What explains the distress risk puzzle: death or glory?

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This draft: March 2012

Abstract

Campbell, Hilscher, and Szilagyi (2008) show that firms with a high probability of default have significantly low average future returns. We show that firms which have a high potential for death (default) also tend to have a high potential for glory (extremely high returns over the next year), with over 50% of firms in the top distress risk quintile also in the top quintile of predicted glory. Consistent with Barberis and Hwang (2008), we find that stocks with high predicted probabilities for glory earn abnormally low average returns. We distinguish between the effects of distress and glory on expected returns using variables like leverage, sales growth and M/B, and past return skewness that differ in their predictions for distress and glory. Where the two factors can be separated, the results suggest that it is glory, rather than distress, which is responsible for the low expected returns in securities with high predict default probability.

JEL: G11, G12, G32, G33
Keywords: Distress risk, bankruptcy, skewness, stock returns

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Abstract

Campbell, Hilscher, and Szilagyi (2008) show that firms with a high probability of default have significantly low average future returns. We show that firms which have a high potential for death (default) also tend to have a high potential for glory (extremely high returns over the next year), with over 50% of firms in the top distress risk quintile also in the top quintile of predicted glory. Consistent with Barberis and Hwang (2008), we find that stocks with high predicted probabilities for glory earn abnormally low average returns. We distinguish between the effects of distress and glory on expected returns using variables like leverage, sales growth and M/B, and past return skewness that differ in their predictions for distress and glory. Where the two factors can be separated, the results suggest that it is glory, rather than distress, which is responsible for the low expected returns in securities with high predict default probability.

1 Introduction

Default risk is an important consideration for prospective creditors in determining the quantity and price of credit to advance to corporations. Default risk may also be important for stockholders who hold well-diversified portfolios. Chan and Chen (1991) and Fama and French (1996) hypothesize that default risk bears a positive risk premium and is the underlying cause of the size and value effects in the cross section of equity returns. However, the direction of the effect of default risk on the cross-section of stock returns is controversial. Campbell, Hilscher, and Szilagyi (2008) (henceforth CHS) build a hazard model to predict default and find that stocks with high default probabilities have abnormally *low* returns, suggesting that investors place a higher value on these securities. [1]

At first glance, investing in stocks with high default risk seems singularly unattractive. CHS report that a portfolio consisting of stocks in the top percentile of predicted default probability have four factor alphas of -20% per year, with a standard deviation of 39.5% per year. These stocks also have higher market betas as compared to low default probability stocks, and load like small, value stocks on the Fama-French factors, consistent with greater systematic risk. However, we find that stocks with high default probability have one feature that may be attractive to investors – their pay-offs resemble lottery tickets, with a small probability of extremely high returns[2]. For example, the realized probability of log returns greater than 100%

[1] Kapadia (2011) shows that distress risk has a positive premium if it is measured as a covariance with aggregate distress, and this premium explains the size and value effects in the cross-section of equity returns. However, since he finds that stocks with high default probability do not covary with measures of aggregate distress, he does not provide a rationale for their low returns.

[2] One of the possible explanations offered by CHS is that distressed stocks have certain characteristics that appeal to certain investors, such as positive skewness of returns.

over the next year more than doubles from 1.4% to 3.7% as we move from the lowest to the highest default probability decile.

We argue that this small probability of extremely high returns (‘glory’) is responsible for the low average returns of such stocks. Our central hypothesis is that firms which have a high potential for ‘death’ tend to also have a strong potential for glory. As a consequence, the relation between distress and expected returns may instead reflect a relation between glory and expected returns. An investor preference for lottery-like pay-offs, leading to high prices and low expected returns for those securities, is certainly more intuitive than a preference for distress and is supported by recent theory. Barberis and Huang (2008) build a model in which investors with prospect theory based utility functions display a strong preference for assets with a small probability of high returns, causing them to have high prices and low expected returns in equilibrium.

In order to understand whether the lottery-like payoffs of high default probability stocks are responsible for their low average returns, we proceed in four steps. First, we build a model to predict ‘glory’, defined as returns in excess of 100% in the next year. Second, we investigate whether high predicted glory stocks also have low average returns. Third, we examine the correlations between ex-ante probabilities of distress and glory. Finally, we attempt to distinguish between the effects of distress and glory on expected returns.

In the first step, we build a model that is similar to the CHS logit model to predict distress. Instead of a binary variable with future realized distress on the left hand side, we have a binary variable that takes the value of one if returns over the next year for that stock are greater than 100% and zero otherwise. The explanatory variables include variables used by prior research to predict skewness (Chen, Hong, and Stein (2001) and Boyer, Mitton and Vorkink (2010)) such as past returns, volatility, skewness, share turnover, and size, and three new variables, firm age, sales growth, and asset tangibility. Besides the ease of comparison with the default risk literature, the binary variable set-up also corresponds with the skewed asset payoff modeled by Barberis and Huang (2008), which is also binary. This set-up also focuses on events that may be more salient for investors – extremely high returns – rather than on moments of the return distribution. We find three key variables predict glory: firm size, volatility and age, with younger, smaller and more volatile firms more likely to be glory firms.

Second, we compute ex-ante predicted probabilities of glory by implementing this model out-of-sample. We find that sorts on predicted glory produce similar alphas as sorts on predicted distress, with four factor alphas of the extreme predicted glory decile of about -12% per year.

Third, we show that ex-ante probabilities of distress and glory are highly correlated, with pair-wise correlations of approximately 40%. More than 50% of the firms in the highest quintile of predicted distress are also in the highest quintile of predicted glory. Also, the returns to a long-short strategy that exploits the distress effect (long the lowest decile of default probability, short the highest decile) are highly correlated with the long-short strategy that exploits the glory effect. In fact, the glory strategy along with the market renders the alpha of the distress strategy insignificant.

Given the commonality between distress and glory it is not clear from these results which factor is driving the low average returns. Consequently, in our fourth step, we try to distinguish between the effect of distress and glory on average returns. Traditional techniques like two dimensional portfolio sorts and Fama-Macbeth regressions have limited success in this regard because of the correlation between predicted glory and predicted distress. We therefore construct subsamples of firms based on variables related to the economic rationale behind distress and glory, rather than the model-based predictions, to help distinguish between the effect of distress and glory on expected returns.

Our first variable is leverage. We know that market leverage is strongly correlated with the probability of default, but leverage does not predict glory in our logit specification. We examine whether the glory effect is present in firms with zero leverage, a situation in which financial distress is particularly unlikely. We find that zero leverage firms with high predicted glory have low average returns, with a similar four factor alpha as for the full sample, and with an average CHS default probability of approximately the full sample median. That is, in this subsample we find evidence that high glory firms have low average returns, even in cases where predicted default probability is low.

Next, we examine whether high distress firms have low returns when predicted glory is low.   To proxy for predicted glory, we examine two sets of variables: past return skewness and two variables related to growth – M/B and sales growth. We find that the low returns documented by CHS are concentrated in those firms in the top 30% of realized daily log return skewness over the past three months and are not present in firms that comprise the bottom 30% of realized past skewness. We also sort firms in the highest predicted distress quintile into 'traditional distressed firms' and 'speculative distressed firms'. Traditional distressed firms are defined as firms with low sales growth and low market to book ratios (in the bottom 30% of the full sample for both) and speculative distressed firms are those with high market to book ratios and high sales growth (in the top 30% of the full sample for both). The average probability of distress is high (in the top quintile by construction) and of similar magnitude for both these sets of firms, however speculative distress firms have twice the probability of glory as the traditional distress firms. We find that only the speculative firms have low subsequent average returns, with four factor alphas of -2% a month, while the alpha for the traditional distress firms is not different from zero.

This cross-sectional evidence is consistent with the hypothesis that low subsequent returns to firms with high predicted distress are a result of the overlap between high predicted distress and high predicted glory. Our final-time series tests provide additional evidence in this regard – we find that the distress premium is large and statistically significant in times when the overlap between the highest quintiles of distress and glory is above its median and is much smaller in magnitude and statistically insignificant when the overlap is below its median. On the other hand, the premium for glory is of roughly equal magnitude (~0.9% per month) and is statistically significant when overlap is above or below its median.

Our paper is related to the extensive literature that examines the relation between distress risk and expected stock returns. Fama and French (1996) and Vassalou and Xing (2004) argue that there is a positive relation between distress risk and expected returns. Dichev (1998) finds that firms with high 'O-scores', from the Ohlson (1980) model, have low average returns. Griffin and Lemon (2002) argue that the results in Dichev (1998) are driven by mispricing amongst high distress risk stocks with high M/B ratios. This result is similar to our result that the low returns to stocks with high default probability documented by CHS are visible in speculative stocks but not in traditional distress stocks. We also show that speculative stocks have much larger probabilities for glory than traditionally distressed stocks, providing an economic rationale for their high valuations.

Recent explanations for the CHS results include Chava and Purnandam (2001), George and Hwang (2010), and Garlappi and Yan (2011), who argue that small-sample effects, the costs of financial distress, and differences in shareholder recovery, respectively, are responsible for the low average returns of high default probability stocks. We show that these findings are unlikely to apply to glory stocks, since the low returns to glory stocks are present in every decade in our sample, and also in stocks with no leverage, where both the costs of financial distress and differences in shareholder recovery are unlikely to be large.

Our paper is organized as follows: in Section 2 we describe the logit model for estimating glory; in Section 3 we examine whether a potential for glory can explain the low returns of stocks with high default risk; in Section 4 we distinguish between the effects of distress and glory on expected returns; we conclude in Section 6.

2 A Logit Model for Extremely High Returns

In this section, we define glory, describe our model to predict future glory, understand the key determinants of glory, and investigate the out-of-sample forecasting power of our model.

2.1 Defining Glory

We define glory as log returns greater than 100% over the next year. We choose to define glory as a binary event for several reasons. First, similar to bankruptcy, an extremely high return is a salient event that attracts investor attention. Prior research has shown that investors' risk attitudes towards rare events are very different from their attitudes to normal events. Psychological studies such as Tversky and Kahneman (1992) show that investors behave as if they overweight small probability events. Equilibrium models like Liu, Pan and Wang (2005) show that rare events require a significant risk premium and this premium helps explain the option volatility smirk in the index option market. Second, defining glory as a binary event allows us to use the same logit model as in CHS, which makes it easier to examine the relationship between the two. Third, this binary definition closely corresponds to the skewed asset pay-off in Barberis and Huang (2008).[3] Since our cut-off of annual log returns in excess of 100% is ad-hoc, we try different cutoffs in defining glory and obtain similar results in our robustness tests.

Figure 1 shows the time series of mean glory with NBER dated recessions in gray. The time series suggests that glory is typically high just when the economy is coming out of a recession, although there are exceptions, such as the 1997-1999 period when internet stocks did exceptionally well.

2.2 The Logit model to predict glory

We model the probability of a firm achieving a glory return in the next 12 months as a logistic distribution given by:

$$P_{t-1}\left(Glory_{i,t} = 1\right) = \frac{\exp\left(a + b \times X_{i,t-1}\right)}{1 + \exp\left(a + b \times X_{i,t-1}\right)},$$

where $Glory_{i,t}$ is a dummy variable that equals one if the firm's log return in the next 12 month period is larger than 100%, and $X_{i,t-1}$ is a vector of independent variables known at $t-1$. An increase in the value of $a + b \times X_{i,t-1}$ indicates that the probability of achieving a glory return in the next 12 month is higher. We estimate this model once a year (in June), to avoid overlapping returns.

[3] There are other possible setups. For example, we could forecast individual stock return skewness directly as in Boyer, Mitton and Vorkink (2010). However, if stock returns are lognormally distributed then skewness in arithmetic returns is an increasing function of return volatility. Distressed portfolios show an increase in individual stock volatility as well as return skewness and our logit setup avoids this mechanical correlation with volatility. We could also estimate risk-neutral skewness, as in Bakshi, Kapadia and Madan (2003). However, this would require us to specify a pricing kernel to convert risk-neutral skewness into the physical measure. For comparison to CHS, we choose to measure physical measures of tail events instead.

We use variables employed by prior skewness research (Chen, Hong, and Stein (2001) and Boyer, Mitton and Vorkink (2010)) to predict glory. These variables include the stock's (log) return over the last 12 months (RET12), volatility (STDEV) and skewness (SKEW) of daily log returns) over the past three months, stock turnover (TURN : detrended six month volume / shares outstanding), and size (SIZE: log market capitalization). We augment these variables with three new variables: firm age (AGE: number of years since first appearance on CRSP), asset tangibility (TANG: Gross Property Plant and Equipment / Total Assets), and sales growth (SALESGRTH) over the prior year. Our priors are that young, rapidly growing firms with less tangible assets are more likely to exhibit extremely high returns. All accounting data are lagged by six months, to ensure that these data are known to investors. Appendix 1 provides further details on the construction of these variables.

Table 1, Panel A provides summary statistics for these variables over the 1963-2010 sample period. Panel B examines these variables for firms that subsequently realized glory over the next year. Glory firms tend to be smaller, younger, more volatile, with fewer tangible assets, and have lower prior returns than firms on average. We examine the relative importance of these variables in a multivariate context below.

2.3 What predicts glory?

Table (2) Panel A reports results from our baseline model in predicting glory. All variables are statistically significant. Stocks with higher past skewness, higher returns in the past 12 months, higher sales growth rate and higher volatility are associated with a higher probability for glory. Note that although the results in Table 1 show that glory firms have low average past returns in a univariate context, this negative correlation is not evident once we control for the other variables in our model. Younger firms, firms with less tangible assets, lower stock market turnover and smaller stock market capitalization are more likely to have glory returns. Nevertheless, the importance of these variables is quite different. In the fourth column, we report the percentage change in the odds ratio for a one standard deviation change in the independent variable. The odds ratio is the log of the ratio of the probability of a glory return divided by the probability of not achieving a glory return. Among all the variables, AGE, STDEV and SIZE have the largest impact on the odds ratio of the logistic regression. A one standard deviation increase in firm age reduces the odds ratio for glory by 27%, a one standard deviation increase in STDEV increases the odds ratio by 32.9%, and a one standard deviation increase in firm size reduces the odds ratio by 34.9%.

2.4 Predictive power

The baseline logit model achieves a pseudo R-square of 5.76%. The relatively low R-square is not surprising, since it is well-known that extreme events are difficult to forecast. We test whether this relatively low predictive power allows us to generate reliable measures of distress out-of-sample. Starting from 1972, we use all available data (expanding annual rolling windows) to re-estimate our baseline model and then generate out-of-sample forecasts for the probability of glory with these estimated parameters. We borrow from the default prediction literature (see Vassalou and Xing (2004)) in using the accuracy ratio to evaluate the effectiveness of the out-of-sample predictability. The accuracy ratio reveals the ability of a model to predict actual glory over a one-year horizon. Appendix 2 describes the construction and underlying rationale of the accuracy ratio.

Our out-of-sample predicted glory probability has an accuracy ratio of 77.41% in predicting realized glory. In particular, the 63% of stocks that realize an *ex post* glory return are in the top 1% of ex-ante predicted glory probability; 70% of stocks that realize a glory return are in the top 10% of predicted glory. We also compare the predictability of our model to the predictive power obtained using only volatility to predict glory. Even though volatility is very important in forecasting glory, our out-of-sample predicted glory probability measure has substantially higher predictability for realized glory than volatility does. Using volatility alone, only 3.36% of stocks that realize glory are in the top 1% stocks with highest volatility; 23.88% of stocks that realize glory returns are in the top 10% of volatility. The accuracy ratio for volatility itself is only 37.8%. This shows that our model is not just driven by volatility – the other variables also matter a great deal in predicting glory.

Foreshadowing our primary result, we compute the accuracy ratio from using CHSDP, the probability of default according to the model in CHS, to predict glory. We find that CHSDP does remarkably well, with an accuracy ratio of 54.07%. Thus, predicted default does a much better job of predicting glory than using volatility alone, although it fares worse than our full model for predicting glory out-of-sample. This result also indicatess that the commonality between the two measures of predicted distress and glory is not driven by volatility alone.

2.5 Alternate specifications

We explore several other specifications for forecasting glory. Panel B of Table (2) reports alternative logit models. In Model 2 we use variables that are not included in the model in CHS. The aim behind this exercise is to examine whether predicted distress is correlated with predicted glory even if no common variables are used to forecast the two. Model 2 therefore includes SKEW, RET12, AGE, TANG and SALESGRTH, none of which are in the original CHS model. All of these variables remain statistically significant and have the same sign as in the baseline model in Panel A. The pseudo R-square for model 2 is 2.64%, considerably lower than 5.76% in the baseline model.

In Model 3 we replace the size variable in the baseline model with two dummy variables: *SMALLDUMMY* and *MEDIANDUMMY*. *SMALLDUMMY* is a dummy variable which equals one if the market capitalization of the stock belongs to the bottom tercile and equals zero otherwise. Similarly, *MEDIANDUMMY* is a dummy variable for the middle market capitalization tercile. The introduction of the size dummy variable is to accommodate potential non-linearity in the size effect. We also add in a dummy variable for firms listed on NASDAQ. The two size dummy variables and the NASDAQ dummy all show up significantly.

Model 4 includes exactly the same variables used in CHS. Variables are constructed as described in their paper, except that ours are based on annual rather than quarterly CompuStat data (See Appendix 1 for details). These variables are return on market assets (ROMA), relative size (RELSIZE), market leverage (MLEV), cash and short-term investments as percentage of market equity and total liability (CASH), average past 12-month return over S&P500 index return (EXRAVG), return volatility (STDEV), market-to-book ratio (MB) and log of stock price truncated at $15 (PRC15). All enter the logit regression with a significant coefficient with the exception of ROMA and MLEV. RELSIZE and PRC15 have a negative sign in predicting glory as well as for default. That is, being a relatively small size firm or low price stock increase the probability of both glory and distress. High cash holding reduces the distress probability but increases glory probability; high past EXRAVG lowers a firm’s distress probability and increases glory probability. STDEV has same effect on both distress and glory, high STDEV leads to both high distress and glory probabilities. Being a growth firm (high MB) also increases both distress and glory probabilities. Return on asset (ROMA) and market leverage (MLEV) are significant in predicting distress but are not significant in forecasting glory. Both model 3 and model 4 achieve higher pseudo R-squares of 6.07% and 6.39% respectively. We show in subsequent tests that alternative models produce similar results in out-of-sample forecasts as our baseline model.

3 Can glory explain the distress risk puzzle?

We are interested in whether a high probability for glory can explain the low average returns of high distress risk stocks. First, in Section 3.1, we examine whether stocks with high predicted glory have low average returns. In Section 3.2 we analyze the correlation between predicted glory and predicted distress and between returns of portfolios formed from sorts on these two measures.

3.1 Average Returns on Predicted Glory

We examine whether trading strategies based on predicted glory can generate similar return patterns as those based on CHS default probability. At month t, we use out-of-sample predicted glory for month $t+1$ to sort all stocks into ten deciles and compute value-weighted portfolio returns for month $t+1$. The portfolios are rebalanced each month.[4]

Table (3) reports the results from tests on value-weighted decile portfolios formed from sorts on out-of-sample predicted glory probability. In Panel A, we report average excess returns over the risk free rate for these portfolios as well as the alphas estimated from three different models: CAPM, Fama and French (1993) three-factor model, and Carhart (1997) four-factor model. The average excess returns in the first row of Panel A do not show a monotonic pattern. In fact, average excess returns increase from decile one to decile four before decreasing. The

[4] The rebalancing is due to changes in market variables like size, volatility and past annual returns, since the other accounting based variables only change annually. We have similar results if we rebalance our portfolios annually and these results are available upon request.

sharp drop in excess returns comes in decile nine (-0.02% per month) and decile ten (-0.7% per month). A long-short portfolio that holds the decile of stocks with the lowest glory probability and goes short the decile with the highest glory probability yields an average return of 1.14% per month.

Turning to risk-adjusted returns, we find that controlling for risk using the CAPM, Fama and French three-factor or Carhart (1997) four-factor model does not help explain the low returns of the portfolios with high glory probability. In fact, if anything, the poor performance of high predicted glory probability stocks looks worse after using these models. The alpha on the long-short portfolio increases to 1.50% for the CAPM, 1.51% for the Fama French three-factor model, and 1.23% for the Carhart (1997) four-factor model respectively. In each model, the alpha is highly significant. In Panel B of Table (3), we report the loadings on MKT, SMB, HML and WML in the four-factor model for the ten glory portfolios. The variation in factor loadings across the glory portfolios is striking. The loading on MKT increases from decile 1 to decile 8 and then falls slightly in decile 9 and decile 10. The SMB loading across the ten glory portfolios increases monotonically from -0.27 in decile 1 to 1.70 in decile 10 and the HML loading decreases from 0.04 to -0.43 going from lowest glory probability decile to highest glory probability decile. This is indicative of the prevalence of small and growth stocks in the deciles with high glory probabilities. High glory probability stocks are also likely to be loser stocks as they load negatively on the momentum factor WML.

The glory strategy has an annualized excess return of 13.68% and a standard deviation of 30.48%. The Sharpe ratio is 0.45, higher than the stock market (0.32) over the same time period, and comparable to that of HML (0.49) and WML (0.55). In comparison, the distress strategy has an annual excess return of 11.76% and an annual standard deviation of 30.52%, or a Sharpe ratio of 0.39. The first nine deciles of glory sorted portfolios have zero (decile 8) or negatively skewed portfolio returns, while decile 10 has positive skewness of 0.42. In untabulated results, we find that over our sample of 1972 to 2010, the long-short glory strategy is in fact the best-performing strategy among MKT, SMB, HML and the distress strategy in terms of cumulative returns.

In Table (4), we examine the robustness of our results with the glory trading strategy. We report the glory strategy's performance 1) with different specifications to forecast glory; 2) in each decade separately; 3) with different cut-offs in defining of glory. All portfolios formed remain value-weighted. For brevity, we only report the alpha from the Carhart (1997) four-factor model in this table.

In Panel A, we use different specifications to forecast glory probability. Model 2 has the fewest independent variables, with none used in the original CHS forecasting model for failure probability. Note from Panel B of Table (2) that this model has the lowest R-square. With this specification, we first re-estimate the out-of-sample glory probability and then re-construct the glory strategy. The one minus ten portfolio return has an alpha of 0.39% per month with a t-statistic of 2.1. In Model 3, we introduce nonlinearity in size by adding two indicator variables for size categories. In addition, we add a dummy variable for NASDAQ firms. Model 4 includes exactly the same set of variables as in the CHS distress forecasting specification. Both model 3 and model 4 generate very similar glory strategy returns as our baseline model. There is a sharp drop in the four-factor alpha in decile 10 for both models. In Model 3, going from decile 9 to decile 10, the alpha drops from -0.44% to -1.08%; in Model 4, the alpha drops from -0.21% to -1.00% from decile 9 to decile 10. For Model 3, while the alpha is relatively flat and not statistically significant from decile 1 to decile 7, it is significantly negative for decile 8, 9 and 10.

Overall, regardless of the specification used, the glory strategy returns remain statistically and economically significant.

In Panel B of Table (4), we report our baseline results for different sub-sample periods. We divide our full sample into four sub-samples: 1972 to 1979, 1980 to 1989, 1990 to 1999 and 2000 to 2009. The glory strategy has the highest return in the 1980-1990 sub-period, with a four factor alpha of 1.77%. Though smaller in magnitude, in other sub-samples, the glory strategy return remains strongly positive and significant in all sub-samples.

Next we examine whether the low average returns of high predicted glory stocks depend on how glory is defined. In our baseline model, glory is defined as log returns greater than 100% over the next 12 month period. In Panel C of Table (4), we use the same baseline model to forecast glory out-of-sample, with glory defined as arithmetic returns above 50%, 75%, or 100% over the next 12-month period. The results are very similar to Panel A in Table (3) where glory is defined as log return above 100%. The glory strategy alpha increases when the cutoff return for glory increases. All strategies are highly significant.

Summarizing, these results indicate that stocks with a high predicted probability of glory also have low subsequent average returns; this result is robust to different definitions of, and models for predicting, glory.

3.2 The similarities and differences between high predicted glory and high predicted distress firms

Table 5 presents characteristics of firms that are in portfolios formed from sorts on CHSDP, the default probability measure in CHS, and those formed from sorts on OSGLORYP, our out-of-sample predicted glory measure. We see many similarities and some differences. First, it interesting to note that the fraction of firms in the top decile portfolio that subsequently realize glory is a little higher (3.75%) for the highest CHSDP portfolio than for the highest OSGLORYP sorted one. Second, as both CHSDP and OSGLORYP increase, size and past twelve month returns decrease and M/B ratios increase, although the magnitudes are different, especially for past twelve month returns. Third, CHSDP portfolios display no pattern in sales growth, increasing leverage and declining skewness of daily log returns. OSGLORYP portfolios display very different patterns for these variables, with increasing sales growth, flat leverage and increasing skewness.

Figure (2) also shows that CHSDP and OSGLORYP sorted portfolios have similar patterns in factor loadings for MKT, HML, and SMB, but have sharply different patterns for HML. Loadings on HML increase as CHSDP increases, but decrease as OSGLORYP increases. This is surprising as both sets of portfolios have similar patterns in B/M ratios. Most likely this difference in loadings is a result of difference in leverage: when we restrict stocks in the highest default probability portfolios to have smaller leverage, HML loadings decline (untabulated results).

We return to these differences in characteristics in section 4.3, where we use them to distinguish between distress and glory. First, we examine whether the similarities described above result in correlations between predicted distress and predicted glory.

3.3 The relation between distress and glory

For glory to be a plausible explanation for the low returns of high distress stocks, ex-ante measures of these two variables should be highly correlated with each other. In this section we investigate the relation between ex-ante distress and glory. Table (6), Panel A presents pairwise Spearman correlations between predicted distress from the CHS model (CHSDP) and different measures of out-of-sample predicted glory. OSGLORYP, the predicted probability of glory from our baseline model, has a correlation of 41.8% with predicted distress. Model 2 predicted glory has a correlation of 22.4% with CHSDP. Note that model 2 includes none of the variables used by the CHS model. Thus, despite using mutually exclusive variables, the correlation between distress and glory remains high. For all other glory predictions from alternate models and other glory cut-offs, pair-wise correlations with distress are in the neighborhood of 40%. Thus, firms with a high potential for 'death' are also likely to have a high potential for glory.

Next, we examine the correlation between returns of a long-short strategy designed to exploit the CHS distress effect and one designed to exploit the glory effect. The distress strategy, CHSDPLS, is long stocks in the bottom CHSDP decile and short stocks in the top CHSDP decile, while the glory strategy, GLORYLS, is long stocks in the bottom decile of OSGLORYP and short stocks in the top decile OSGLORYP. All portfolios are value-weighted. Going long the safest stocks or thoseleast likely to achieve glory ensures positive average returns for both strategies.

First, in Panel B of Table (5), we use the standard four-factor model to explain returns of the distress strategy. Over our full sample,[5] the distress strategy has a four-factor alpha of 0.97% per month, with an R-square of 55%. The loadings on MKT, SMB and HML are -0.54, -1.06 and -0.5 accordingly, and are all significant. The negative loadings mean that the distress strategy

[5]Chava and Purnanandam (2010) find that the distress effect documented in CHS is only statistically significant in the 1980's. In a longer sample, with the same model for distress as CHS, we find the distress effect is significant over other subsamples from 1972 to 2009, although it is largest in the 1980s. The difference in our results is likely due to differences in the models used to forecast glory. Chava and Purnanandam (2010) use the same model as Shumway (2001), while CHS modify that model and show that their modifications improve forecasting power for defaults. For example, for their definition of profitability, CHS use geometrically declining weights over the past four quarters of Net Income / Market Total Assets, while Chava and Purnanandam (2010) using annual Net Income / Book Total Assets.

(long the *least* distressed decile and short the *most* distressed) co-varies negatively with the market, and positively with large stocks and growth stocks. It also loads significantly on WML, indicating it performs like winner stocks. However, the four factor model does not help explain the profitability of the distress strategy. The four-factor alpha of 0.97% per month is not very different from the simple average monthly return of the distress strategy of 0.98%.

In the next specification in Panel B of Table (5), we examine how returns of the glory strategy co-vary with the distress strategy's returns. Using the glory strategy return as an explanatory variable explains 29.48% of the time-series variation in the distress strategy. Furthermore, the alpha is now reduced to 0.36% per month and becomes statistically insignificant. The glory strategy return has a significantly positive coefficient of 0.54 with a t-statistic of 3.12.

We also examine the importance of the glory strategy return in explaining the distress strategy return while controlling for the four standard factors. When we add the glory strategy's return to the four-factor model, the coefficient on the glory strategy (0.38) remains significant with a t-statistic of 2.80. The loadings on the four factors have the same sign as before, although SMB is no longer significant. When the glory strategy return is added, the R-square increases slightly from 55% in the four-factor model to 58.86%; the alpha is reduced from 0.97% to 0.51% per month and is no longer significant.

In sum, returns to a distress strategy co-vary strongly with returns to a glory strategy and, after controlling for the variance in the glory strategy returns, the alpha of the distress strategy is not significant. This suggests that these two strategies are closely linked to each other. Combined, the results in the last two sections indicate that high predicted glory is a plausible explanation for the low average returns of stocks with high default probability. Stocks with high glory also have low average returns, and tend to have high predicted distress. The returns of portfolios sorted on predicted glory are correlated with those sorted on predicted distress. In the next section, we try to distinguish between the effects of these two factors.

4 Distinguishing between the effects of distress and glory on expected returns

We use several methods to separate out the effects of distress and glory. First, we use standard techniques including portfolio sorts (section 4.1) and Fama-Macbeth regressions (section 4.2). Using these methods, we find it difficult to differentiate between the effects of distress and glory on expected returns, in part due to their strong collinearity. In Section 4.3, we use firm characteristics, motivated by economic arguments, to construct subsamples of firms which differ sharply between predicted distress and predicted glory, to distinguish between their effects.

4.1 Independent sorts on glory and distress

Given the high correlation between the two trading strategies presented in Table (5), we explore whether a double sort on glory and distress allows us to identify whether glory or distress is responsible for the low average returns of these strategies. We report the results of an independent sort on OSGLORYP and CHSDP in Table (7). Panel A lists alphas from the four-factor model. Across each row from left to right, we see returns decrease as CHSDP increases. The return difference between the stocks with lowest CHSDP and highest CHSDP is 0.42% in the lowest glory quintile and it increases to 2.01% for the highest glory quintile. The distress strategy is significant in the top three glory quintiles. In a very similar fashion, the glory strategy is significant only in the top three distress quintiles. The return difference between the smallest glory probability quintile and highest glory probability quintile is positive, in each distress risk quintile, with the exception of the lowest distress quintile. The magnitude of the glory strategies alpha increases from lowest distress risk quintile to highest distress quintile.[6] Thus, predicted glory needs to be high for predicted distress to lead to significant returns; the reverse is true as well.

The high correlation (44% cross-sectional rank correlation) between predicted distress and predicted glory leads to relatively few stocks in the off-diagonal bins in the five by five independent sorts, as shown in Panel C, where we report average number of firms in each of the double sort bin. There are on average 58 stocks in the bin of lowest distress quintile and highest glory quintile; and on average only 27 stocks in the lowest glory quintile and highest distress quintile. As a result, it is difficult to generate sufficient power to distinguish between these two effects.

4.2 Fama-MacBeth regressions

Fama-Macbeth regressions may allow us to make finer distinctions between distress and glory, since we can use continuous variables rather than discrete quintiles while controlling simultaneously for other variables (like past volatility) that have been shown to affect expected return and are correlated with both these measures.

In Table (8), Panel A, specification 1, we include the following variables that have been shown to have an effect on returns in the cross-section: book-to-market (BM), lagged past 12 month return (Ret(t-12,t-2)), market capitalization (SIZE) and stock return volatility (STDEV).

[6] W obtain similar results from sequential sorts as well – predicted glory needs to be high (in the top two quintiles) for there to be a significant spread in returns (and alphas) in subsequent sorts on distress and vice-versa. These results are available from the authors on request.

All variables are observed at the end of previous month. All variables carry significant coefficients with the expected sign. Coefficients on BM, Ret(t-12,t-2) and size are consistent with findings on value, momentum and size. Consistent with Ang, Hodrick, Xing and Zhang (2006), past volatility carries a significant negative sign. In specification 2, we add predicted glory probability to these firm characteristics. The coefficient on OSGLORYP is -0.265 with a t-statistic of -3.24. In specification 3, we drop glory probability and add distress probability CHSDP. The coefficient on CHSDP is -9.36 and is statistically significant with a t-statistic of -9.88. Note that the difference in magnitude of the two coefficients is linked to differences in the scale of the two variables; CHSDP is monthly, while OSGLORYP is annual. When both OSGLORYP and CHSDP are introduced into the Fama-MacBeth regression in specification 4, we see the sign and magnitude of the coefficients on OSGLORYP and CHSDP are consistent with those in specification 2 and 3. Finally, the last specification restricts the sample to stocks with price >$5. If anything, this increases the magnitudes of the coefficients for OSGLORYP and CHSDP, suggesting that measurement errors in low priced stocks may reduce the magnitude of the observed coefficients. In terms of economic significance, the last column displays the effect of a one-standard deviation change in each independent variable on expected returns for the final specification. OSGLORYP and CHSDP have similar economic significance, with a predicted impact of -0.37% and -0.4% on expected returns for a 1 sigma shock respectively. This is the same order of magnitude as the momentum effect (0.38% per month for this sample).

Thus, controlling for distress does not drive out the effect on returns nor vice-versa. If anything, the standard techniques of portfolio sorts and Fama-Macbeth regressions suggest that both distress and glory have an impact on expected returns. In the next section, we attempt to construct subsamples of firms which are designed to have sharp differences in glory and distress.

4.3 Distinguishing between distress and glory using firm characteristics

We create portfolios of firms with dispersion in the probability of distress or glory, but not both. These portfolios may provide sharper tests of whether distress or glory is the more important determinant of the low average returns shown in CHS. We use three sets of characteristics: leverage, past return skewness, and sales growth and M/B. We have strong prior beliefs and empirical evidence (in Section 3.2) that these characteristics predict either distress or glory (but not both). Note that for ease of comparison, all results in this section are for the sample where both predicted distress and predicted glory can be computed.

4.3.1 Test 1: Firms with no leverage

In our first test, we examine whether the glory effect is present among firms with no leverage. Firms with no leverage are defined as those firms in which the book value total debt (short-term plus long-term) is less than 1% of the market value of equity. For these firms, traditional financial distress is extremely unlikely. Using such firms, we seek to create dispersion in predicted glory, in firms which have very low or no default probability.

Besides creating a portfolio with high predicted glory and low predicted default probability, investigating a sample of firms with no leverage is also important in the context of the existing literature. Prior research focuses on explaining the distress risk puzzle using market imperfections related to *financial* and not *economic* distress. The costs of financial distress in George and Huang (2010) and shareholder recovery in Garlappi and Yan (2011) are critical ingredients in explaining the low returns of high distress risk firms. These are unlikely to apply in the case of firms with no leverage. In particular, firms with no leverage should have the highest *ex-ante* costs of distress in the George and Hwang (2010) model and should therefore have the highest expected returns. Also, there are unlikely to be differences in shareholder recovery across firms with no leverage. Thus, understanding whether glory firms with no leverage also have low returns allows us to test an alternate story: the effect of glory on expected returns is actually caused by financial distress for the reasons articulated in Garlappi and Yan (2011) or George and Hwang (2010).

In Table 9, Panel A, we sort firms with little or no leverage into quintile portfolios based on their predicted glory probability. The dispersion in average (value-weighted) returns and four factor alphas are similar to those observed in the full sample. Quintile 5 has a statistically significant four factor alpha of -0.89% per month, comparable to the alpha of the highest decile of predicted glory in the full sample (-1.19%). Thus, high glory firms earn low average returns even when financial distress is not a factor. We confirm that the predicted probability of distress is small for the high glory portfolio at 0.96% per year, about the full sample median.

4.3.2 Test 2: Skewness

We use the next two characteristics to create samples for which we expect high predicted default probability, while generating dispersion in glory probabilities. We first sort firms in the highest CHS default probability quintile based on the skewness of their daily log returns over the past three months. Panel B shows that amongst firms in the highest quintile of default probability, firms with skewness less than the 30^{th} percentile for the full sample do not have abnormally low four factor alphas (-0.33% per month). The low returns of high default probability stocks are concentrated in the portfolio of firms in the top 30% of skewness, with a four-factor alpha of almost -1% per month. The difference between these two portfolios is statistically significant, with a four factor alpha of 0.64% per month for the portfolio which is long the low skewness firms and short the high skewness firms amongst the firms with high default probability. We also confirm our prior belief that differences in past skewness do not result in differences in predicted default probability, but do create differences in predicted glory probabilities.

4.3.3 Test 3: Sales growth and M/B

We sort firms in the highest CHS predicted default probability quintile into ‘traditionally distressed’ firms and ‘speculative’ firms. Traditionally distressed firms are defined as those firms that have low sales growth and low market-to-book ratios (in the bottom 30% of the full sample for both), while speculative firms are those with high market-to-book ratios and high sales growth (in the top 30% of the full sample for both). This procedure allows us to create sets of portfolios with similar distress probabilities but different glory probabilities, which may help pin down the source of the low returns to high distress risk firms.

Panel B of Table 9 presents results for value-weighted portfolios of both traditional distress firms and speculative firms. Within the quintile of the highest distress probability, 184 stocks are traditional distressed firms, while 58 stocks are categorized as speculative. The average annualized default probability for traditional distress stocks (2.76%) is, if anything, higher than that for speculative distress stocks (2.40%). However, traditional distressed firms do not earn abnormally low returns in subsequent periods, and have four factor alphas of -0.08% that are no different from zero. In sharp contrast, the *speculative* firms in the highest CHS default probability quintile have a four-factor alpha of -1.99% per month with a t-value of -5.7. Even though the average distress probability is similar between these two groups, the average predicted glory is much higher for the speculative stocks at 1.89% as compared to 0.92% for traditional distress stocks. Thus, the results in Panel B of Table 9 show that among stocks with high default probability, traditional distressed firms do not go on to earn abnormally low returns, while speculative firms do. Both sets of firms have similar default probabilities, but speculative firms have twice the glory probability of traditional distressed firms.

This test is reminiscent of previous results in the literature on the effect of distress risk on the cross section of stock returns. Dichev (1998) shows that stocks classified as high default risk according to the Ohlson (1980) model have low average returns. Griffin and Lemmon (2002) show that these low returns are concentrated in stocks with high M/B ratios. They argue that such stocks are overvalued. We show that the low returns that CHS report are concentrated in speculative stocks as described above and not in traditionally distressed stocks. We also show that such speculative stocks have much larger probabilities for glory than traditionally distressed stocks, providing an economic rationale for their high valuations.

4.3.4 Test 3: Time-series overlap

In this section, we test the hypothesis that the low returns to the portfolio of firms in the highest CHS predicted default probability quintile is a result of the overlap of this portfolio with firms with high predicted glory. To do so, we first compute overlap every month as the fraction of firms in the top CHS default probability quintile that are also in the top OSGLORYP quintile. We then divide the full time-series of sample into two subsamples based on whether the overlap is above or below its time-series median (55%). In Panel C, we find that the alpha on the distress strategy (long quintile 1 with lowest distress probability and short quintile 5 with highest distress probability) is more than twice as large in the subsample when overlap is above its median. In particular, the alpha of distress strategy when overlap is below its median is 0.39% and statistically insignificant (t-value of 1.36) and is 0.93 when overlap is above its median (t-value of 4.87). On the other hand, the alpha for the glory strategy is of roughly equal magnitude (0.83%

and 0.94%) in statistically significant (t-value of 2.51 and 5.23) in both low and high overlap subsamples.

Overall, our results are consistent with the hypothesis that even though distress probability and glory probability are closely related to each other, the underlying cause of the low average returns of high distress risk stocks is a potential for glory.

5 Conclusion

The CHS result that firms with high default risk earn low returns is surprising because of the direction of the effect that ‘risk’ has on average returns. We show that there is a large overlap between stocks classified as high default risk by the CHS model and those that are likely to produce extremely high returns (over 100%) over the next year. Thus, we show that these stocks possess a feature that investors desire: lottery-like payoffs that lead to high valuations and low expected returns. This is consistent with the model in Barberis and Huang (2008), where investors with prospect theory based utility functions display a strong preference for such stocks, resulting in low average returns in equilibrium.

We build a model to predict which stocks have lottery-like returns (‘glory’ stocks), using a logit model similar to the model in CHS, except that our dependent variable is 1 if returns over the next year are over 100%. We estimate this model on an expanding out-of-sample window and find that stocks with a high predicted probability of glory do indeed have low average returns. We find that the predicted probability of glory is highly correlated with the probability of default from the model of CHS. Therefore, a high probability of glory is a plausible explanation for the results in CHS.

We provide four tests to distinguish between the effects of glory and default on expected stocks returns. First, we show that the glory effect is large in stocks with no leverage, where default is unlikely. Second we find that amongst stocks with high default probability, low average returns are only present in stocks in the top 30% of daily return skewness in the past three months and not in those with the lowest 30% of skewness. Third, we show that the low returns that CHS report are concentrated in 'speculative stocks' with high sales growth and high M/B ratios and not in 'traditionally distressed' stocks with low sales growth and low M/B ratios. Finally we show that the negative four-factor alpha for high distress risk portfolios is only present in times when there is a high degree of overlap between the high distress and high glory portfolios. The four-factor alpha is much smaller in absolute magnitude and not different from zero in times when the overlap between the strategies is low. However the negative four-factor alpha is large and significant irrespective of the degree of overlap between distress and glory.

These results suggest that a high probability of glory rather than death (or default to be precise) is responsible for the low average returns of stocks with high default probability.

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Appendix 1: Definition of key variables

Name	Description
$Glory_t$	1 if firm has continuously compounded returns > 100% over months *t*+1 to *t*+12, 0 otherwise. For firms that delist within the next 12 months we use returns over as many months as are available, adjusted for any delisting returns on CRSP.
OSGLORYP	Predicted probability of glory from out-of-sample regressions (specification as in Table 2, Model 2)
CHSDP	Predicted probability of distress from the main model in Campbell, Hilscher, Szilagyi (2008) (Table IV,12 month lag, page 2913 of CHS). Note, this is in-sample and computed based on quarterly CompuStat data.
The next set of variables are used to predict glory in out main specification	
SKEW	Skewness of log daily returns over the last 3 months, centered around 0
RET12	Log return over the past year
SALEG	Sales growth in year 'y' is Ln ($Sales_y$ /$Sales_{y-1}$)
AGE	Time (in years) since appearance on CRSP
TANG	Gross PPE/Total assets
TURN	Detrended stock turnover. Computed as in Chen, Hong, and Stein (2001), as average past 6-month turnover minus average past 18-month turnover
STDEV	Standard deviation of daily returns over the past 3 months, centered around zero
SIZE	Log (Market capitalization in thousands)
The following variables are used to predict glory in Model 4 and are defined in a similar manner as CHS (except we use annual rather than quarterly COMPUSTAT data)	
ROMA	Return on Market Assets = Net Profits / (Market Equity + Total Liabilities)
MLEV	(Short term + Long term Debt) / (Market equity + Short term + Long term Debt)
RELSIZE	Log (Firm market cap / market cap of S&P 500)
CASH	Cash / (Market cap +Book value of Total liabilities)
PRC15	Log of stock price, truncated at $15
EXRAVG	Excess returns of the stock over the S&P 500 over the last 12 months with geometrically declining weights
MB	Market to Book. Book Value of Equity is computed as in CHS, based on the procedure in Cohen, Polk, and Vuolteenaho (2003)
Note: All accounting data is lagged by six months, to ensure that they are known by investors	

Appendix 2: The Accuracy Ratio

Let us suppose a model ranks the firms according to some measure of glory probability. Suppose there are *N* firms in total in our sample and *M* of those actually have a glory return in the next one year. Let $\theta = \frac{M}{N}$ be the percentage of firms that will actually have a glory return. For every integer λ between zero and 100, we look at how many firms actually have a glory return within λ% of firms with the highest glory probability. Of course, this number of glory returns cannot be more than *M*. We divide the number of firms that actually have a glory return within the first λ% of firms by *M* and denote the result by $f(\lambda)$. Then $f(\lambda)$ takes values between zero and one, and is an increasing function of λ. Moreover, $f(0)=0$ and $f(100)=0$.

Suppose we had the "perfect measure" of future glory probability, and we were ranking stocks according to that. Our model would then have been able to perfectly predict glory for each integer λ, and $f(\lambda)$ would be given by:

$$f(\lambda) = \frac{\lambda}{\theta} \qquad \text{for } \lambda < \theta \text{ and,}$$

$$f(\lambda) = 1 \qquad \text{for } \lambda \geq \theta$$

Suppose we also calculate the average $f(\lambda)$ for all months covered by the sample. The graph of this function of average $f(\lambda)$ is shown as the kinked line in Figure A.1, graph B. At the other extreme, suppose we had zero information about future glory probability, and we were ranking the stocks randomly. If we did that a large number of times, $f(\lambda)$ would be equal to λ. Graphically, the average $f(\lambda)$ would correspond to the 45 degree line in the graphs of Figure A.1.

We measure the amount of information in a model by how far the graph of the average , $f(\lambda)$ function lies above the 45 degree line. Specifically, we measure it by the area between the 45-degree line and the graph of average $f(\lambda)$. The accuracy ratio of a model is then defined as the ratio between the area associated with that model's average *f(λ)* function, and the one associated with the "perfect" model's average *f(λ)* function. Under this definition, the "perfect" model has accuracy ratio of one, and the zero-information model has an accuracy ratio of zero.

Figure A.1: Illustrating the accuracy ratio

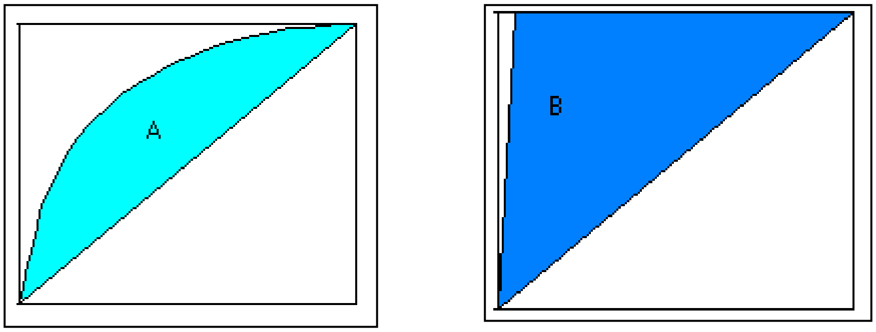

Table 1: Summary statistics

This table reports summary statistics for key variables used in this paper. These summary statistics are for firm-months where data is available for all variables from 1953-2009. Panel B reports statistics for the sub-sample of firms that will realize glory over the next twelve months.

Panel A: Baseline Model: Logistic regression that predicts glory

	SKEW	RET12	AGE	TANG	SALESGRTH	TURN	STDEV	SIZE
MEAN	0.23	-0.02	15.51	0.53	0.17	0	0.57	4.64
STD	1.33	0.58	14.53	0.35	0.3	0.08	0.43	2.13
MIN	-145.91	-8.01	0.5	0.05	-0.27	-5.16	0	-4.55
MAX	11.47	4.42	83.92	1.22	0.98	14.83	11.45	13.31
N	1892940							

Panel B: 'Glory' Subsample

	SKEW	RET12	AGE	TANG	SALESGRTH	TURN	STDEV	SIZE
MEAN	0.28	-0.15	9.68	0.47	0.19	0	0.81	3.44
STD	1.42	0.72	9	0.33	0.36	0.08	0.52	1.74
MIN	-8.19	-3.93	0.5	0.05	-0.27	-1.28	0.03	-1.18
MAX	8.19	2.63	78.92	1.22	0.98	1.98	9.03	10.93
N	3316							

Table 2: In-sample predictors of glory

This table reports annual in-sample logit regressions of 'glory', a dummy variable that equals one if a stock's log return over the next 12 months (July to June) exceeds 100%, on a set of predictive variables. from 1970-2009. The key predictive variables are defined in Table A.1. All predictive variables are known as of end June, with accounting data lagged by six months to ensure availability. In addition, NASDAQ, SMALLDUMMY, and MEDIANDUMMY are dummy variables that take the value of 1 for nasdaq listed firms, firms in the bottom

	Variable	Coefficient	T-stats	%change in odds ratio for a 1 σ change in X	R^2
Panel A: Baseline Model					
	Intercept	-3.29	-36.00		5.76%
	SKEW	0.06	3.37	7.40%	
	RET12	0.18	4.42	9.10%	
	AGE	-0.02	-8.75	-27.60%	
	TANG	-0.25	-3.45	-8.20%	
	SALESGRTH	0.29	4.10	8.20%	
	TURN	-0.43	-2.18	-3.50%	
	STDEV	0.99	16.43	32.90%	
	SIZE	-0.22	-15.94	-34.90%	
Panel B: Alternative Models					
Model 2	Intercept	-3.48	-71.76		2.64%
	SKEW	0.08	4.13	9.50%	
	RET12	-0.11	-2.60	-5.20%	
	AGE	-0.04	-16.21	-43.70%	
	TANG	-0.36	-5.23	-11.80%	
	SALESGRTH	0.14	1.99	4.10%	
Model 3	Intercept	-5.18	-56.48		6.07%
	SKEW	0.06	3.17	7.60%	
	RET12	0.17	4.27	7.90%	
	AGE	-0.02	-8.03	-27.70%	
	TANG	-0.13	-1.86	-4.20%	
	SALESGRTH	0.25	3.60	6.40%	
	TURN	-0.37	-1.91	-3.20%	
	STDEV	0.88	13.81	29.20%	
	NASDAQ	0.15	2.97	7.30%	
	SMALLDUMMY	1.18	16.51	45.00%	
	MEDIANDUMMY	0.77	10.61	40.70%	
Model 4	Intercept	-5.60	-21.23		6.39%
	ROMA	0.02	0.06	0.00%	
	MLEV	0.10	0.93	2.00%	
	RELSIZE	-0.19	-11.06	-31.10%	
	CASH	0.51	4.21	6.70%	
	EXRAVG	3.98	10.39	21.40%	
	STDEV	0.63	9.09	19.30%	
	MB	0.05	7.05	15.40%	
	PRC15	-0.50	-9.91	-24.10%	

Table 3: Portfolios formed from univariate sort on out-of-sample predicted glory

This table presents statistics of portfolios formed from decile sorts of predicted glory probability. Predicted glory probability is from out-of-sample, expanding window, logit regressions of our baseline model (Table 2). Panel A reports excess returns and alphas of these portfolios from CAPM, Fama-French, and four factor (Fama-French and momentum) regressions. Panel B presents portfolio loadings in the four factor regression, while Panel C presents the characteristics of these portfolios. The sample period is 1972-2009.

Panel A: 4 factor alphas (in % per month) of value-weighted portfolios sorted on OSGLORYP 1972-2009											
Decile	1	2	3	4	5	6	7	8	9	10	1 minus 10
Excess Return	0.45	0.52	0.62	0.65	0.49	0.49	0.55	0.31	-0.02	-0.70	1.14
t-stat	2.34	2.17	2.29	2.19	1.49	1.31	1.41	0.72	-0.05	-1.44	2.80
CAPM Alpha	0.07	0.05	0.09	0.08	-0.12	-0.18	-0.13	-0.41	-0.75	-1.43	1.50
t-stat	1.27	0.71	1.00	0.75	-0.86	-0.95	-0.61	-1.73	-2.75	-4.51	4.17
3-factor Alpha	0.09	0.07	0.10	0.06	-0.08	-0.13	-0.07	-0.37	-0.69	-1.43	1.51
t-stat	2.29	1.12	1.29	0.69	-0.88	-1.22	-0.53	-2.33	-4.07	-6.87	6.75
4-factor Alpha	0.04	0.10	0.17	0.09	-0.03	-0.03	0.07	-0.24	-0.53	-1.19	1.23
t-stat	0.88	1.80	2.46	1.15	-0.26	-0.33	0.46	-1.44	-2.82	-5.93	5.61
Panel B: Factor Loadings in the four-factor Model											
MKT	0.91	1.03	1.09	1.15	1.18	1.21	1.23	1.28	1.25	1.20	0.28
t-stat	70.12	59.58	46.76	43.24	42.62	48.69	36.18	25.76	21.50	18.49	3.91
SMB	-0.27	0.09	0.32	0.56	0.73	0.99	1.04	1.28	1.37	1.70	1.96
t-stat	-18.48	3.24	7.63	13.88	21.61	23.90	22.88	20.67	14.41	10.44	11.63
HML	0.04	-0.07	-0.11	-0.07	-0.25	-0.33	-0.38	-0.39	-0.45	-0.43	-0.48
t-stat	1.39	-1.81	-2.80	-1.73	-6.53	-7.34	-5.56	-4.34	-4.30	-3.11	-2.98
WML	0.05	-0.04	-0.07	-0.04	-0.06	-0.09	-0.14	-0.13	-0.16	-0.23	-0.28
t-stat	2.90	-1.69	-3.20	-2.02	-2.19	-2.98	-3.27	-2.20	-2.23	-2.69	-2.99
Panel C: Portfolio Characteristic											
Portfolio STD	4.12	5.13	5.83	6.39	7.11	7.94	8.32	9.22	9.55	10.45	8.80
Portfolio Skew	-0.43	-0.48	-0.40	-0.64	-0.60	-0.22	-0.26	0.02	-0.12	0.42	1.07

Table 4: Alternate specifications and sample periods for portfolios fromed on sorts on predicted glory

This table presents four-factor alphas of portolios formed from alternate specifications (Panel A), time periods (Panel B), different definitions of glory (Panel C). Panel A reports four-factor alphas of portfolios formed from out-of-sample predicted glory based on the three models with different predictor variables for glory, as defined in Table 2. Panel B examines alphas from our baseline model over different sub-samples. Panel C reports alphas of portfolios formed based on out-of-sample predictions of glory with our baseline variables, with different definitions of Glory

Panel A: Different models to forecast glory											
Decile	1	2	3	4	5	6	7	8	9	10	1 minus 10
Model 2	0.05	0.03	-0.07	0.09	0.24	0.16	0.02	0.06	-0.08	-0.34	0.39
t-stat	0.86	0.40	-0.95	0.97	2.45	1.76	0.18	0.59	-0.71	-1.96	2.10
Model 3	0.02	-0.05	0.17	0.12	0.03	0.31	-0.05	-0.27	-0.44	-1.08	1.10
t-stat	0.25	-0.71	1.89	1.15	0.22	1.80	-0.39	-2.00	-2.36	-5.81	4.78
Model 4	0.06	0.03	0.06	-0.10	-0.01	-0.12	0.04	-0.27	-0.21	-1.00	1.05
t-stat	1.56	0.52	0.94	-1.15	-0.07	-1.19	0.29	-1.81	-1.10	-4.42	4.35
Panel B: Sub-samples											
Decile	1	2	3	4	5	6	7	8	9	10	1 minus 10
1972-1979	0.01	0.17	0.19	0.08	-0.03	0.22	-0.28	-0.22	-0.49	-1.40	1.41
t-stat	0.12	1.51	1.34	0.50	-0.20	1.01	-1.26	-0.78	-2.00	-5.53	5.12
1980-1989	0.05	0.13	0.16	0.00	0.15	-0.06	0.03	-0.37	-1.00	-1.72	1.77
t-stat	0.94	1.72	1.63	0.04	1.07	-0.44	0.20	-2.53	-5.61	-6.58	6.62
1990-1999	0.05	0.14	0.06	0.12	0.04	-0.20	0.04	-0.05	-0.17	-1.05	1.10
t-stat	0.82	1.43	0.39	0.82	0.24	-0.95	0.16	-0.12	-0.52	-2.50	2.40
2000-2009	0.09	-0.07	0.20	0.31	-0.19	-0.17	-0.01	-0.45	-0.58	-1.00	1.09
t-stat	1.00	-0.47	1.34	1.67	-0.99	-0.84	-0.04	-1.38	-1.61	-2.82	2.85
Panel C: Different definitions of glory											
Decile	1	2	3	4	5	6	7	8	9	10	1 minus 10
Glory as 50%	0.04	0.15	0.14	0.09	0.02	-0.07	-0.23	-0.26	-0.77	-0.99	1.02
t-stat	1.13	2.75	1.83	1.10	0.19	-0.64	-1.95	-2.12	-5.22	-4.47	4.52
Glory as 75%	0.03	0.18	0.07	0.06	0.12	-0.01	-0.19	-0.36	-0.59	-1.16	1.19
t-stat	0.88	2.98	0.95	0.69	1.27	-0.10	-1.46	-2.28	-4.03	-5.40	5.22
Glory as 100%	0.04	0.12	0.17	-0.04	0.04	0.13	-0.23	-0.18	-0.71	-1.18	1.22
t-stat	1.13	2.15	2.26	-0.52	0.37	1.24	-1.44	-0.98	-4.09	-5.92	5.72

Table 5: Firm Characteristics

This table presents average individual firm characteristics for portfolios sorted on predicted default probability according to the Campbell, Hilsher and Szilagyi (2008) model in Panel A and for portfolios sorted on out-of-sample predicted glory probability in Panel B. The variables are defined as in Table A1. Realized glory is the average of the binary variable glory, that is 1 if log returns over the next 12 months are greater

Panel A: Individual stock characteristics of CHSDP sorted portfolio

	1	2	3	4	5	6	7	8	9	10
OSGLORYP	0.94%	0.90%	0.95%	1.04%	1.17%	1.33%	1.54%	1.80%	2.24%	3.39%
Realized glory	1.37%	1.36%	1.42%	1.44%	1.50%	1.56%	1.71%	1.90%	2.48%	3.75%
RET12	25.54%	21.10%	16.77%	12.83%	8.96%	4.67%	0.43%	-5.61%	-18.17%	-44.29%
SIZE	5.46	5.77	5.61	5.41	5.17	4.90	4.53	4.12	3.62	2.97
BM	0.62	0.59	0.66	0.72	0.78	0.84	0.91	0.98	1.09	1.26
SALESGRTH	14.54%	17.55%	18.19%	18.26%	18.25%	17.85%	17.64%	17.20%	16.81%	14.50%
MLEV	5.94%	11.03%	15.13%	18.56%	21.52%	24.37%	27.07%	30.21%	33.79%	39.21%
SKEW	0.58	0.42	0.35	0.30	0.26	0.22	0.20	0.15	0.06	-0.01

Panel B: Individual stock characteristics of OSGLORYP sorted portfolio

	1	2	3	4	5	6	7	8	9	10
OSGLORYP	0.18%	0.37%	0.53%	0.70%	0.90%	1.13%	1.41%	1.79%	2.40%	4.65%
Realized glory	0.11%	0.32%	0.52%	0.83%	1.28%	1.76%	2.19%	2.68%	3.03%	3.55%
RET12	9.81%	10.13%	10.50%	10.45%	9.58%	7.68%	5.78%	2.73%	-3.28%	-16.30%
SIZE	8.09	6.88	6.18	5.61	5.13	4.72	4.35	3.97	3.56	2.93
BM	0.74	0.74	0.75	0.77	0.79	0.81	0.83	0.85	0.89	1.01
SALESGRTH	9.12%	11.07%	12.96%	14.52%	16.13%	17.69%	19.05%	21.00%	23.77%	26.76%
MLEV	25.91%	24.53%	23.10%	22.42%	22.16%	22.07%	21.85%	21.20%	20.91%	22.33%
SKEW	0.08	0.12	0.16	0.20	0.22	0.24	0.28	0.31	0.34	0.44

Table 6: The relaton between distress and glory

Panel A presents Spearman correlations between predicted glory and predicted distress. Predicted glory is from the different models in Table 4, with different predictor variables (models 2-4) and different cut-offs used in defining glory (arithmetic returns of 50%, 75% and 100% over the subsequent year). Panel B presents time-series regresses of returns of the 'distress strategy' on different factors. The distress strategy is long the bottom 10% of stocks (lowest default probability) and short the top 10% of stocks (highest default probability) according to the default probability model in Campbell, Hilsher and Szilagyi (2008). Specification 1 presents results of Carhart four factor regressions for the distress strategy. Specification 2 regresses the distress strategy on GLORYLS. GLORYLS is a portfolio of stocks that is long the decile least likely to achieve glory and short the decile most likely to achieve glory, according to the baseline out-of-sample glory prediction model. Specification 3 uses both the four factor model as well as returns to the glory

Panel A: Spearman correlations witth predicted default probability from CHS (CHSDP)

	Correlation
OSGLORYP	41.80%
OSGLORYP Model 2	22.36%
OSGLORYP Model 3	39.54%
OSGLORYP Model 4	39.26%
OSGLORYP50	45.43%
OSGLORYP75	45.26%
OSGLORY100	45.64%

Panel B: Explaining the returns of the distress strategy

	Coef.	*t-value*	*Coef.*	*t-value*	*Coef.*	*t-value*
Intercept	0.97	3.38	0.36	0.79	0.51	1.51
MKT	-0.54	-5.63			-0.43	-3.79
SMB	-1.06	-4.80			-0.32	-1.85
HML	-0.50	-2.57			-0.68	-4.28
WML	0.90	6.84			0.80	5.19
GLORYLS			0.54	3.12	0.38	2.80
R-square		55.00%	29.48%			58.86%

Table 7: Independent sorts on predicted distress and predicted glory

This table presents results of independent sorts on predicted distress according to the Campbell, Hilsher and Szilagyi (2008) model and our out-of-sample glory prediction model. Panel A presents four factor alphas of value-weighted portfolio returns, Panel B presents the t-statistics for the

Panel A: Alphas

	CHSDP Low	2	3	4	CHSDP High	Low-High
OSGLORYP						
Low	-0.05	0.05	0.18	0.27	-0.47	0.42
2	0.29	0.05	-0.05	0.09	0.01	0.28
3	0.23	0.10	-0.02	-0.46	-0.44	0.67
4	0.69	0.12	-0.25	-0.26	-0.66	1.35
High	0.43	-0.31	-0.29	-0.79	-1.59	2.01
Low-High	-0.48	0.37	0.47	1.05	1.11	.

Panel B: t-stat

	CHSDP Low	2	3	4	CHSDP High	Low-High
OSGLORYP						
Low	-0.63	0.82	2.29	2.27	-1.96	1.59
2	2.45	0.48	-0.51	0.75	0.05	1.19
3	1.79	0.70	-0.14	-3.57	-2.39	2.91
4	3.64	0.77	-1.45	-1.51	-3.53	5.17
High	1.50	-1.29	-1.42	-3.59	-6.88	6.00
Low-High	-1.60	1.40	2.05	3.90	3.45	

Panel C: Number of firms

	CHSDP Low	2	3	4	CHSDP High
OSGLORYP					
Low	174	184	139	78	27
2	149	143	139	114	58
3	122	121	131	136	95
4	99	97	114	146	150
High	58	59	81	130	274

Panel D: Average Market Cap

	CHSDP Low	2	3	4	CHSDP High
OSGLORYP					
Low	7.81	7.66	7.44	7.20	6.83
2	6.12	6.14	5.97	5.86	5.63
3	5.21	5.22	5.04	4.88	4.73
4	4.44	4.48	4.32	4.16	4.01
High	3.64	3.67	3.55	3.39	3.07

Table 8: Fama Macbeth regressions

This table presents results of monthly Fama-Macbeth regressions. Explanatory variables in include Book-to-market (BM), size (SIZE), momentum returns from t-12 to t-2 (Ret (t-12,t-2), stock return volatility (STDEV), out of sample predicted probability of glory (OSGLORYP) and predicted probability of distress (CHSDP). All variables (except returns) are winsorized at their 5th and 95th percentiles. All explanatory variables are known as of 't-2', while returns on the left hand side are of month 't'. Specifications 1 to 4 introduce different combinations of these variables, while specification 5 filters out stocks with price < $ 5 in month. The sample is restricted to firm months where OSGLORYP is available in all specifications and the time

	(1)		(2)		(3)		(4)		(5) Price >$5		
Variable	Coeff.	t Value	Coeff.	t Value	Coeff.	t Value	Coeff.	t Value	Coeff.	t Value	1σ shock
Intercept	0.022	7.28	0.026	8.06	0.024	8.24	0.021	8.87	0.030	9.27	
BM	0.003	3.48	0.003	3.21	0.004	5.27	0.003	5.03	0.003	4.01	0.16%
Ret (t-12,t-2)	0.115	6.92	0.113	6.72	0.088	5.41	0.086	5.23	0.090	5.36	0.38%
SIZE	-0.001	-3.55	-0.002	-4.93	-0.002	-4.34	-0.002	-5.59	-0.002	-6.08	-0.41%
STDEV	-0.018	-5.11	-0.012	-3.31	-0.010	-2.96	-0.004	-1.28	-0.002	-0.48	-0.05%
OSGLORYP			-0.265	-3.24			-0.262	-3.18	-0.447	-5.21	-0.37%
CHSDP					-9.362	-9.88	-9.286	-9.71	-10.092	-9.28	-0.40%

Table 9: Distinguishing between the effects of distress and glory on expected returns

In Panel A, we sort firms with no leverage (Debt /(Debt +Market Cap) <1%) into quintiles based on predicted out of sample glory and compute value-weighted returns and four factor alphas. In Panel B we sort firms in the top predicted distress quintile into 'traditional distress' (the bottom 30% of all firms in terms of sales growth and bottom 30% in M/B or with negative book equity) and 'speculative' (top 30% of all firms in terms of sales growth and top 30% of M/B) and compute value-weighted returns and four factor alphas. In Panel C, we first compute overlap as the fraction of firms in the top predicted default quintile that are also in the top predicted glory quintile. We then examine returns of predicted distress and predicted glory quintile portfolios

Panel A: Sorts on predicted glory for firms with no leverage

OSGLORYP quintile	Lo	2	3	4	Hi	Lo-Hi
Mean return	1.15%	1.22%	0.66%	0.50%	0.11%	1.04%
4 factor alpha	0.42%	0.13%	-0.43%	-0.63%	-0.89%	1.31%
t-value	3.15	0.71	-1.91	-2.50	-2.89	
Mean CHSDP (annualized)	0.36%	0.36%	0.48%	0.60%	0.96%	
Mean OSGLORYP	0.37%	1.03%	1.49%	2.08%	3.65%	
N						

Panel B: Sorts of stocks in the highest default probability quintile by firm characterisitcs

	Skewness			Sales Growth and M/B		
	Lo	Hi	Lo-Hi	Distress	Speculative	Dist.-Spec.
Mean return	0.58%	0.17%	0.41%	1.11%	-0.9%	2.00%
4 factor alpha	-0.33%	-0.98%	0.64%	-0.08%	-1.99%	1.91%
t-value	-1.43	-4.08	2.18	-0.32	-5.70	
Mean CHSDP (annualized)	2.40%	2.64%		2.76%	2.40%	
Mean OSGLORYP	1.01%	1.48%		0.92%	1.89%	
N	339	186		184	58	

Panel C: Time series evidence

	Times when overlap is below its median					
CHSDP Quintile	1	2	3	4	5	1-5
4 factor alpha	-0.03%	-0.04%	0.09%	0.19%	-0.43%	0.39%
t-value	-0.38	-0.54	1.08	1.15	-1.76	1.36
OSGLORYP Quintile	1	2	3	4	5	1-5
4 factor alpha	0.04%	0.11%	-0.16%	-0.02%	-0.79%	0.83%
t-value	1.02	1.11	-1.14	-0.09	-2.49	2.51
	Times when overlap is above its median					
CHSDP Quintile	1	2	3	4	5	1-5
4 factor alpha	0.09%	0.10%	-0.11%	-0.20%	-0.84%	0.93%
t-value	1.57	1.53	-1.13	-1.50	-4.87	4.87
OSGLORYP Quintile	1	2	3	4	5	1-5
4 factor alpha	0.05%	0.12%	0.01%	-0.13%	-0.89%	0.94%
t-value	1.12	1.27	0.06	-1.13	-5.60	5.23

Figure 1: The time-series of mean glory

This figure plots mean realized glory for all stocks from 1960 to 2008. Glory is a binary variable equal to 1 if log returns over the next year for a stock are greater then 100%. For example, the point at 31 Dec 1975 reflects the fraction of stocks that have log retuns greater than 100% from 01 Jan 1976 to 31 Dec 1976.

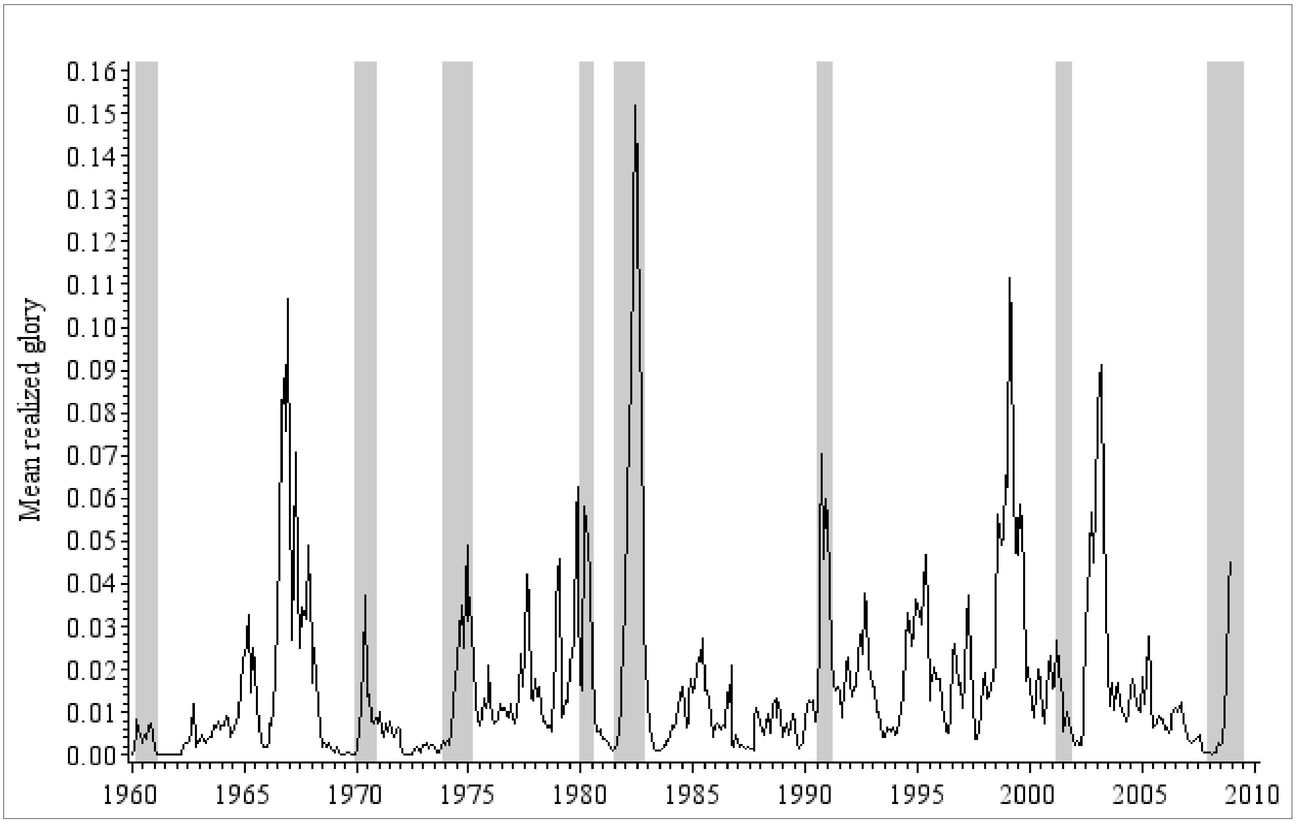

Figure 2: Carhart four-factor regression loadings for distress and glory strategies

This figure plots loadings on the factors in the Carhart four-factor model for both the ten CHSDP portfolios