conditional performance measures and, as such, provides a valuable confirmation of the results in panels B and C of Table 2. Moreover, the use of alternative sets of instruments allows us to develop a deeper understanding of what drives the observed time variation in conditional betas for distressed firms.

Table 4 reports instrumental variables results for the *CHS* portfolios. For each set of instruments, the first set of results are parameter estimates and the adjusted R^2 from the first-stage beta regression. The second set of results are for the second-stage return regression. The second-stage regression parameters are estimated via the generalized method of moments (GMM). Boguth et al. (2011) also developed a GMM test for the difference in alphas under different information sets. For each case, the table reports a p-value for the one-tailed test that the conditional alpha is greater than or equal to the unconditional alpha for the long–short portfolio.[17]

As a starting point, case (1) in Table 4 shows the performance of the *CHS* portfolios with no instruments for beta. The long–short portfolio alpha is -0.73% and is identical in magnitude to the unconditional alpha reported in panel A of Table 2. In case (2), the four traditional instruments from the conditional CAPM literature do reasonably well in forecasting conditional portfolio betas. The first-stage regressions have R^2-values of 11% for the low-distress portfolio and 25% for the high-distress portfolio. The conditional alpha for the long–short portfolio is -0.40% per month, which is considerably smaller in magnitude than the unconditional alpha in case (1).

Cases (3) and (4) show results using the instruments recommended by Boguth et al. (2011), namely, lagged betas from prior estimation windows and prior excess market returns and volatilities. Using lagged portfolio betas as instruments substantially improves the first-stage R^2 for the low-distress portfolio. The long–short portfolio alpha estimate is -0.50%. Adding prior market returns and volatilities as instruments leads to a modest improvement in the beta regression R^2, and the hedge portfolio alpha increases to -0.44% per month.

The next two cases provide an economic interpretation for the observed variation in equity betas for distressed firms. Following Johnson (2004), I interpret the portfolio-level measure of dispersion in analysts' forecasts, *DIS*, as a proxy for unpriced information risk, reflecting investor uncertainty about firm fundamentals. Panel A of Figure 4 plots the time series of *DIS* for the high- and low-distress *CHS* portfolios. It is clear from the plot that distressed firms as a group typically have much higher measures of uncertainty, and *DIS* for the high-distress group also shows substantially more time-series variability. Moreover, the model developed in §3 yields qualitative implications on the relation among equity beta, information risk, and leverage. Specifically, the theory suggests that, for firms with high leverage, portfolio betas should be inversely related to measures of investor uncertainty. Panel B of Figure 4 plots the time series of portfolio leverage, *LEV*, for each portfolio. Given that the *CHS* model explicitly includes a measure of firm leverage as a predictor variable, it is not surprising to see that firms with low probabilities of bankruptcy or default tend to have relatively low levels of leverage. For the high-distress group, however, it is quite common to see measures of leverage of 0.50 or higher. According to the model in the previous section, these firms are exactly the ones for which parameter uncertainty should have the greatest impact on equity betas.

Thus, the theory yields the following predictions: (i) portfolio betas for stocks with a high probability of failure should be negatively related to measures of investor uncertainty in the time series, and (ii) portfolio betas for stocks with a low probability of failure should be unrelated to measures of investor uncertainty in the time series.[18]

[17] See Appendix A.5 of Boguth et al. (2011) for estimation details. I implement the Newey and West (1987) procedure with $m = 5$. All results are robust to other choices of m.

[18] These predictions are relevant for the current task of explaining time-series patterns in betas for distress-sorted portfolios. One could also test the cross-sectional implications of the model by running Fama and MacBeth (1973) regressions of equity betas on proxies for firm-level information risk, leverage, and the interaction between these two explanatory variables. In unreported results, I generally confirm the cross-sectional implications of the theory that equity betas are positively related to leverage and inversely related to information risk in highly levered firms.

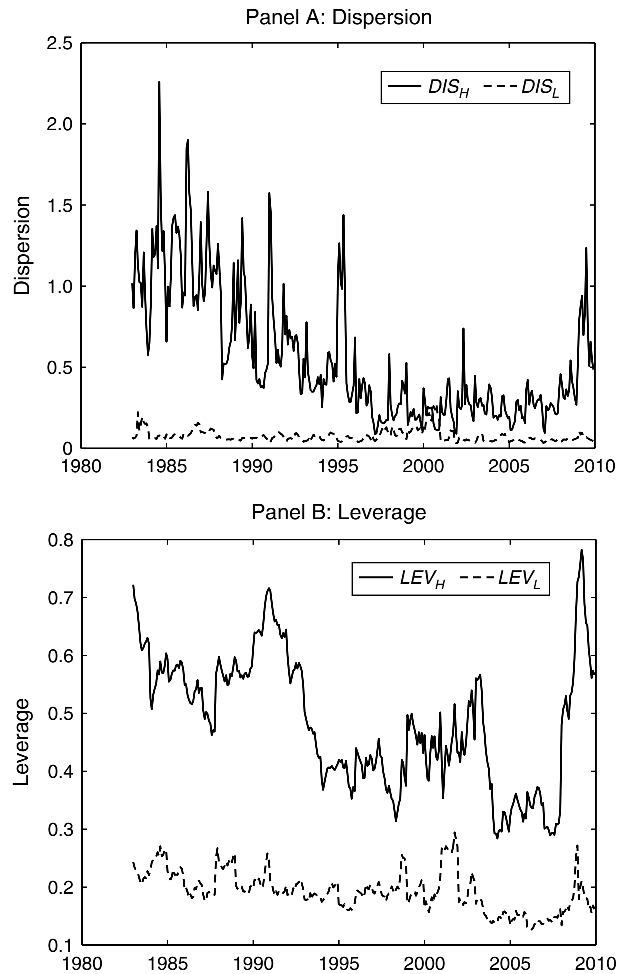
Table 4 Instrumental Variables Methods for *CHS* Portfolios, 1983–2009

	Stage 1 regression											Stage 2 regression			
	γ_0	*DIS*	*LEV*	$\hat{\beta}^{lp3}$	*RM*	*VOL*	*DP*	*DEF*	*TS*	*TB*	R^2	α^{IV}	ϕ_0	ϕ_1	R^2
(1) *L*	0.93											0.24		0.91	0.90
	(71)											(2.8)		(50)	
H	1.33											−0.49		1.19	0.64
	(28)											(−1.6)		(31)	
HL												−0.73			
												(−2.1)			
(2) *L*	1.97						0.21	−18.0	−1.68	−0.31	0.11	0.19	0.42	0.49	0.90
	(7.0)						(3.8)	(−5.1)	(−1.1)	(−0.4)		(2.3)	(2.5)	(2.6)	
H	−4.64						−1.29	53.5	25.3	1.72	0.25	−0.20	0.48	0.70	0.66
	(−4.9)						(−6.8)	(4.5)	(5.2)	(0.6)		(−0.7)	(2.6)	(5.0)	
HL												−0.40			
												(−1.2)	*p*-value = 0.000		
(3) *L*	0.31			0.67							0.21	0.19	0.20	0.73	0.91
	(4.5)			(9.2)								(2.4)	(1.4)	(4.4)	
H	0.44			0.67							0.23	−0.30	0.49	0.76	0.68
	(4.4)			(9.9)								(−1.1)	(2.6)	(5.3)	
HL												−0.50			
												(−1.6)	*p*-value = 0.036		
(4) *L*	0.38			0.61	−0.10	−7.68					0.22	0.18	0.21	0.75	0.91
	(5.1)			(8.1)	(−0.2)	(−2.4)						(2.3)	(1.6)	(5.1)	
H	0.45			0.62	−1.45	20.7					0.24	−0.26	0.45	0.7	0.68
	(4.4)			(9.1)	(−0.8)	(1.8)						(−0.9)	(2.9)	(6.5)	
HL												−0.44			
												(−1.4)	*p*-value = 0.020		
(5) *L*	0.92	0.15									−0.00	0.24	−1.77	2.81	0.91
	(31)	(0.4)										(2.9)	(−0.8)	(1.1)	
H	1.61	−0.50									0.05	−0.39	0.40	0.88	0.65
	(20)	(−4.4)										(−1.3)	(1.7)	(4.7)	
HL												−0.64			
												(−1.9)	*p*-value = 0.028		
(6) *L*	0.43	0.12	−0.56	0.64							0.21	0.20	0.20	0.74	0.91
	(4.0)	(0.4)	(−1.6)	(8.6)								(2.5)	(1.3)	(4.5)	
H	0.44	−0.34	0.53	0.62							0.24	−0.27	0.50	0.75	0.68
	(2.1)	(−2.6)	(1.2)	(8.9)								(−1.0)	(2.7)	(5.5)	
HL												−0.47			
												(−1.5)	*p*-value = 0.031		
(7) *L*	1.05	0.24	−1.17	0.47			0.09	−8.63	1.13	0.91	0.23	0.19	0.31	0.63	0.91
	(3.1)	(0.7)	(−2.6)	(5.4)			(1.4)	(−2.3)	(0.8)	(0.9)		(2.3)	(2.3)	(4.1)	
H	−3.56	−0.16	0.76	0.36			−0.90	29.6	18.1	1.81	0.29	−0.16	0.36	0.78	0.67
	(−3.1)	(−1.0)	(1.3)	(4.2)			(−3.8)	(2.1)	(3.5)	(0.6)		(−0.6)	(2.5)	(6.8)	
HL												−0.35			
												(−1.1)	*p*-value = 0.002		

Notes. This table presents two-stage instrumental variables regression results for portfolios sorted based on the Campbell et al. (2008) failure probability. "*H*" is the high-distress quintile, "*L*" is the low-distress quintile, and "*HL*" is their difference. The first set of results are for the following first-stage regressions of contemporaneous (monthly) portfolio betas on lagged state variables: $\beta^{cp}_{i,\tau} = \gamma_{i,0} + \gamma'_{i,1} Z_{i,\tau-1} + \epsilon_{i,\tau}$. The state variables include portfolio dispersion (*DIS*), portfolio leverage (*LEV*), lagged portfolio beta computed from the prior three months of daily returns ($\hat{\beta}^{lp3}$), the excess market return over the prior three months (*RM*), market volatility over the prior three months (*VOL*), the log dividend-to-price ratio (*DP*), the default premium (*DEF*), the term premium (*TS*), and the short-term interest rate (*TB*). The second-stage results are for the regression $r_{i,t} = \alpha^{IV}_i + \phi'_{i,0} R_{m,t} + \phi'_{i,1} \hat{\beta}^{cp}_{i,\tau} R_{m,t} + u_{i,t}$, and R^2 is the adjusted R^2-value from each regression. This table also reports a *p*-value for the test of the null hypothesis that the conditional and unconditional alphas for the long–short portfolio are equal.

It should be noted that applying the theory developed in §3 to explain the observed covariation between conditional betas and the market risk premium requires some additional economic arguments that are outside of the scope of the model. Specifically, because the model does not allow for time variation in forecast dispersion, the market risk premium, or market volatility, it does not yield any direct

Figure 4 Portfolio-Level Dispersion and Leverage, 1983–2009



Notes. This figure presents portfolio-level measures of information risk (*DIS*) and market leverage (*LEV*) for portfolios sorted based on the Campbell et al. (2008) failure probability. Panel A shows the time series of *DIS* for the high- and low-distress quintile portfolios. Panel B shows the time series of *LEV* for the high- and low-distress portfolios.

predictions about covariation between betas and market moments. Although the primary role of the theory is to show that forecast dispersion is a useful instrument for conditional beta, we would also like to apply the theory in a time-series setting to explain the negative covariance between betas for distressed firms and the market risk premium. Establishing this link relies on the additional logic that investor uncertainty about distressed firms rises during bad economic times.[19]

The first-stage beta regression results in case (5) with *DIS* as the only instrument for conditional beta largely support the two hypotheses. For the high-distress portfolio, *DIS* is negatively associated with beta in the time series, and the coefficient estimate is highly significant. In contrast, there is no significant association between information risk and conditional beta for the low-*CHS* portfolio as predicted. Instrumenting with only *DIS* provides only a moderate increase in the long–short alpha estimate, however. Case (6) adds leverage and lagged beta as instruments, which the theory implies could be important determinants of beta. Information risk remains significantly negatively related to equity beta for the high-*CHS* portfolio and unrelated to beta for the low-distress portfolio. The first-stage R^2-values also increase substantially to values similar to those in cases (2)–(4) using alternative instruments. The long–short alpha increases to -0.47% per month and is not statistically different from zero.

Finally, case (7) combines the three instruments from case (6) with the four traditional instruments. The long–short alpha estimate increases to -0.35% per month, which is similar in magnitude to the estimates reported in panels B and C of Table 2 using various proxy methods. For cases (2)–(7), Table 4 also reports a p-value for the test of the null hypothesis that the conditional and unconditional alphas for the long–short portfolio are equal. The increases in portfolio alpha from conditioning are statistically significant at the 5% level in all cases.

Table 5 reports the instrumental variables results for the *O*-score portfolios using the same combinations of instruments for betas. The conclusions are consistent with those in Table 4. The unconditional long–short alpha (case (1)) is -0.56% per month. Modeling conditional betas as functions of the standard instruments (case (2)) results in an increase in alpha to -0.28% per month, which is not significantly different from zero at the 5% level. In case (5), there is no significant association between investor uncertainty and equity beta for firms with a low probability of bankruptcy and a pronounced inverse relation between equity beta and *DIS* for distressed stocks. Using the expanded set of instruments (case (7)), the long–short alpha is -0.28%

[19] The economic arguments that follow largely focus on using the model to explain the market-timing results in Table 3. At first glance, the positive volatility-timing results in Table 3 seem difficult to reconcile with the model. Specifically, one might expect forecast dispersion for distressed stocks to rise during times of high market volatility, which is also used as a measure of investor uncertainty in some applications. Following this logic, we would expect to see a negative relation between betas for distressed stocks and market volatility, but this result is the oppositive of the empirical findings. These findings are not necessarily inconsistent with the model, however, as realized market volatility and portfolio-level information risk appear to capture different aspects of investor uncertainty. The correlation between monthly market volatility and information risk for the high-*CHS* (high-*O*-score) portfolio is -0.13 (-0.10). I also note that the volatility-timing effect typically has an econometric interpretation. As discussed by Boguth et al. (2011), returns from high-volatility periods are more influential in ordinary least squares regressions. As such, positive volatility timing leads to unconditional beta estimates that overstate the average conditional beta and unconditional alpha estimates that understate the average conditional alpha.

Table 5 Instrumental Variables Methods for O-Score Portfolios, 1983–2009

	Stage 1 regression											Stage 2 regression			
	γ_0	DIS	LEV	$\hat{\beta}^{lp3}$	RM	VOL	DP	DEF	TS	TB	R^2	α^{IV}	ϕ_0	ϕ_1	R^2
(1) L	1.09											0.05		0.94	0.91
	(65)											(0.5)		(63)	
H	1.29											−0.50		1.11	0.70
	(31)											(−2.1)		(39)	
HL												−0.56			
												(−2.2)			
(2) L	0.74						−0.09	−15.2	3.69	2.25	0.06	0.03	0.25	0.75	0.91
	(2.0)						(−1.2)	(−3.3)	(1.9)	(2.1)		(0.3)	(2.5)	(7.6)	
H	−4.83						−1.36	33.7	21.7	4.94	0.24	−0.24	0.33	0.76	0.72
	(−5.8)						(−8.0)	(3.2)	(5.0)	(2.0)		(−1.0)	(2.4)	(6.7)	
HL												−0.28			
												(−1.1)	p-value = 0.000		
(3) L	0.56			0.48							0.08	0.07	−0.03	0.98	0.91
	(5.9)			(5.5)								(0.7)	(−0.1)	(4.6)	
H	0.42			0.67							0.20	−0.40	0.49	0.71	0.72
	(4.1)			(9.1)								(−1.7)	(2.9)	(5.5)	
HL												−0.47			
												(−1.9)	p-value = 0.133		
(4) L	0.63			0.45	−1.54	−9.53					0.10	0.06	0.06	0.91	0.91
	(6.2)			(5.0)	(−2.3)	(−2.2)						(0.6)	(0.3)	(5.6)	
H	0.41			0.66	−0.08	10.9					0.20	−0.39	0.49	0.7	0.72
	(3.8)			(8.7)	(−0.0)	(1.1)						(−1.6)	(2.8)	(5.5)	
HL												−0.44			
												(−1.8)	p-value = 0.091		
(5) L	1.03	0.70									0.00	0.06	−0.49	1.38	0.91
	(25)	(1.6)										(0.6)	(−0.7)	(2.0)	
H	1.63	−0.84									0.08	−0.43	0.26	0.90	0.71
	(21)	(−5.3)										(−1.8)	(1.3)	(5.7)	
HL												−0.50			
												(−2.0)	p-value = 0.138		
(6) L	0.63	0.51	−0.59	0.46							0.08	0.07	0.00	0.95	0.91
	(5.0)	(1.1)	(−1.1)	(5.1)								(0.7)	(0.0)	(4.5)	
H	1.03	−0.29	−0.77	0.52							0.23	−0.36	0.46	0.73	0.72
	(5.3)	(−1.7)	(−2.4)	(6.4)								(−1.5)	(2.8)	(5.9)	
HL												−0.44			
												(−1.8)	p-value = 0.084		
(7) L	0.76	0.74	−0.21	0.35			0.01	−14.0	2.05	0.87	0.10	0.04	0.25	0.75	0.91
	(1.7)	(1.5)	(−0.2)	(3.7)			(0.1)	(−2.6)	(1.1)	(0.7)		(0.4)	(2.5)	(7.4)	
H	−2.82	−0.33	−0.50	0.32			−0.82	31.3	17.7	5.80	0.28	−0.24	0.37	0.74	0.72
	(−2.2)	(−1.8)	(−0.7)	(3.6)			(−3.0)	(2.7)	(3.9)	(2.2)		(−1.0)	(3.0)	(7.2)	
HL												−0.28			
												(−1.1)	p-value = 0.001		

Notes. This table presents two-stage instrumental variables regression results for portfolios sorted based on Ohlson's (1980) bankruptcy probability. "H" is the high-distress quintile, "L" is the low-distress quintile, and "HL" is their difference. The first set of results are for the following first-stage regression of contemporaneous (monthly) portfolio betas on lagged state variables: $\beta^{cp}_{i,\tau} = \gamma_{i,0} + \gamma'_{i,1} Z_{i,\tau-1} + \epsilon_{i,\tau}$. The state variables include portfolio dispersion (DIS), portfolio leverage (LEV), lagged portfolio beta computed from the prior three months of daily returns ($\hat{\beta}^{lp3}$), the excess market return over the prior three months (RM), market volatility over the prior three months (VOL), the log dividend-to-price ratio (DP), the default premium (DEF), the term premium (TS), and the short-term interest rate (TB). The second-stage results are for the regression $r_{i,t} = \alpha^{IV}_i + \phi'_{i,0} R_{m,t} + \phi'_{i,1} \hat{\beta}^{cp}_{i,\tau} R_{m,t} + u_{i,t}$, and R^2 is the adjusted R^2-value from each regression. This table also reports a p-value for the test of the null hypothesis that the conditional and unconditional alphas for the long–short portfolio are equal.

per month. This estimate is again not significantly different from zero at the 5% level but is significantly larger than the unconditional estimate from case (1) (p-value is 0.001).

In summary, the results in Tables 4 and 5 further confirm the primary message of this paper that much of the poor unconditional performance for financially distressed firms can be explained by allowing for

Table 6 Subperiod Analysis, 1983–2009

		CHS portfolios			*O*-score portfolios		
Subperiod	Date	*L*	*H*	*H* − *L*	*L*	*H*	*H* − *L*
		Panel A: Unconditional portfolio alphas					
i	1983–1989	0.26	−1.20	−1.46	−0.06	−0.82	−0.76
		(1.95)	(−3.01)	(−2.98)	(−0.44)	(−2.61)	(−2.04)
ii	1990–1999	0.31	−0.07	−0.38	0.27	−0.33	−0.60
		(3.08)	(−0.20)	(−1.00)	(1.57)	(−1.05)	(−1.74)
iii	2000–2009	0.15	−0.41	−0.56	−0.08	−0.45	−0.37
		(0.83)	(−0.61)	(−0.72)	(−0.40)	(−0.84)	(−1.72)
		Panel B: Conditional portfolio alphas					
i	1983–1989	0.22	−0.71	−0.92	−0.06	−0.37	−0.31
		(1.72)	(−2.20)	(−2.34)	(−0.45)	(−1.37)	(−0.95)
ii	1990–1999	0.26	0.18	−0.08	0.18	−0.22	−0.40
		(2.72)	(0.55)	(−0.21)	(1.06)	(−0.71)	(−1.21)
iii	2000–2009	0.10	−0.12	−0.22	−0.03	−0.16	−0.12
		(0.59)	(−0.19)	(−0.30)	(−0.18)	(−0.31)	(−0.25)

Notes. This table presents alphas by subperiod for portfolios sorted on financial distress. *CHS* is the Campbell et al. (2008) failure probability. *O*-score is Ohlson's (1980) bankruptcy probability. "*H*" is the high-distress quintile, "*L*" is the low-distress quintile, and "*H* − *L*" is their difference. The alpha estimates are for the following three subperiods: (i) 1983 to 1989, (ii) 1990 to 1999, and (iii) 2000 to 2009. The parameters are estimated following the two-stage instrumental variables methods described in Tables 4 and 5, but alphas are allowed to vary by subperiod. The "unconditional" alphas in panel A correspond to case (1). The conditional models in panel B are estimated using the same set of state variables as case (7) in Tables 4 and 5. The numbers in parentheses are *t*-statistics.

time variation in exposure to market risk. Moreover, the results also support the theoretically motivated explanation for why betas for distressed firms covary negatively with the market risk premium. I show empirically that the observed changes in equity betas are related to changes in investor uncertainty about the fundamentals of distressed stocks.

5.3. Subperiod Analysis

Chava and Purnanandam (2010) show that the poor unconditional performance of financially distressed stocks in the post-1980 period is almost entirely concentrated in the decade of the 1980s. They conclude that the financial distress anomaly can be explained by investors being negatively surprised by lower than expected returns in the 1980s. Given these established results, it seems worthwhile to consider the performance of the conditional CAPM across subperiods. The findings are summarized in Table 6.

In conducting the analysis, I build on the instrumental variables method described in §2.2.2. Specifically, I examine the unconditional performance of the distress-sorted portfolios by estimating Equations (7) and (8) with no instruments for beta and allowing the intercept in the return regression to vary by decade. The results in panel A are consistent with those in Chava and Purnanandam (2010). The long–short *CHS* strategy has an unconditional alpha of −1.46% per month in the 1980s. In contrast the alpha estimates for the 1990s and 2000s are −0.38% and −0.56%, respectively. The differences in unconditional alpha across subperiods for the long–short *O*-score portfolio are much less extreme, but the worst performance still occurs in the 1980s.

Panel B of Table 6 reports the conditional performance for the same portfolios across subperiods. I use the full set of instrumental variables from case (7) in Tables 4 and 5 and again allow for a different return-regression intercept each decade. The central message from the table is that instrumenting for beta alleviates the poor unconditional performance of the long–short strategies across all time periods and proxies for distress risk. For the long–short *CHS* portfolio the conditional performance estimate for the 1980s is −0.92% per month, which is statistically significant at the 5% level. Thus, although the conditional CAPM does not fully explain the financial distress anomaly in the 1980s, the performance estimate is improved substantially (by 0.54%) relative to the unconditional measure. The conditional *CHS* alphas for the 1990s and 2000s are not significant and are also higher than the corresponding unconditional estimates. For the *O*-score portfolios, the conditional CAPM does explain the poor unconditional performance in the 1980s. The long–short alpha estimate increases from −0.76% to −0.31%, which is not significantly different from zero at the 5% level. Instrumenting for beta also improves estimated performance in the 1990s and 2000s.

6. Conclusion

In this paper, I show that the conditional CAPM explains the apparent underperformance of financially distressed stocks. Using several empirical methods, I find that the average conditional alphas for long–short portfolios sorted on either the Campbell et al. (2008) failure probability or Ohlson's (1980) *O*-score are not significantly different from zero. The conditional CAPM successfully explains the distress anomaly because conditional betas for financially distressed stocks are negatively correlated with the market risk premium and positively correlated with market volatility. In particular, betas for distressed stocks tend to decline in times when business conditions are weak and investors demand a large premium for bearing market risk. I also show that these results are consistent with a simple equity valuation model that incorporates investor uncertainty about underlying firm fundamentals. Specifically, building on the model of Johnson (2004), I demonstrate that equity betas for levered firms are negatively related to information risk. The predicted effects are economically significant. Moreover, the empirical results suggest that the model goes a long way in explaining the observed time-series patterns in systematic risk for distressed stocks.

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References
Altman, E. I. 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *J. Finance* **23**(4) 589–609.

Avramov, D., S. Cederburg, S. Hore. 2010. Cross-sectional asset pricing puzzles: An equilibrium perspective. Working paper, University of Maryland, College Park.

Avramov, D., T. Chordia, G. Jostova, A. Philipov. 2009. Credit ratings and the cross-section of stock returns. *J. Financial Markets* **12**(3) 469–499.

Barron, O. E., M. H. Stanford, Y. Yu. 2009. Further evidence on the relation between analysts' forecast dispersion and stock returns. *Contemporary Accounting Res.* **26**(2) 329–357.

Boguth, O., M. Carlson, A. Fisher, M. Simutin. 2011. Conditional risk and performance evaluation: Volatility timing, overconditioning, and new estimates of momentum alphas. *J. Financial Econom.* **102**(2) 363–389.

Campbell, J. Y., J. H. Cochrane. 1999. By force of habit: A consumption-based explanation of aggregate stock market behavior. *J. Political Econom.* **107**(2) 205–251.

Campbell, J. Y., J. Hilscher, J. Szilagyi. 2008. In search of distress risk. *J. Finance* **63**(6) 2899–2939.

Carhart, M. 1997. On persistence in mutual fund performance. *J. Finance* **52**(1) 57–82.

Chava, S., R. A. Jarrow's. 2004. Bankruptcy prediction with industry effects. *Rev. Finance* **8**(4) 537–569.

Chava, S., A. Purnanandam. 2010. Is default risk negatively related to stock returns? *Rev. Financial Stud.* **23**(6) 2523–2559.

Chen, L., R. Novy-Marx, L. Zhang. 2010. An alternative three-factor model. Working paper, Washington University in St. Louis, St. Louis.

Constantinides, G. M., D. Duffie. 1996. Asset pricing with heterogeneous consumers. *J. Political Econom.* **104**(2) 219–240.

Cooper, M. J., S. Gubellini. 2011. The critical role of conditioning information in determining if value is riskier than growth. *J. Empirical Finance* **18**(2) 289–305.

Da, Z., P. Gao. 2010. Clientele change, liquidity shock, and the return on financially distressed stocks. *J. Financial Quant. Anal.* **45**(1) 27–48.

Dichev, I. D. 1998. Is the risk of bankruptcy a systematic risk? *J. Finance* **53**(3) 1131–1147.

Diether, K. B., C. J. Malloy, A. Scherbina. 2002. Differences of opinion and the cross section of stock returns. *J. Finance* **57**(5) 2113–2141.

Duffie, D., D. Lando. 2001. Term structure of credit spreads with incomplete accounting information. *Econometrica* **69**(3) 633–664.

Fama, E. F., K. R. French. 1989. Business conditions and expected returns on stocks and bonds. *J. Financial Econom.* **25**(1) 23–49.

Fama, E. F., K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *J. Financial Econom.* **33**(1) 3–56.

Fama, E. F., K. R. French. 1996. Mutlifactor explanations of asset pricing anomalies. *J. Finance* **51**(1) 55–84.

Fama, E. F., K. R. French. 2006. Profitability, investment, and average returns. *J. Financial Econom.* **82**(3) 491–518.

Fama, E. F., J. MacBeth. 1973. Risk, return, and equilibrium: Empirical tests. *J. Political Econom.* **81**(3) 607–636.

Ferson, W. E., C. R. Harvey. 1999. Conditioning variables and the cross section of stock returns. *J. Finance* **54**(4) 1325–1360.

Ferson, W. E., R. W. Schadt. 1996. Measuring fund strategy and performance in changing economic conditions. *J. Finance* **51**(2) 425–462.

Garlappi, L., H. Yan. 2011. Financial distress and the cross-section of equity returns. *J. Finance* **66**(3) 789–822.

Garlappi, L., T. Shu, H. Yan. 2008. Default risk, shareholder advantage, and stock returns. *Rev. Financial Stud.* **21**(6) 2743–2778.

George, T. J., C.-Y. Hwang. 2010. A resolution of the distress risk and leverage puzzles in the cross section of stock returns. *J. Financial Econom.* **96**(1) 56–79.

Grant, D. 1977. Portfolio performance and the "cost" of timing decisions. *J. Finance* **32**(3) 837–846.

Griffin, J. M., M. L. Lemmon. 2002. Book-to-market equity, distress risk, and stock returns. *J. Finance* **57**(5) 2317–2335.

Güntay, L., D. Hackbarth. 2010. Corporate bond credit spreads and forecast dispersion. *J. Banking Finance* **34**(10) 2328–2345.

Jagannathan, R., Z. Wang. 1996. The conditional CAPM and the cross-section of expected returns. *J. Finance* **51**(1) 3–53.

Johnson, T. C. 2004. Forecast dispersion and the cross section of expected returns. *J. Finance* **59**(5) 1957–1978.

Johnson, T. C., T. Chebonenko, I. Cunha, F. D'Almeida, X. Spencer. 2011. Endogenous leverage and expected stock returns. *Finance Res. Lett.* **8**(3) 132–145.

Lewellen, J., S. Nagel. 2006. The conditional CAPM does not explain asset-pricing anomalies. *J. Financial Econom.* **82**(2) 289–314.

Lintner, J. 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Rev. Econom. Statist.* **47**(1) 13–37.

Merton, R. C. 1974. On the pricing of corporate debt: The risk structure of interest rates. *J. Finance* **29**(2) 449–470.

Newey, W. K., K. D. West. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* **55**(3) 703–708.

Ohlson, J. A. 1980. Financial ratios and the probabilistic prediction of bankruptcy. *J. Accounting Res.* **18**(1) 109–131.

Petkova, R., L. Zhang. 2005. Is value riskier than growth? *J. Financial Econom.* **78**(1) 187–202.

Rapach, D. E., J. K. Strauss, G. Zhou. 2010. Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *Rev. Financial Stud.* **23**(2) 821–862.

Sharpe, W. F. 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *J. Finance* **19**(3) 425–442.

Shumway, T. 1997. The delisting bias in CRSP data. *J. Finance* **52**(1) 327–340.

Shumway, T. 2001. Forecasting bankruptcy more accurately: A simple hazard model. *J. Bus.* **74**(1) 101–124.

Vassalou, M., Y. Xing. 2004. Default risk in equity returns. *J. Finance* **59**(2) 831–868.

Zmijewski, M. E. 1984. Methodological issues related to the estimation of financial distress prediction models. *J. Accounting Res.* **22**(Supplement) 59–82.