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Death and jackpot: Why do individual investors hold overpriced stocks?☆

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ABSTRACT

Campbell, Hilscher, and Szilagyi (2008) show that firms with a high probability of default have abnormally low average future returns. We show that firms with a high potential for default (death) also tend to have a relatively high probability of extremely large (jackpot) payoffs. Consistent with an investor preference for skewed, lottery-like payoffs, stocks with high predicted probabilities for jackpot returns earn abnormally low average returns. Stocks with high death or jackpot probabilities have relatively low institutional ownership and the jackpot effect we find is much stronger in stocks with high limits to arbitrage.

1. Introduction

Campbell, Hilscher, and Szilagyi (2008; henceforth CHS) present convincing evidence that stocks with a high probability of default have low subsequent returns. This result is puzzling; as they point out, it suggests that the market has not priced distress risk appropriately. In considering possible explanations for this anomaly, CHS note that individual securities with high failure probabilities, as well as portfolios of distressed stocks, have positive skewness. They conjecture that investors with a strong preference for positive skewness could bid up the prices of these securities, leading to low subsequent returns.

This conjecture is a natural one given recent papers on the relation between skewness and returns. For example, Barberis and Huang (2008; BH) consider an economy in which investors have cumulative prospect theory preferences. They show that, in such an economy, positively skewed securities can become overpriced and earn negative average excess returns. Also, growing empirical evidence shows that securities with positive skewness or a high probability of extreme positive outcomes (jackpots)[1]

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[1] Throughout the paper, we call these extreme positive outcomes 'jackpots' or jackpot returns, following Barberis and Huang (2008).

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have low subsequent returns (see, e.g., Mitton and Vorkink, 2007; Kumar, 2009; Boyer, Mitton, and Vorkink, 2010; Bali, Cakici, and Whitelaw, 2011; Conrad, Dittmar, and Ghysels, 2013). However, both CHS and BH argue that, for such an effect to persist, risks or costs must exist to prevent other rational investors (with potentially different preferences) from arbitraging this effect away. Thus, two important questions arise regarding the low average returns of distressed stocks: (1) Is it skewness that motivates investors to hold these stocks despite their low expected returns? (2) Why are these low returns not arbitraged away? In this paper, we focus primarily on understanding the first question, by examining whether skewed, lottery-like payoffs make stocks with high default probabilities attractive to a segment of investors, resulting in low average returns. Similar to CHS, we provide some evidence on the second question by showing that the jackpot effect we find is strongest in stocks for which arbitrage trades could be relatively costly.

The connection between high default risk and high jackpot probability can be understood in the context of the Merton (1974) model, which views equity as a call option on the assets of the firm. For firms close to the default boundary, this optionality is more important, leading to more skewed payoff distributions. Recent research finds that options with greater skewness earn lower returns (Ni, 2009; Boyer and Vorkink, 2011) and that options on individual stocks, unlike index options, are traded more heavily by individual investors (Ni and Lemmon, 2009). Similarly, we argue that stocks that are close to default and have skewed payoff distributions appeal to individual investors with a preference for skewness and, therefore, have low average returns.

We begin by confirming that distressed stocks have lottery-like payoffs. We go on to perform a calibration, based on the BH model, and show that the distribution of returns of highly distressed stocks is sufficiently lottery-like that a heterogeneous-holdings equilibrium exists in which these stocks have negative expected returns. The predicted returns for high default probability stocks from the calibrated BH model match the low returns we observe in the data.

To investigate the relation between the effects of high default probabilities and the probability of extreme positive returns, we develop measures of both for individual securities. Specifically, following CHS, we use a logit model to predict both distress (death) and extreme positive payoffs (jackpots). This framework is also similar in spirit to that of BH, who model skewed securities as having binary payoffs, with jackpot payoffs arising with some probability q. In our model, we use several benchmarks for the payoff to a security to be considered a jackpot. We find that stocks with high predicted probability of having a jackpot return subsequently earn low average returns and have negative four-factor alphas, with magnitudes similar to stocks with high default probability. We also find that exante probabilities of death and jackpots are highly correlated, with pairwise correlations of approximately 40% in our sample. More than 50% of the firms in the highest quintile of predicted distress are also in the highest quintile of predicted jackpot. This correlation does not arise from volatility, as we find that the probability of death is a far better predictor of future jackpots than using volatility alone. Thus the jackpot and the death effects are closely linked.

Because prior research argues that the preference for skewness is more likely to be displayed by retail investors than institutions (Kumar, 2009), we examine the ownership structure for stocks with high default and high jackpot probability. We find that the degree of institutional ownership declines significantly moving to higher default and jackpot probability deciles in the cross section. Over time, institutional ownership has increased in US markets, particularly in smaller stocks as institutions search for "greener pastures" (Bennet, Sias, and Starks, 2003). However, we find that, compared with the median stock, institutional ownership has increased at a slower rate for stocks in both the highest death and highest jackpot deciles. Finally, using an event-study, we show that the level of institutional ownership in a firm declines from four quarters prior to the firm's entry into the top death or jackpot probability decile and that this decline continues for the four quarters subsequent to entry into the decile. This suggests that retail investors are net buyers of a stock as it approaches default or becomes more likely to have a jackpot payoff, consistent with the hypothesis that these stocks are largely owned by retail investors, who are more likely to display a preference for skewness.

We also examine the sensitivity of jackpot stocks' low returns to three measures of limits to arbitrage: size, residual analyst coverage, and residual institutional ownership (in which both residuals are calculated by controlling for size). We find that the abnormally low returns of jackpot stocks are statistically and economically significant among securities when limits to arbitrage are expected to be high: in small market capitalization, low residual institutional ownership, and (weakly) low analyst coverage firms. Abnormal returns are reduced substantially in magnitude (typically to half or less of their original value) and are statistically insignificant for all measures when limits to arbitrage are low. Thus, low returns to jackpot stocks are associated with high limits to arbitrage in such stocks.

Finally, we examine the relation between the effects of jackpot probability and default probability on expected returns. That is, we test whether the jackpot effect is separate from the effect of default probabilities. Jackpot and default probabilities are sufficiently strongly correlated that we begin with an indirect test of whether high default probability firms have low returns when the probability of a jackpot payoff is relatively low. To proxy for predicted jackpots, we examine two sets of variables: past return skewness and two variables related to growth (market-to-book ratio and sales growth). We find that the low returns shown 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) for both these sets of firms. However, speculative distress firms have almost twice the probability of a jackpot payoff as the traditional distress firms. We find that only the speculative firms have low subsequent average returns, with four-factor alphas of −1.7% a month, while the alpha for the traditional distress firms is not statistically different from zero. This result suggests that the effect of a high jackpot probability—or positive skewness—on subsequent returns is not merely a different way to measure the effect of a high distress probability on returns.

We also report results from Fama and MacBeth regressions that allow us to test whether both default and jackpot probabilities are important in predicting returns while controlling simultaneously for other variables that have been shown to affect expected return and are correlated with both these measures. Given the relatively strong relation between default and jackpots, we cannot rule out the possibility that measurement error in jackpot and distress probabilities could influence our results. However, we find that both distress and jackpots have a significant impact on expected returns after including standard controls such as past volatility, market capitalization, and book-to-market equity ratio. The effect of a 1 standard deviation shock to both jackpot and distress generates an effect of very similar magnitude on returns. This result also suggests that distress and jackpots could have distinct effects, with both having an impact on pricing and, as a consequence, on subsequent returns.[2]

Overall, our results are consistent with the hypothesis that a preference for lottery-like payoffs explains why rational investors (individuals with prospect theory–based utility functions) hold on to distressed stocks even though they have low average returns, with these low returns persisting due to limits to arbitrage.

Our paper is also related to the extensive literature that examines the relation between distress risk and expected stock returns. Fama and French (1996), Vassalou and Xing (2004), and Kapadia (2011) argue that a positive relation exists between distress risk and expected returns.[3] In contrast, Dichev (1998) finds that firms with high O-scores from the Ohlson (1980) model, have low average returns. Griffin and Lemmon (2002) argue that the results in Dichev (1998) are driven by mispricing amongst high distress risk stocks with high market-to-book ratios. This result is similar to our evidence that the low returns to stocks with high default probability, as shown by CHS, are visible in speculative stocks but not in traditional distress stocks. We also show that speculative stocks have much larger probabilities for a jackpot payoff than traditional distressed stocks, providing an economic rationale for their high valuations.

Recent explanations for the CHS results include Chava and Purnanandam (2010), 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. However, Gao, Parsons, and Shen (2012) find that the distress effect is present in a sample of 39 countries and is not related to the extent of creditor protection. Another hypothesis is that idiosyncratic volatility is responsible for the low returns of stocks with high default probabilities, as Ang, Hodrick, Xing, and Zhang (2006) find that stocks with high idiosyncratic volatilities have significantly lower average returns. In their tests, CHS report that this does not appear to hold, because they find that other variables in their model besides volatility are important in predicting the low returns of such stocks. In our own tests, we find that both default probability and the probability of a jackpot payoff retain their statistical and economic significance in predicting returns in Fama and MacBeth regressions after controlling for volatility. In fact, these variables render idiosyncratic volatility insignificant in these regressions.

Our paper is organized as follows. In Section 2 we show that stocks with high default probability have lottery-like payoffs and calibrate the Barberis and Huang (2008) model to examine whether such payoffs would earn negative average returns in the model. Section 3 describes the model for estimating the probability of a jackpot payoff. In Section 4, we examine whether a potential for a jackpot return can explain the low average returns of stocks with high default risk. In Section 5, we provide additional results on the relation between the effects of distress and jackpots on expected returns. Section 6 includes further robustness checks, and we conclude in Section 7.

2. Motivation: the link between default probability and jackpots

In this section, we test our conjecture that the probability of jackpot returns drives the default risk effect, by examining whether sorts on default probability also result in sorting on jackpot returns. We then perform a calibration exercise, based on the BH model, to examine whether stocks with high default probability have sufficient skewness for the BH equilibrium to exist.

2.1. Are distressed stocks likely to have jackpots payoffs?

This section examines the link between default probability and the probability of earning jackpot returns. We first construct a measure of default probability (*DEATHP*) of each stock from the model in CHS (Table 4, 12-month lag, p. 2913). This measure is constructed as described in CHS and requires quarterly Compustat data, restricting the sample from 1972 to 2009. We recalculate *DEATHP* every month and sort stocks into deciles based on *DEATHP*. Table 1, Panel A, examines the properties of decile portfolios based on *DEATHP*. We skip a month between computing *DEATHP* and measuring returns to ensure that our results are not driven by short-term reversals. We first

[2] In a simulation exercise, we show that, in the presence of measurement error, Fama and MacBeth regressions containing two correlated independent variables find both variables to be significant, even if only one is truly correlated with expected returns.

[3] Da and Gao (2010) argue that liquidity shocks associated with changes in clientele are related to the results in Vassalou and Xing (2004).

Table 1
Motivation.

This table reports results for portfolios formed from sorts on *DEATHP*, the probability of default from the model in Campbell, Hilscher, and Szilagyi (2008). Portfolios are value-weighted, are formed monthly, and skip a month between portfolio formation and measuring returns. Panel A reports excess returns and four-factor (Fama and French three factors and momentum) alphas for these portfolios, the fraction of firms in each portfolio that realize annual returns greater than three benchmarks over the next year, and the average skewness of daily returns of each stock over the next 12 months. The benchmarks are log returns over 100%, arithmetic returns over 100%, and arithmetic returns over 75% over the next year. Panel B calibrates the Barberis and Huang (2008) model. The payoffs of the lottery asset are L with probability q, and l otherwise. We set $L=5$ and $l=1$. For a given q, we search for a price P, such that the heterogeneous holding equilibrium exists. We report P, L/p, l/P, and $E(r-rf)$, the expected excess returns of the lottery asset. The sample period is 1972–2009.

Panel A: Key statistics of DEATHP sorted portfolios

	1	2	3	4	5	6	7	8	9	10	1–10
Excess return	0.62	0.53	0.55	0.45	0.41	0.41	0.35	0.24	0.00	−0.67	1.28
t-Statistic	2.74	2.44	2.40	1.96	1.65	1.54	1.18	0.72	−0.01	−1.44	3.40
Four-factor alpha	0.11	0.01	0.11	0.05	−0.05	0.01	0.01	−0.19	−0.33	−1.10	1.21
t-Statistic	1.20	0.09	1.37	0.68	−0.61	0.12	0.08	−1.15	−1.84	−4.46	4.32
Logreturns > 100%	1.4%	1.4%	1.5%	1.5%	1.6%	1.6%	1.8%	2.0%	2.6%	3.9%	−2.5%
Arithmetic returns > 100%	4.6%	4.8%	4.9%	4.8%	5.0%	5.2%	5.6%	6.0%	7.1%	9.1%	−4.5%
Arithmetic returns > 75%	8.1%	8.1%	8.2%	8.1%	8.4%	8.8%	9.3%	9.5%	10.7%	12.5%	−4.5%
Skewness ($t+1$, $t+12$)	0.68	0.58	0.62	0.67	0.75	0.84	0.94	1.03	1.25	1.58	−0.90
Median institutional ownership	42.7%	45.2%	42.7%	39.6%	35.6%	30.6%	24.5%	18.7%	14.5%	12.5%	30.2%

Panel B: Barberis and Huang (2008) calibration

q	P	L/P	l/P	$E(r-rf)$
0.1	1.38	3.63	0.73	−0.33%
0.09	1.35	3.70	0.74	−1.28%
0.08	1.32	3.78	0.76	−2.22%
0.07	1.29	3.86	0.77	−3.14%
0.06	1.27	3.95	0.79	−4.00%
0.05	1.23	4.05	0.81	−4.78%
0.04	1.20	4.16	0.83	−5.43%
0.03	1.16	4.29	0.86	−5.86%
0.02	1.12	4.45	0.89	−5.90%
0.01	1.07	4.66	0.93	−5.10%

show that the findings in CHS extend to our sample: Stocks with high predicted default probability have low returns and low Carhart four-factor alphas. The difference between the safest and the most likely to default decile is about −1% per month for both returns and four factor alphas. Thus, stocks with high default probability seem singularly unattractive to investors. However, they have one redeeming feature. As the next three rows of Table 1 show, these stocks have high probabilities of delivering jackpot returns. For example, the fraction of stocks in the safest portfolio that has log returns greater than 100% over the next year is 1.4%. This fraction almost triples, to 3.9%, for the portfolio with the highest default probability. Similarly, the average skewness of daily stock returns in the safest portfolio decile over the next year is 0.68, and the average skewness observed in the portfolio with the highest default probability increases to 1.58. We also examine the time series average of median institutional ownership for these portfolios. We can see that stocks with high *DEATHP* have low institutional ownership. This suggests that these stocks are largely owned by retail investors, who are more likely to display a preference for skewness (Kumar, 2009). These stocks are also likely to have high arbitrage costs, consistent with the arguments in CHS and Barberis and Huang (2008).

Barberis and Huang (2008) investigate the pricing of jackpot assets in an economy composed of investors with cumulative prospect theory utility functions. Investors with such utility functions apply subjective probability distributions in evaluating gambles. These distributions overweight the tails of the objective probability distribution to reflect experimental evidence consistent with a preference for skewed gambles. Barberis and Huang (2008) show that a heterogeneous holding equilibrium exists in which investors with cumulative prospect theory utility functions are indifferent between holding the market portfolio and an underdiversified portfolio in which the asset with jackpot returns has a nontrivial weight. The asset with jackpot returns earns negative expected returns in this equilibrium. However, for the equilibrium to exist, the payoffs of the jackpot asset must be sufficiently skewed. We calibrate the Barberis and Huang (2008) model to test whether stocks with high distress risk have sufficient skewness for the heterogeneous holding equilibrium to exist.

2.2. Calibrating the Barberis and Huang (2008) model

In Barberis and Huang (2008), the jackpot asset has a binary payoff structure (L,q; l, $1-q$), earning a gross payoff of L with probability q, and a payoff of l with probability $1-q$.[4] To closely mimic this setup, we model the payoff of

[4] We thank the referee for suggesting that we calibrate the Barberis and Huang (2008) model.

the typical stock in the highest distress risk decile portfolio as binary. We set a jackpot return as a log return greater than 100% over the next year. Thus, the likelihood of a jackpot return is $q = Probability\ of\ Log(R_{i,t}) > 1$, where $R_{i,t}$ is the gross return of stock i, at time t, in the highest distress risk portfolio.

In the jackpot state, the expected gross return of a typical stock in this portfolio with price P is L/P. Given our definition of a jackpot return, this return is $E(R_{i,t}|\ \mathrm{Log}(R_{i,t}) > 1)$. Similarly, the expected return in the bad state is $l/P = E(R_{i,t}|\ \mathrm{Log}(R_{i,t}) \leq 1)$. We measure q, L/P, and l/P using their sample means from the pooled sample of all stocks in the highest distress decile portfolio from 1972 to 2009. We find that $\hat{q} = 3.9\%$, $\widehat{L/P} = 4.24$, and $\widehat{l/P} = 0.91$.

To see if this payoff structure supports the heterogeneous-holdings equilibrium, we solve the BH model for different values of q, using their assumptions regarding values for parameters of the utility function, the risk-free rate, etc. In our initial calibration, we set $L=5$ and $l=1$. This results in expected returns that are close to those in the data. To determine whether the heterogeneous-holdings equilibrium exists, we follow the procedure in BH. The intuition underlying the solution method in BH is to search for an equilibrium with two groups of investors. One group's optimal portfolio is the market and the risk-free asset, and the other's is the market, a position in the risk free asset and a long position in the jackpot stock. Given the payoff structure of the jackpot asset, BH search for a price for that asset such that both groups have the same utility for their optimal portfolios. They find that such a price (and, hence, equilibrium) exists only if the jackpot security is sufficiently skewed.

For a given value of q, we follow BH and search for a price P, such that the heterogeneous-holdings equilibrium exists. Table 1, Panel B, shows prices, returns in each state, and expected returns for equilibria with values of q ranging from 0.01 to 0.10. As the table shows, for $q = 4\%$, the gross returns in the good state are 4.16, in the bad state, 0.83. These values of q, L and l are similar to those observed in the sample: 3.9%, 4.24, and 0.91, respectively. The close correspondence between the model results and the data indicates that stocks in the highest portfolio of distress risk are sufficiently lottery-like to have negative expected returns in the BH model. Using our calibrated parameters, the expected excess return over the risk-free rate for such stocks is -5.4%. In the calibration, the market risk premium is 7.5% per year. Therefore,, the high *DEATHP* portfolio should earn a return in excess of the market of -12.9% per year according to the model. This return is of similar magnitude to the excess return over the market that the high *DEATHP* portfolio earns in the data, of -13.1% per year.[5]

[5] We also try additional calibrations, similar to Barberis and Huang (2004) in which we use the full distribution (in bins of 50 stocks) of returns and search for a value of c such that when returns of high distress risk stocks are shifted by c the heterogeneous holdings equilibrium obtains. We find that high distress stocks are underpriced according to the model even after taking into account their low returns. We need to reduce the returns of high distress stocks by approximately 0.6% per month for the equilibrium to exist.

These results indicate that the possibility of earning jackpot returns in our sample has the potential for explaining these securities' low subsequent returns.

3. A logit model for jackpot returns

In this section, we build a model to predict the exante likelihood of jackpot returns and examine whether a correlation between jackpot and distress offers an explanation of why individuals might hold these stocks. Coupled with limits to arbitrage, these findings could explain the low returns earned by distressed firms. In particular, we define jackpot returns (Section 3.1), describe our model to predict the likelihood of future jackpot payoffs (Section 3.2), examine the key determinants of jackpot probabilities (Section 3.3), investigate alternate specifications (Section 3.4) and analyze the out-of-sample forecasting power of our model (Section 3.5).

3.1. *Defining jackpots*

We define jackpot returns as log returns greater than 100% over the next year. We choose to define jackpots as a binary event for several reasons. First, this corresponds to the skewed asset payoff in Barberis and Huang (2008), which is binary, thereby making it easier to relate our results to those in Barberis and Huang (2008), as in the calibration exercise described above. Second, similar to bankruptcy, an extremely high return is a salient event that attracts investor attention and is easier to understand and measure as compared with moments of the return distribution. Prior research has shown that investors' risk attitudes to such 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 such as 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. Third, defining jackpots as binary events allows us to use the same logit model that CHS used in measuring default probabilities, which makes it easier to examine the relation between the two probability measures. Because our cutoff of annual log returns in excess of 100% is adhoc, we try different cutoffs in defining jackpot returns and obtain similar results in our robustness tests.

Fig. 1 shows the time series of ex post jackpot probabilities, or the fraction of firms that realize returns greater than 100% over the next year, with National Bureau of Economic Research dated recessions in gray. The time series suggests that the chance of earning jackpot returns 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.

3.2. *A logit model to predict jackpots*

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

$$P_{t-1}(Jackpot_{i,t,t+12}=1)=\frac{\exp(a+b\times X_{i,t-1})}{1+\exp(a+b\times X_{i,t-1})}, \quad (1)$$

where $Jackpot_{i,t,t+12}$ 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 jackpot return in the next 12 months is higher. For each firm, we begin by estimating the parameters of a baseline logit model using at least 20 years of historical data and then construct out-of-sample estimates of jackpot probabilities. We reestimate this model once a year (in June) to avoid overlapping returns.

We use variables employed by prior skewness research (Chen, Hong, and Stein, 2001; Boyer, Mitton, and Vorkink, 2010) to predict jackpot returns. These variables include the stock's (log) return over the last 12 months (*RET*12), volatility (*STDEV*) and skewness (*SKEW*) of daily log returns over the past three months, detrended stock turnover ((*TURN*: (six-month volume/shares outstanding) minus (18-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 the Center for Research in Security Pricing data set), asset tangibility (*TANG*: gross property plant and equipment (PPE)/total assets), and sales growth (*SALESGRTH*) over the prior year. Appendix A provides further details on the construction of these variables. 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, and all independent variables are winsorized at 5% and 95%, following CHS. The accounting variables that we use to predict a jackpot return are constructed from annual Compustat data. Our sample begins with accounting data for the year ending December 1950, matched to CRSP data for June 1951. The data are relatively sparse initially, with 326 firms with non-missing total assets at the end of June 1951, rising to a maximum of 6,834 firms in June 1997 and declining to 3,972 firms at the end of our sample in 2009. Any potential survivorship bias in the early years of the Compustat sample does not affect our results, because all of our key tests are based on out-of-sample predicted probabilities for jackpots beginning in 1972. Beginning our sample construction in 1951 enables us to have 20 years of data to estimate our first set of out-of-sample jackpot probabilities in 1972.

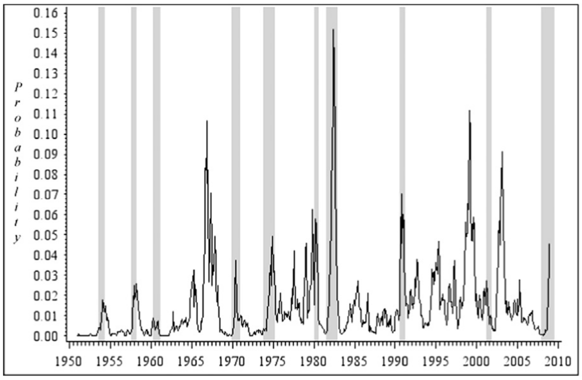

Fig. 1. The time-series of mean jackpot probability.
This figure plots mean realized jackpot probability for all stocks from 1951 to 2008. Jackpot is a binary variable equal to one if log returns over the next year for a stock are greater than 100%. For example, the point at 31 Dec 2008 reflects the fraction of stocks that have log returns greater than 100% from January 01, 2009 to December 31, 2009.

Table 2, Panel A, provides summary statistics for these variables over the 1951–2009 sample period. Panel B examines these variables for firms that subsequently realized jackpot returns over the next year. Jackpot firms tend to be smaller, younger, and more volatile and have fewer tangible assets and lower prior returns than firms on average. We examine the relative importance of these variables in a multivariate context below.

3.3. *What predicts jackpot returns?*

Table 3, Panel A, reports results from our baseline model for predicting jackpot returns. All variables are statistically significant. Stocks with higher past skewness, higher returns in the past 12 months, higher sales growth

Table 2
Summary statistics.
This table reports summary statistics for key variables used in this paper. These variable are defined in Appendix A. Panel A reports statistics for all firm-months when data are available for all variables. Panel B reports statistics for the sub-sample of firms that realize a jackpot return (log return > 100%) over the next 12 months measured from June each year. The sample period is 1951–2009.

	SKEW	*RET12*	*AGE*	*TANG*	*SALESGRTH*	*TURN*	*STDEV*	*SIZE*
Panel A: Summary statistics for key variables								
Mean	0.213	−0.007	15.773	0.532	0.170	0.00162	0.035	4.753
Standard deviation	1.006	0.574	14.671	0.348	0.292	0.082	0.027	2.062
Minimum	−7.734	−8.007	0.496	0.048	−0.268	−5.156	0.001	−4.550
Maximum	7.809	4.416	83.915	1.216	0.983	14.829	0.716	13.309
Number of observations	1,824,924							
Panel B: Summary statistics for jackpot subsample								
Mean	0.273	−0.133	9.764	0.462	0.197	0.00174	0.051	3.584
Standard deviation	1.011	0.721	9.132	0.323	0.354	0.079	0.033	1.666
Minimum	−6.988	−3.928	0.496	0.048	−0.268	−1.276	0.006	−0.717
Maximum	5.564	2.627	78.918	1.216	0.983	1.982	0.564	10.927
Number of observations	3,136							

rate, and higher volatility are associated with a higher probability for jackpots. Although the results in Table 2 show that jackpot 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 and firms with less tangible assets, lower stock market turnover, and smaller stock market capitalization are more likely to have jackpot returns. Nevertheless, the importance of these variables is different. In the table, we report the percentage change in the odds ratio for a 1 standard deviation change in the independent variable. The odds ratio is the log of the ratio of the probability of a jackpot return divided by the probability of not achieving a jackpot return. Among all the variables, *AGE*, *STDEV*, and *SIZE* have the largest impact on the odds ratio of the logistic regression. A 1 standard deviation increase in firm age reduces the odds ratio for jackpots by 27%, a 1 standard deviation increase in *STDEV* increases the odds ratio by 32.9%, and a 1 standard deviation increase in firm size reduces the odds ratio by 34.9%.

3.4. Alternate specifications

We explore several other specifications for forecasting jackpot returns to understand the robustness of our results to model specification. Panels B and C of Table 3 report alternative logit models. In Model 2 we replace the size variable in the baseline model with two dummy variables: *SMALLDUMMY* and *MEDIANDUMMY*. *SMALLDUMMY* is a dummy variable that 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 nonlinearity 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 3 includes exactly the same variables used in CHS. Variables are constructed as described in their paper, except that ours are based on annual instead of quarterly Compustat data (see Appendix A 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 the Standard & Poor's (S&P) 500 index return (*EXRAVG*), return volatility (*STDEV*), market-to-book ratio (*MB*) and the log of stock price truncated at \$15 (*PRC*15). All enter the logit regression with a significant coefficient with the exception of *ROMA* and *MLEV*. *RELSIZE* and *PRC*15 are inversely related to jackpots as well as to default. That is, being a relatively small size firm or low priced stock increases the probability of both jackpot returns and distress, consistent with a limits-to-arbitrage explanation of why these returns persist. High cash holding reduces the distress probability but increases jackpot probability. High past *EXRAVG* lowers a firm's distress probability and increases jackpot probability. *STDEV* has the same effect on both distress and jackpots, with high *STDEV* associated both with high distress and jackpot probabilities. Being a growth firm (high *MB*) also increases both distress and jackpot probabilities. Return on market assets (*ROMA*) and market leverage (*MLEV*) are significant in predicting distress but are not significant in forecasting jackpots. Both Model 2 and Model 3 achieve higher pseudo *R*-squares of 6.07% and 6.39%, respectively. We show in subsequent tests that these alternative models produce similar results in out-of-sample forecasts as our baseline model and that returns earned in strategies based on these models are also similar to those obtained using the baseline model.

Table 3
In-sample predictors of jackpot returns.

This table reports annual in-sample logit regressions of 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 1951 to 2009. The key predictive variables are defined in Appendix A. All predictive variables are known as of the end of 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 one for Nasdaq listed firms, and firms in the bottom and median tercile of market capitalization, respectively.

Variable	Coefficient	*t*-Statistic	Percent change in odds ratio for a 1σ 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: Model 2				
Intercept	−5.18	−56.48	6.07	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	
Panel C: Model 3				
Intercept	−5.60	−21.23	6.39	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	

3.5. Predictive power

The baseline logit model achieves a pseudo *R*-square of 5.76%. The relatively low *R*-square is not surprising, as 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 jackpot returns out-of-sample. Starting from 1951, we use all available data (expanding annual rolling windows) to reestimate our baseline model and then generate out-of-sample forecasts for the probability of jackpot returns with each set of estimated parameters. The first predicted out-of-sample jackpot return is in 1972; the last out-of-sample forecast is in 2009. The 1972–2009 forecasts match the availability of the CHS default probability measure that we use, along with the jackpot probabilities reported in other tests. 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 jackpot returns over a one-year horizon. A completely uninformative model yields an accuracy ratio of zero and a perfect model yields an accuracy ratio of 100%. Appendix B describes the construction and rationale underlying the accuracy ratio.

The out-of-sample predicted jackpot probability from our baseline model has an accuracy ratio of 77.41% in predicting realized jackpot returns. In particular, 63% of stocks that realize an ex post jackpot return are in the top 1% of exante predicted jackpot probability; 70% of stocks that realize a jackpot return are in the top 10% of predicted jackpot. We also compare the predictability of our model with the predictive power obtained using only volatility to predict jackpots. Even though volatility is very important in forecasting jackpots, our out-of-sample predicted jackpot probability measure has substantially higher predictability for realized jackpots than volatility does. Using volatility alone, only 3.36% of stocks that realize jackpot returns are in the top 1% of stocks with highest volatility; 23.88% of stocks that realize jackpot 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. Other variables also matter a great deal in predicting jackpots.

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

4. Can the probability of jackpot returns explain the distress risk puzzle?

In this section, we test whether a high probability of earning jackpot returns can explain the low average returns of high distress risk stocks. In Section 4.1, we examine whether stocks with a high probability of jackpot returns have low average returns. In Section 4.2, we investigate the ownership structure of stocks sorted on the basis of *DEATHP* and *JACKPOT*. In Section 4.3, we examine the effect of limits to arbitrage on the returns of stocks with high jackpot probability. In Section 4.4, we compare both characteristics and factor loadings of distress-sorted portfolios and predicted jackpot sorted portfolios. Finally, in Section 4.5, we analyze the correlation between the probability of jackpots and the probability of distress and examine how the distress strategy and jackpot strategy are related to each other.

4.1. Average returns for strategies based on predicted jackpot probability

We examine whether trading strategies based on the probability of jackpot returns can generate similar return patterns as those based on CHS default probability. At month t, we use the out-of-sample predicted jackpot probability computed using available information to sort all stocks into ten deciles and compute value-weighted portfolio returns for month $t+2$. We skip a month between portfolio formation and measuring returns to alleviate concerns regarding the potentially confounding microstructure effects such as bid-ask bounce. Portfolios are rebalanced each month.[6] Our out-of-sample predicted jackpot probability measures begin in 1972, to allow at least 20 years of data for the initial estimation.

In Table 4, we report the results from tests on value-weighted decile portfolios formed from sorts on out-of-sample predicted jackpot 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: capital asset pricing model (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 1 to Decile 4 before decreasing. The sharp drop in excess returns comes in Decile 9 (0.03% per month) and Decile 10 (-0.62% per month). A long-short portfolio that holds the decile of stocks with the lowest jackpot probability and goes short the decile with the highest jackpot probability yields an average return of 1.06% per month.

Turning to risk-adjusted returns, we find that controlling for risk using the CAPM, Fama and French three-factor models or Carhart (1997) four-factor model does not help explain the low returns of the portfolios with high jackpot probability. In fact, if anything, the poor performance of high predicted jackpot probability stocks looks worse after using these models. The alpha on the long-short portfolio increases to 1.39% for the CAPM, 1.39% for the Fama and French three-factor model, and 1.1% for the Carhart four-factor model. In each model, the alpha is highly significant. In Panel B of Table 4, we report the loadings on MKT (market), SMB (small minus big), HML (high minus low), and WML (winner minus loser) in the four-factor model for the ten jackpot portfolios. The variation in factor loadings across these portfolios is striking. The loading

[6] The rebalancing is due to changes in market variables such as size, volatility, and past annual returns, because the other accounting-based variables change only annually. We have similar results if we rebalance our portfolios annually (four-factor alpha for the '1–10' portfolio of 0.65% per month) or if we do not skip a month between measuring jackpot probability and returns (four-factor alpha for the '1–10' portfolio of 1.1% per month). These results are available upon request.

Table 4
Portfolios formed from a univariate sort on out-of-sample predicted jackpot probability.

This table presents statistics of portfolios formed from decile sorts on predicted jackpot probability (*JACKPOTP*). *JACKPOTP* is from out-of-sample, expanding window, logit regressions of our baseline model (Table 3). Panel A reports excess returns and alphas of these portfolios from Capital asset pricing model, Fama and French, and four -factor (Fama-French and momentum) regressions. Panel B presents portfolio loadings in the four factor regression, and Panel C presents the characteristics of these portfolios. The sample period is 1972 to 2009.

	1	2	3	4	5	6	7	8	9	10	1–10
Panel A: Four factor alphas (in % per month) of value-weighted portfolios sorted on JACKPOTP											
Excess return	0.44	0.52	0.54	0.61	0.53	0.56	0.45	0.24	0.03	−0.62	1.06
t-statistics	2.29	2.15	1.97	2.04	1.61	1.53	1.14	0.58	0.06	−1.29	2.63
CAPM alpha	0.07	0.05	0.02	0.06	−0.06	−0.08	−0.22	−0.44	−0.69	−1.32	1.39
t-statistics	1.31	0.84	0.21	0.48	−0.43	−0.44	−0.99	−1.84	−2.54	−4.11	3.84
Three-factor Alpha	0.09	0.07	0.03	0.05	−0.04	−0.01	−0.16	−0.40	−0.64	−1.30	1.39
t-Statistics	2.43	1.10	0.39	0.50	−0.41	−0.11	−1.28	−2.61	−3.64	−6.22	6.28
Four-factor Alpha	0.04	0.11	0.12	0.06	0.01	0.08	−0.06	−0.24	−0.45	−1.06	1.10
t-Statistics	0.98	1.80	1.67	0.65	0.16	0.82	−0.44	−1.37	−2.48	−5.01	4.85
Panel B: Factor Loadings in the four-factor Model											
Market	0.91	1.03	1.10	1.14	1.18	1.20	1.24	1.23	1.26	1.17	−0.26
t-Statistics	70.13	60.43	49.85	40.94	52.37	42.35	32.38	25.18	23.60	16.94	−3.54
SMB	−0.26	0.07	0.30	0.56	0.76	0.90	1.11	1.18	1.39	1.62	−1.88
t-Statistics	−18.40	2.83	6.90	13.61	21.84	19.50	23.42	18.68	12.68	13.20	−14.70
HML	0.04	−0.06	−0.12	−0.09	−0.23	−0.35	−0.37	−0.39	−0.45	−0.48	0.52
t-Statistics	1.30	−1.48	−3.50	−1.98	−5.76	−6.59	−6.08	−4.14	−4.13	−3.13	3.01
WML	0.05	−0.04	−0.09	−0.01	−0.05	−0.10	−0.10	−0.16	−0.18	−0.23	0.28
t-Statistics	2.76	−2.19	−4.74	−0.43	−1.82	−2.75	−1.78	−2.75	−2.51	−2.95	3.20
Panel C: Portfolio characteristics											
Portfolio standard deviation	4.79	4.65	4.91	4.86	5.26	5.74	6.36	6.96	8.28	9.86	7.47
Portfolio skew	−0.18	−0.15	−0.25	−0.25	−0.44	−0.41	−0.30	−0.30	0.13	0.70	−0.48

on MKT increases from Decile 1 to Decile 9 and then falls slightly in Decile 10. The SMB loading across the ten jackpot portfolios increases monotonically from −0.26 in Decile 1 to 1.62 in Decile 10, and the HML loading decreases from 0.04 to −0.48 going from lowest jackpot probability decile to highest jackpot probability decile. This is indicative of the prevalence of small and growth stocks in the deciles with high jackpot probabilities. High jackpot probability stocks are also likely to be loser stocks as they load negatively on the momentum factor WML.

The jackpot strategy (going long the least likely and short the most likely decile of *JACKPOTP*) has an annualized excess return of 12.71% and a standard deviation of 25.88%. The Sharpe ratio is 0.49, higher than the stock market (0.32) over the same time period and comparable to that of HML (0.49) and WML (0.55). The first eight deciles of jackpot-sorted portfolios have negatively skewed portfolio returns, while Deciles 9 and 10 have positive skewness of 0.13 and 0.70, respectively.

4.2. Institutional ownership

In the previous subsection, we present evidence that investors bid up the price of securities with a high probability of a jackpot payoff, consistent with a preference for skewness. BH suggest that individual investors are more likely than institutions to display a preference for stocks with lottery-like payoffs. Kumar (2009) finds that retail investors exhibit a preference for stocks with lottery-like features, while institutions do not. We, therefore, investigate the ownership structure of stocks sorted on the basis of *DEATHP* and *JACKPOTP*. Institutional ownership is defined as the fraction of shares owned by institutions in the Thomson Reuters Institutional Holdings database. Fig. 2 plots the median institutional ownership for the median firm and for the tenth deciles of *DEATHP* (Panel A) and *JACKPOTP* (Panel B). Consistent with prior research (e.g., Bennet, Sias, and Starks, 2003), Panel A shows that median institutional ownership has increased dramatically in the United States from 15% at the start of the sample in 1980 to 58% at the end of the sample in 2009. High *DEATHP* stocks have substantially less institutional ownership than the median stock for which *DEATHP* data are available, with their institutional ownership increasing from 3% at the start of the sample to 15% at the end. The difference between institutional ownership for the median stock for which *DEATHP* data are available and a high *DEATHP* stock has increased over time. A regression of this difference on a linear time-trend results in a significant coefficient on the time-trend of 0.68% per year (not tabulated). Thus, the increase of institutional ownership for the median stock has been more rapid than that for a stock in the highest *DEATHP* quintile. Similarly, Panel B shows that high *JACKPOTP* stocks also have lower institutional ownership than the median stock (for which data are available to compute *JACKPOTP*).[7] The difference in institutional ownership between the median firm and high *JACKPOTP* firms also increases significantly over time, with a coefficient of 1.05% per year.

[7] The median firm is defined differently in the two panels. In Panel A, we compute the median over all firms for which *DEATHP* is available, and in Panel B we do it for all firms for which *JACKPOTP* is calculated. Because CHS substitute cross-sectional means for any missing data items, and we do not include firms with missing data while computing *JACKPOTP*, *DEATHP* is available for more firms than *JACKPOTP*.

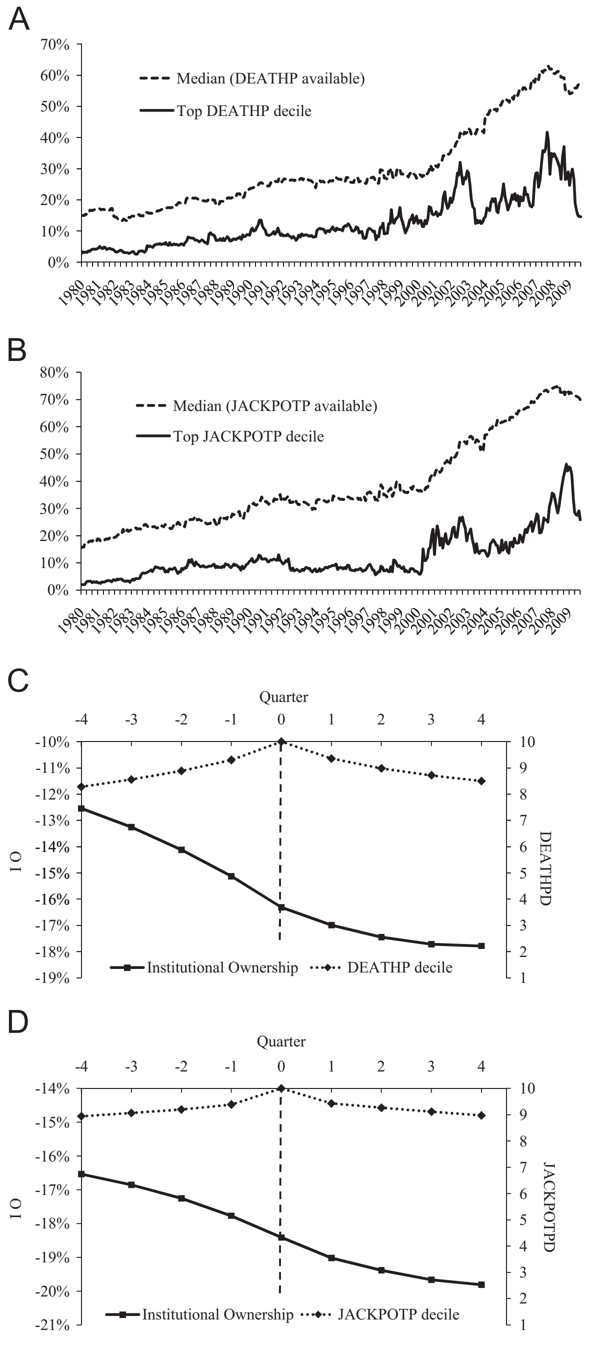

Fig. 2. Institutional ownership, default, and jackpot probability.
This figure plots institutional ownership for the top jackpot probabililty and default probability decile portfolios. Panel A reports median institutional ownership for the top *DEATHP* decile along with median institutional ownership for all firms with sufficient data available to compute *DEATHP*. Panel B reports median institutional ownership for the top JACKPOTP decile, along with median institutional ownership for all firms with sufficient data available to compute jackpot probability. Panels C and D report results for an event -study, in which the event is the entry of a firm into the top *DEATHP* (Panel C) or jackpot probability (Panel D). We present average excess institutional ownership of the firm over the mean institutional ownership that quarter (IO, left axis), for four quarters before and four quarters after entry into the top decile, along with the average *DEATHP* or *JACKPOT DECILE (*right axis). To ensure a comparable sample, we restrict the sample to those firms that have data for the four prior quarters.

We also find evidence that institutional ownership is sensitive to increases in default and jackpot probabilities. Panels C and D present results of an event-study in which the event is the entry of the firm into the top *DEATHP* (Panel C) or *JACKPOTP* (Panel D) quintile. We de-mean institutional ownership by subtracting the mean institutional ownership for all firms that month, and compute average demeaned institutional ownership for all firms in event time. Panel C shows that demeaned institutional ownership declines from −12.5%, four quarters prior to the entry into the top decile of *DEATHP*, to −16.3% at the quarter of entry into the top decile and declines further post-entry to −17.8% four quarters after entry into the top decile. Both changes (from Quarter −4 to Quarter 0 and from Quarter 0 to Quarter 4) are statistically significant with *p*-values from a test of equality of means of less than 0.01. Similarly, Panel D shows that de-meaned institutional ownership around entry into the highest *JACKPOTP* decile declines from −16.5% to −18.4% from Quarter −4 to Quarter 0 and further declines to −19.8% in Quarter 4. Again, both changes are statistically significant, with *p*-values of less than 0.01.[8]

Overall, this subsection shows that despite the increase in institutional ownership in the US stock market, stocks classified as high *DEATHP* or high *JACKPOTP* firms have a majority of stocks held by retail investors. Also, the increase in institutional ownership for such firms over time has been slower than that of the median firm. Finally, institutional ownership declines significantly four quarters prior and four quarters subsequent to entry into the top DEATH or JACKPOT decile. This suggests that retail investors (noninstitutions) are net buyers of such stocks as they approach default or become more likely to be jackpots. This evidence is consistent with implications from the BH model.

4.3. Limits to arbitrage and the jackpot effect

In the BH model, which is populated solely by investors with prospect theory utility functions, the high prices and low expected returns for jackpot assets are not arbitrage opportunities, because they are consistent with preferences in equilibrium. However, BH argue that in a more realistic setting, where both expected utility and prospect theory utility–based investors coexist, limits to arbitrage could result in expected utility investors being unable or unwilling to short-sell jackpot assets to exploit their low returns. We, therefore, test the hypothesis that the jackpot effect is stronger when limits to arbitrage are high, using three measures of limits to arbitrage: size, institutional ownership, and analyst coverage. Following CHS, for each limits to arbitrage variable, we first sort stocks into two groups, one with low and the other with high levels of the variable every month. Then, within each group, we form portfolios long the 20% of stocks with highest jackpot probability and short the bottom 20%. Each of these portfolios is value-weighted and skips a month between portfolio formation and measuring returns. Table 5

[8] The significant changes in institutional ownership in the four quarters prior to the entry of the firm into the top *DEATHP* or *JACKPOTP* decile is consistent with investors rebalancing based on exante estimates of default and jackpot payoff probabilities.

Table 5
The jackpot effect and limits to arbitrage.

This table presents evidence on the effects of limits to arbitrage on the low average returns of jackpot stocks. We consider three measures of limits to arbitrage: size, residual institutional ownership, and residual analyst coverage. We first classify stocks into two groups, based on the level of the limits to arbitrage variable, and then examine returns of the portfolio long the highest jackpot probability quintile and short the lowest jackpot probability quintile within each group. Both long and short portfolios are value-weighted. We present mean returns of this portfolio, Capital asset pricing model and four -factor alphas, and mean relative size of each group. We also present the difference in mean *JACKPOTP* between the lowest and highest quintile of *JACKPOTP* within each group. Small (big) stocks are smaller (larger) than the 30th (70th) NYSE size percentile. For institutional ownership and analyst coverage, we first measure the residual of each variable in a regression on *RELSIZE* and time dummies. 'Low' institutional ownership or analyst coverage stocks are in the smallest tercile, while 'High' stocks are in the largest tercile of their respective residual. Size results are for 1972 to 2009, and institutional ownership and analyst coverage are for 1980 to 2009. All portfolios are value-weighted and skip a month between portfolio formation and measuring returns.

	Size		Institutional ownership		Analyst coverage	
Decile	Small	Big	Low	High	Low	High
Mean Returns	−1.18	−0.05	−1.23	−0.33	−0.42	−0.37
t-Statistics	−3.95	−0.19	−2.76	−0.86	−0.90	−0.85
CAPM alpha	−1.44	−0.37	−1.70	−0.67	−0.86	−0.82
t-Statistics	−5.32	−1.48	−4.21	−1.89	−2.59	−2.09
Four-factor Alphas	−0.86	0.01	−1.19	−0.41	−0.54	−0.25
t-Statistics	−2.96	0.05	−4.45	−1.59	−1.52	−0.79
Mean *JACKPOTP* spread	3.8%	0.6%	2.4%	3.1%	2.2%	2.4%
Mean *RELSIZE*	−11.01	−6.83	−9.58	−9.61	−9.76	−9.22

presents mean returns, CAPM, and four-factor alphas for each of these long-short portfolios.

Our first variable is size. Small firms are defined as firms smaller than the NYSE 30% cut off, and large firms are larger than the NYSE 70% cut off. The jackpot effect is clearly strong in small firms and not present at all in large firms. The long-short portfolio has returns of −1.18% (*t*-statistic = −3.95) per month amongst small firms and average returns of −0.05% (*t*-statistic = −0.19) per month amongst large firms. Similarly, four-factor alphas are at −0.86% (*t*-statistic = −2.96) per month for small firms and at 0.01% (*t*-statistic = 0.05) per month for large firms.

Our next two variables, residual institutional ownership and residual analyst coverage explicitly control for size, so that results for these variables are not just restatements of the results for size (because raw values of these variables are highly correlated with size). To control for size, we follow CHS and compute residuals from a regression of each of these variables on *RELSIZE* and time dummies. We then sort residuals into terciles and examine the long-short jackpot portfolio within each tercile. Institutional ownership is the fraction of shares owned by institutions in each stock from the Thomson Reuters data set on Wharton Research Data Services (WRDS) and is available quarterly. It is particularly interesting to examine institutional ownership in the context of the jackpot effect. First, both the results of the preceding subsection and the evidence in Kumar (2009) indicate that individuals and institutions have different preferences for lottery-like stocks. Individuals display a strong preference for such stocks, and institutions are relatively averse to these securities. Second, institutional ownership is a commonly used proxy for the supply of lendable shares in the short-selling market (see, for example, Nagel, 2005). Because arbitragers must short stocks with high jackpot probabilities to take advantage of their abnormally low returns, a low supply of shortable shares is an important limit to arbitrage.

We find that the jackpot effect is much stronger in firms with low residual institutional ownership, with returns of the long-short portfolio of −1.23% (*t*-statistic = −2.76) per month versus −0.33% (*t*-statistic = −0.86) for the high residual institutional ownership subsample. Also, four-factor alphas of −1.19% (*t*-statistic = −4.45) for the low institutional ownership subsample are much larger in absolute magnitude than those of −0.41% (*t*-statistic = −1.59) for the high institutional ownership subsample. Also, the size control works. Both the low and the high residual institutional ownership samples have similar average size and spread in jackpot probability between the long-short portfolio in each institutional ownership groups. This shows that stocks with similar jackpot probability have very different average returns, depending on the level of limits to arbitrage.

We find broadly similar results, although with smaller magnitudes, for residual analyst coverage. Analyst coverage is the natural log of one plus the number of analysts that have issued an earnings forecast for the stock on the Institutional Brokers' Estimate Systems (I/B/E/S) data set within the last fiscal year. The jackpot effect is stronger for firms with low residual analyst coverage, with four-factor alphas equal to −0.54% per month (*t*-statistic = −1.52) as compared with −0.25% (*t*-statistic = −0.79) for firms with high residual analyst coverage. As with residual institutional ownership, both low and high analyst coverage firms have similar spreads in jackpot probabilities and average size.[9]

To summarize, these results demonstrate that the jackpot effect is concentrated amongst stocks with high limits to arbitrage. As a consequence, high limits to arbitrage could help explain why these pricing effects persist in the data.

[9] One possible reason that results using analyst coverage are not as strong as those for the other limits to arbitrage proxies is that small firms often have zero analyst coverage, leading to low dispersion in this measure among the set of firms in which we are interested.

Table 6
Firm characteristics.
This table presents average individual firm characteristics for portfolios sorted on predicted default probability according to the Campbell, Hilscher, and Szilagyi (2008) model in Panel A and for portfolios sorted on out-of-sample predicted jackpot probability in Panel B. The variables are defined in Appendix A. Realized jackpot is the average of the binary variable jackpot, that is one if log returns over the next 12 months are greater than 100%. The sample period is 1972–2009.

	Decile									
	1	2	3	4	5	6	7	8	9	10
Panel A: Individual stock characteristics of DEATHP sorted portfolios										
JACKPOTP	0.9%	0.9%	0.9%	1.0%	1.2%	1.3%	1.5%	1.8%	2.2%	3.4%
Realized jackpot	1.4%	1.4%	1.5%	1.5%	1.6%	1.6%	1.8%	2.0%	2.6%	3.9%
RET12	26.0%	21.6%	17.2%	13.2%	9.1%	4.7%	0.2%	−6.0%	−18.8%	−44.9%
SIZE	5.42	5.75	5.58	5.36	5.12	4.84	4.46	4.06	3.57	2.93
BM	0.62	0.59	0.66	0.72	0.79	0.85	0.92	0.99	1.11	1.27
SALESGRTH	14.2%	17.1%	17.9%	17.9%	18.0%	17.7%	17.6%	17.2%	16.7%	14.5%
MLEV	5.9%	11.0%	15.1%	18.6%	21.6%	24.4%	27.1%	30.1%	33.9%	39.4%
SKEW	0.32	0.24	0.22	0.21	0.20	0.19	0.20	0.20	0.18	0.16
Panel B: Individual stock characteristics of JACKPOTP sorted portfolios										
JACKPOTP	0.2%	0.4%	0.5%	0.7%	0.9%	1.1%	1.4%	1.8%	2.4%	4.6%
Realized jackpot	0.1%	0.3%	0.5%	0.8%	1.3%	1.8%	2.2%	2.7%	3.1%	3.6%
RET12	9.6%	9.9%	10.2%	10.2%	9.3%	7.4%	5.5%	2.5%	−3.6%	−16.5%
SIZE	8.10	6.89	6.19	5.62	5.14	4.73	4.35	3.98	3.56	2.94
BM	0.74	0.74	0.75	0.77	0.79	0.81	0.83	0.85	0.89	1.00
SALESGRTH	9.1%	11.1%	13.0%	14.5%	16.2%	17.7%	19.2%	21.1%	23.9%	27.1%
MLEV	25.9%	24.5%	23.1%	22.4%	22.2%	22.1%	21.8%	21.2%	20.9%	22.2%
SKEW	−0.01	0.04	0.08	0.13	0.17	0.20	0.24	0.28	0.33	0.43

4.4. Similarities and differences between high predicted jackpot probability and high predicted distress firms

Table 6 presents characteristics of firms that are in portfolios formed from sorts on *DEATHP*, the default probability measure in CHS, and those formed from sorts on *JACKPOTP*, our out-of-sample predicted jackpot measure. First, the fraction of firms in the top decile portfolio that subsequently realize a jackpot return is slightly higher (3.9%) for the highest *DEATHP* portfolio than for the highest *JACKPOTP* sorted one (3.6%). Second, as both *DEATHP* and *JACKPOTP* increase, size and past 12-month returns decrease and market-to-book ratios increase, although the magnitudes are different, especially for past 12-month returns. Third, *DEATHP* portfolios display no pattern in sales growth, increasing leverage, and declining skewness of daily log returns. *JACKPOTP* portfolios display very different patterns for these variables, with increasing sales growth, flat leverage, and increasing skewness. The skewness reported in this table is the skewness in daily log returns over the past three months, while the skewness reported in Table 1 is the skewness of returns over the next year. Also, although higher default risk portfolios display declining average skewness, there is dispersion in skewness within each portfolio. We show in Section 5.1.1 that the low returns of distressed stocks are present only for distressed stocks with high past skewness.

Fig. 3 shows that *DEATHP*- and *JACKPOTP*-sorted portfolios have similar patterns in factor loadings for MKT, WML, and SMB, but then have sharply different patterns for HML. Loadings on HML increase as *DEATHP* increases but decrease as *JACKPOTP* increases. This is surprising as both sets of portfolios have similar patterns in book-to-market ratios. This difference in loadings is related to differences in leverage. When we restrict stocks in the highest default probability portfolios to have smaller leverage, HML loadings decline (in untabulated results).

We return to these differences in characteristics in Section 5.1, where we use them to try to distinguish between distress and jackpots. In the next subsection, we examine whether the similarities described above result in significant correlations between the probability of default and the probability of jackpots, as well as whether returns on a trading strategy that exploits the jackpot effect are correlated with those of a strategy that exploits the default effect.

4.5. Relation between distress and jackpots

For jackpot returns to be a plausible explanation for the low returns of high distress stocks, exante measures of these two variables should be significantly correlated with each other. In this subsection, we investigate the relation between exante distress and jackpot probabilities. Table 7, Panel A, presents pair-wise Spearman correlations between predicted distress from the CHS model (*DEATHP*) and different measures of the out-of-sample probability of a jackpot return. *JACKPOTP*, the predicted probability of a jackpot return from our baseline model, has a correlation of 41.8% with the probability of distress. We also examine the alternate prediction models from Section 3.4 that use different variables and three additional models that use different cut offs in defining jackpots. For jackpot predictions from alternate models and other jackpot 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 a jackpot payoff.

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 jackpot effect. The distress strategy, *DEATHPLS*, is long stocks in the bottom

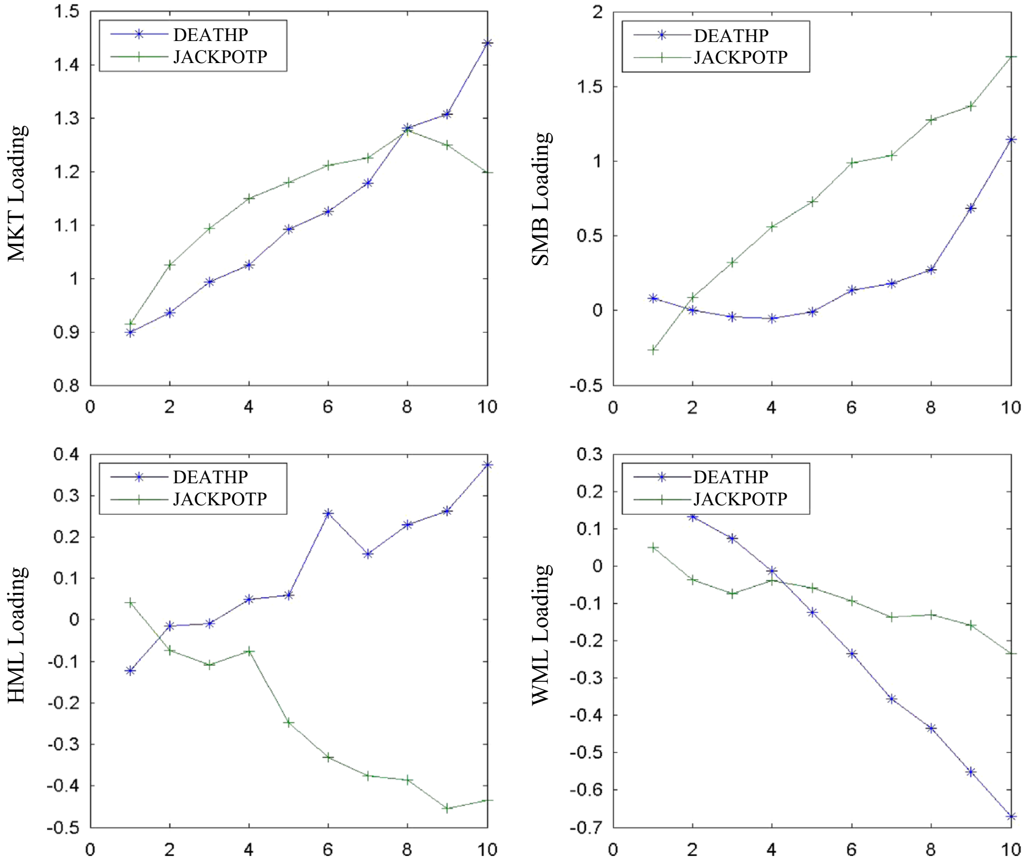

Fig. 3. Carhart four-factor regression loadings for distress and jackpot strategies.
This figure plots loadings on the factors in the Carhart four-factor model for both the ten default probability (*DEATHP*) sorted portfolios and the ten jackpot probability (*JACKPOTP*) sorted portfolios. The estimation period is from 1972 to 2009.

DEATHP decile and short stocks in the top *DEATHP* decile, while the jackpot strategy, JACKPOTLS, is long stocks in the bottom decile of *JACKPOTP* and short stocks in the top decile *JACKPOTP*. All portfolios are value-weighted. Going long the safest stocks or those least likely to achieve a jackpot return ensures positive average returns for both strategies.

In Panels B and C of Table 7, we examine the correlation in the returns of the jackpot and distress strategies, and compare their exposures to the four standard factors. The first specification in Panels B and C reports how returns of the two strategies co-vary with one another. The results indicate a strong relation, with 32.5% of the time series variation in the jackpot (distress) strategy return explained by the distress (jackpot) strategy return. In both specifications, the alpha estimates decline sharply and become statistically insignificant. For example, recall from Table 1 that the four-factor alpha of the distress strategy is 1.21% per month. The alpha when jackpot returns are included in the regression is 0.54% per month.[10]

In the right-hand column of Panels B and C, we include other risk factors (MKT, SMB, HML, and WML) in the analysis. Controlling for these risks leaves both the distress and the jackpot strategy with significant alphas, of 0.71%% and 0.81% per month, respectively. That is, both distress and jackpot strategies appear to be relatively low risk investments.

We do not interpret these regressions as a formal asset pricing model. Instead, these results indicate that a significant relation exists between distress and jackpot strategies. The returns of portfolios sorted on the probability of jackpot returns are correlated with those sorted on the probability of distress. Thus, a high probability of a jackpot return is a plausible explanation for the low average returns of stocks with high default probability although, as the factor loadings in Fig. 3 indicate, some differences exist between the strategies' risk profile. In Section 5, we use these differences in an attempt to disentangle the relation between jackpots and distress further.

[10] Chava and Purnanandam (2010) find that the distress effect shown in CHS is statistically significant only in the 1980s. 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 default. 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.

Table 7
The relation between returns of distress and jackpot strategies.

Panel A presents Spearman correlations between predicted jackpot probability (*JACKPOTP*) and predicted default probability (*DEATHP*). *JACKPOTP* is from the different models in Table 3, with different predictor variables (models 2 to 4) and different cut-offs used in defining jackpot (arithmetic returns of 50%, 75% and 100% over the subsequent year). Panel B presents time-series regressions of returns of the 'distress strategy' on different portfolios. The distress strategy, *DEATHLS*, 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, Hilscher, and Szilagyi (2008). Specification 1 regresses the distress strategy on *JACKPOTLS*. *JACKPOTLS* is a portfolio of stocks that is long the decile least likely to achieve jackpot returns and short the decile most likely to achieve jackpot returns, according to the baseline out-of-sample jackpot prediction model. Specification 2 uses the Four -actor model as well as returns to the jackpot strategy as explanatory variables. Panel B presents time-series regressions of returns of *JACKPOTLS* on different portfolios. The first specification regress *JACKPOTLS* on *DEATHLS*, and the next specification adds in the four factors. The sample period is 1972 to 2009.All portfolios are value-weighted and skip a month between portfolio formation and measuring returns.

Variable	Correlation			
Panel A: Spearman correlations with DEATHP				
JACKPOTP	41.80%			
JACKPOTP Model 2	39.54%			
JACKPOTP Model 3	39.26%			
JACKPOTP50	45.43%			
JACKPOTP75	45.26%			
JACKPOTP100	45.64%			
	(1)		(2)	
	Coefficient	*t*-Value	Coefficient	*t*-Value
Panel B: Explaining the returns of the distress strategy				
Intercept	0.54	1.47	0.71	2.69
MKTRF			−0.35	−5.06
SMB			−0.57	−3.45
HML			−0.38	−2.98
WML			0.79	6.68
JACKPOTLS	0.56	5.18	0.34	5.37
R^2	32.54%			66.18%
Panel C: Explaining the returns of the jackpot strategy				
Intercept	0.40	1.19	0.81	2.86
MKTRF			−0.03	−0.40
SMB			−1.14	−7.00
HML			0.60	3.96
WML			−0.07	−0.73
DEATHPLS	0.58	10.01	0.36	4.66
R^2	32.54%			65.21%

5. Relation between distress and jackpots effects on expected returns

This section investigates the relation between the effects of distress and jackpots on expected returns. In Section 5.1, we use firm characteristics, motivated by economic arguments, to construct subsamples of firms that have similar probabilities of distress but different probabilities of jackpots.[11] These allow us to investigate whether the effect of high default risk on returns is present when jackpots are relatively unlikely. In Section 5.2, we use Fama and MacBeth regressions to test whether one effect subsumes the other.

5.1. Interesting subsamples

We use the following characteristics: past return skewness, sales growth, and market-to-book ratio to construct subsamples in which although the level of default risk is high, the probability of jackpots is low. We have strong prior beliefs and empirical evidence (in Section 3) that these characteristics predict jackpot returns (but not defaults). For ease of comparison, all results in this section are for the sample in which both probabilities of distress and probabilities of jackpot returns can be computed.

5.1.1. Test 1: skewness

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. Portfolios are value-weighted, and we skip a month between portfolio formation and measuring returns. The difference in default probabilities between low-skewness and high-skewness firms is modest (2.28% versus 2.40%), with a relatively larger difference in jackpot probabilities across the low-skew and high-skew subsamples (1.20% versus 1.48%), as expected. Table 8 shows that amongst firms in the highest quintile of default probability, firms with skewness less than the 30th percentile for the full sample do not have abnormally low four-factor alphas (−0.21% per month). Instead, 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 −0.75% per month. The difference in subsequent returns between these two portfolios is statistically significant, with a four-factor alpha of 0.54% per month (and a *t*-statistic of 2.21) for the portfolio that is long the low skewness firms and short the high skewness firms amongst the subsample of firms with high default probability.

5.1.2. Test 2: sales growth and market-to-book ratio

We sort firms in the highest CHS predicted default probability quintile into traditional distressed firms and speculative firms. Traditional 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), and 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

[11] We attempt to create a subsample of firms with low default probabilities and varying jackpot probabilities to investigate whether the jackpot effect is concentrated in firms with high default probabilities. Specifically, in a previous version of the paper we report that in the subsample of firms with zero leverage, which might be associated with low default probabilities, the jackpot strategy provides significant returns (a four-factor alpha of 0.58% per month after skipping a month and 1.3% without skipping a month). Thus, the jackpot effect is present even for firms with no debt. This is not conclusive evidence, however, because firms with no leverage could have significant probabilities of economic distress. And, as stated previously, attempts to use double-sorting on jackpot and distress probabilities resulted in samples that were too small to draw reliable inferences.

Table 8
Distinguishing between the effects of distress and jackpot on expected returns.
This table presents results for firms in the top quintile portfolio of *DEATHP*, the predicted probability of default. We sort firms in the top predicted distress quintile based on their skewness in daily log returns over the past three months into two portfolios, high (greater than the 70th percentile) and low (smaller than the 30th percentile). We also sort firms into distress (the bottom 30% of all firms in terms of sales growth and bottom 30% in market-to-book or with negative book equity) and speculative (the top 30% of all firms in terms of sales growth and top 30% market-to-book) portfolios. We then compute value-weighted returns and four factor alphas for each portfolio, skipping a month between portfolio formation and measuring returns. We also report annualized mean *DEATHP* and mean *JACKPOTP*, the predicted probability of jackpots for each portfolio.

	Skewness			*Sales growth and Market to Book*		
	Low	High	Low-High	Distress	Speculative	Distress–speculative
Mean return	0.53%	0.06%	0.47%	0.87%	−0.9%	1.77%
Four factor alpha	−0.21%	−0.75%	0.54%	−0.14%	−1.70%	1.55%
t-Value	−1.18	−3.3	2.21	−0.55	−4.81	−3.68
Mean *DEATHP*	2.28%	2.40%		2.64%	2.28%	
Mean *JACKPOTP*	1.20%	1.48%		1.09%	1.97%	
Number of observations	277	223		169	53	

sets of portfolios with similar distress probabilities but different jackpot probabilities.

Panel B of Table 8 presents results for value-weighted portfolios of both traditional distressed firms and speculative firms. Within the quintile of the highest distress probability, on average, 169 stocks are traditional distressed firms and 53 stocks are categorized as speculative. The average annualized default probability for traditional distress stocks (2.64%) is, if anything, higher than that for speculative distress stocks (2.28%). However, traditional distressed firms do not earn abnormally low returns in subsequent periods and have a four-factor alpha of −0.14% that is not significantly different from zero. In sharp contrast, the speculative firms in the highest CHS default probability quintile have a four-factor alpha of −1.70% per month with a *t*-value of −4.81. Even though the average distress probability is similar between these two groups, the average probability of a jackpot return is much higher for the speculative stocks at 1.97% as compared with 1.09% for traditional distress stocks. Thus, the results in Panel B of Table 8 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 jackpot probability of traditional distressed firms.[12]

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 market-to-book 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 traditional distressed stocks. We also show that such speculative stocks have much larger probabilities of jackpot returns than traditional distressed stocks, providing an economic rationale for their high valuations. Overall, our results are consistent with the hypothesis that, holding the effect of distress risk constant in the sample, returns to stocks are significantly lower in stocks that have high jackpot probabilities.[13] The results suggest that, on average, it is not merely a high default probability that leads to investors bidding up the price of a security. The payoff distribution must have a significant probability of a relatively large positive outcome as well to become overpriced.

5.2. Fama and MacBeth regressions

Fama and MacBeth regressions allow us to test whether default or jackpot probabilities are important in predicting returns while controlling simultaneously for other variables (such as past volatility) that have been shown to affect expected return and are correlated with both these measures. For our Fama and MacBeth regressions, we standardize each explanatory variable to have a mean of zero and a standard deviation of 1 in every cross section, by subtracting the variable's cross-sectional mean and dividing by its cross-sectional standard deviation. This allows coefficients to be easily interpretable. Each coefficient measures the effect on returns of a 1 standard deviation shock to the explanatory variable. We also lag each explanatory variable by one month. Skipping a month between measuring the explanatory variable and returns allows us to control for microstructure-related effects such as bid-ask bounce.

In Table 9, 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*),

[12] The sorts on skewness, market-to-book, and sales growth do not inadvertently result in sorts on size and thereby replicate the results on limits-to-arbitrage presented earlier. The average size decile for firms high in *DEATHP*, but which have low and high skewness, are virtually identical (6.67 and 6.75), as are those for speculative and distressed portfolios (6.37 and 6.51) with high *DEATHP*.

[13] An earlier version of this paper also reported results for independent portfolio sorts on distress and jackpot probabilities. We find broadly similar results with these portfolios as those with Fama and MacBeth regressions and do not report them in this version for brevity. Also, because the extreme high distress and low jackpot probability, as well as the low distress and high jackpot probability, portfolios are sparsely populated, portfolio results are less reliable than the Fama and MacBeth results we report.

Table 9
Fama and MacBeth regressions.

This table presents results of monthly Fama and MacBeth regressions. Explanatory variables 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 jackpot (*JACKPOTP*), and predicted probability of default (*DEATHP*). All variables (except returns) are winsorized at their 5th and 95th percentiles. All explanatory variables are standardized in each cross section, to have mean zero and standard deviation 1. Therefore, the coefficients can be interpreted as the effect of a 1 standard deviation shock of the explanatory variable on expected returns. All explanatory variables are known as of month $t-2$, and returns on the left hand side are of month t. The sample is restricted to firm-months in which *JACKPOTP* and *DEATHP* are both available and the time period is 1972 to 2009.

Variable	(1)		(2)		(3)		(4)	
	Mean	*t*-Value	Mean	*t*-Value	Mean	*t*-Value	Mean	*t*-Value
Intercept	1.14%	3.93	1.12%	3.84	1.24%	4.16	1.19%	3.97
Log(BM)	0.29%	5.08	0.31%	5.64	0.26%	4.71	0.28%	5.24
Ret ($t-12$,$t-2$)	0.53%	5.82	0.38%	4.35	0.52%	5.78	0.37%	4.41
Log(Sigma)	−0.26%	−2.31	−0.10%	−0.84	−0.03%	−0.25	0.11%	0.97
Size	−0.18%	−2.42	−0.23%	−3.16	−0.38%	−5.24	−0.40%	−5.47
DEATHP			−0.42%	−8.09			−0.41%	−7.63
JACKPOTP					−0.37%	−4.96	−0.33%	−4.27

and log stock return volatility (*LOGSTDEV*). All variables are observed at the end of the previous month. All variables carry significant coefficients with the expected sign. Specifically, coefficients on *BM* (positive), *Ret*($t-12$, $t-2$) (positive), and size (negative) are consistent with stylized facts concerning value, momentum, and size effects. In Specification 2, we add predicted default probability, *DEATHP*, to these firm characteristics. The coefficient on *DEATHP* is −0.42% and is statistically significant. In Specification 3, we drop default probability and add jackpot probability, *JACKPOTP*. The coefficient on *JACKPOTP* at −0.37% per month is very close to that of *DEATHP* and is statistically significant. When both *JACKPOTP* and *DEATHP* are introduced into the Fama and MacBeth regression in Specification 4, the sign and magnitude of the coefficients on *JACKPOTP* and *DEATHP* are very similar to previous specifications. Also, volatility is not significant in the final specification. These results suggest that the results in Ang, Hodrick, Xing, and Zhang (2008), which show that idiosyncratic volatility is negatively related to future returns, is linked to the possibility of death and jackpot returns. These results are consistent with Boyer, Mitton, and Vorkink (2010) and Bali, Cakici, and Whitelaw (2011), who find that a potential for skewness or lottery-like payoffs explains the idiosyncratic volatility effect.

In unreported tests, we find that these results are robust to alternate transformations of variables. For example, using log default or jackpot probabilities, not standardizing variables, or not logging volatility produce similar results. Overall, this section shows that controlling for distress does not drive out the effect of jackpots on expected returns, and controlling for a high probability of a jackpot return does not drive out the effect of distress on expected returns. If anything, the Fama and MacBeth regressions suggest that both distress and jackpot probability have an impact on expected returns.[14]

6. Robustness tests

In Table 10, we examine the robustness of our results with the jackpot trading strategy. We report the jackpot strategy's performance with different specifications to

[14] The Fama and MacBeth cross-sectional regression results should be interpreted with some caution. Given the high correlation between the probability of distress and the probability of a jackpot return, which we observe in our sample, collinearity could affect these results. Related, measurement error in the predicted probabilities of distress and jackpot returns could make it difficult to distinguish between the two variables in Fama and MacBeth regressions. We investigate this possibility by performing a simulation exercise using Fama and MacBeth regressions with correlated independent variables in Appendix C. In our simulation, expected returns depend only on the probability of earning a jackpot return, but the probability of jackpots and death are correlated. In addition, the probabilities of jackpots and death are measured with error. When observed values of the probability of death and jackpot returns are used as explanatory variables in Fama and MacBeth regressions, we find that both are statistically significant, across a range of plausible values for measurement error and true correlation. These results suggest that, given the observed correlation between death and jackpot returns, the results of Fama and MacBeth regressions might not allow us to determine whether one variable is more important than another in driving the effect in returns.

forecast jackpot returns in each decade separately and with different cutoffs in the definition of a jackpot return. All portfolios formed continue to be value-weighted. For brevity, we report the alpha only from the Carhart (1997) four-factor model in this table.

In Panel A, we use the alternate specifications discussed in Section 3.4 to forecast the probability of a jackpot return. Specifically, in Model 2, we introduce nonlinearity in size by adding two indicator variables for size categories. We also add a dummy variable for Nasdaq firms. With this specification, we first reestimate the out-of-sample jackpot probability and then reconstruct the jackpot strategy. We skip a month before portfolio formation to avoid a short-term return reversal effect. The one minus ten portfolio return has an alpha of 0.87% per month with a t-statistic of 3.58. Model 3 includes exactly the same set of variables as in the CHS distress forecasting specification. Both Model 2 and Model 3 generate very similar jackpot strategy returns as our baseline model. There is a sharp drop in the four-factor alpha in Decile 10 for both models. Overall, regardless of the specification used, the jackpot strategy returns remain statistically and economically significant.

In Panel B of Table 10, we report results from our baseline model for different sub-periods. We divide our full sample into four sub-samples: 1972 to 1979, 1980 to 1989, 1990 to 1999, and 2000 to 2009. The jackpot strategy has the highest return in the 1980–1990 sub-period, with a four-factor alpha of 1.67%. Though smaller in magnitude, in other sub-samples, the jackpot strategy return remains strongly positive and significant at conventional levels in all sub-samples with the exception of 1990–1999 subsample, where the p-value on the estimated alpha of 0.89% per month is 0.08.

Next we examine whether the low average returns of stocks with a high probability of earning a jackpot return depend on how jackpot returns are defined. In our baseline model, jackpot returns are defined as log returns greater than 100% over the next 12-month period. In Panel C of Table 10, we use the same baseline model to forecast jackpots out-of-sample, with a jackpot return defined as an arithmetic return above 50%, 75%, or 100% over the next 12-month period. The results are very similar to Panel A in Table 3, where a jackpot return is defined as log return above 100%. The jackpot strategy alpha increases slightly when the cutoff return to be considered a jackpot increases. All strategies are highly significant.

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

7. 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 a large overlap exists 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), in which 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 (jackpot payoffs), using a logit model similar to the model in CHS, except that our dependent variable is one 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 jackpot returns do have low average subsequent returns. We show that stocks with high default and jackpot probabilities have relatively low institutional ownership, consistent with the hypothesis that these are largely owned by retail investors who are more likely to display a preference for total skewness. We also find that low average returns are concentrated in stocks with high limits to arbitrage, consistent with the hypothesis that these limits make it difficult for investors with expected utility preferences to arbitrage these low returns away. We also find that the predicted probability of a jackpot return is highly correlated with the probability of default from the model of CHS. Therefore, a high probability of a jackpot return is a plausible explanation for the results in CHS.

We run a set of tests to examine the relation between the effects of jackpot payoffs and default on expected stocks' returns. The returns of jackpot and distress strategy returns are significantly correlated with each other. We use different subsamples to attempt to disentangle these effects. First, we find that amongst stocks with high default probability, low average returns are present only 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. Second, we show that the low returns that CHS report are concentrated in speculative stocks with high sales growth and high market-to-book ratios and not in traditional distressed stocks with low sales growth and low market-to-book ratios. These results are consistent with the interpretation that it is skewness that leads investors to hold overpriced distressed stocks. We also use Fama and MacBeth regressions to control for variation in both distress and jackpot probabilities, as well as other variables such as volatility. We find evidence that default probabilities do not drive out the significance of jackpot probabilities in explaining subsequent returns. However, jackpot probabilities do not completely subsume the predictive power of default probabilities for subsequent returns.

Overall, our results suggest that a high probability of jackpot payoffs is responsible for at least a portion of the low average returns of stocks with high default probability, with investors bidding up the price of securities with high default probabilities if the securities offer a lottery-like payoff structure. In addition, the magnitude of the average abnormal return in jackpot securities varies with factors that are associated with the costs of arbitrage in these securities.

Appendix A. Definitions of key variables

Following are definitions of the key variables.

Table 10
Alternate specifications and sample periods for portfolios formed from sorts on predicted jackpot probability.

This table presents four-factor alphas of portfolios formed from alternate specifications (Panel A), time periods (Panel B), and different definitions of jackpots (Panel C). Panel A reports four-factor alphas of portfolios formed from out-of-sample predicted jackpot probability based on the two alternate models with different predictor variables defined in Table 3. Panel B examines alphas from our baseline model over different subsamples. Panel C reports alphas of portfolios formed based on out-of-sample predictions of jackpot probability with our baseline variables, with different definitions of jackpots (>50%, 75%, and 100% arithmetic returns over the next year). The sample period is 1972 to 2009.

Panel A: Different models to forecast JACKPOT

	1	2	3	4	5	6	7	8	9	10	1–10
Model 2	0.02	−0.02	0.12	0.24	−0.02	0.45	−0.13	−0.19	−0.57	−0.85	0.87
t-Statistics	0.23	−0.27	1.51	2.07	−0.15	2.96	−0.96	−1.16	−3.26	−4.25	3.58
Model 3	0.07	−0.02	0.10	−0.14	−0.01	0.10	−0.02	−0.14	−0.05	−0.62	0.68
t-Statistics	1.69	−0.39	1.51	−1.74	−0.07	0.75	−0.16	−0.88	−0.27	−2.76	2.83

Panel B: Sub-samples

	1	2	3	4	5	6	7	8	9	10	1–10
1972–1979	0.01	0.14	0.21	0.01	0.12	0.07	−0.15	−0.35	−0.32	−1.11	1.12
t-Statistics	0.09	1.38	1.57	0.06	0.70	0.40	−0.64	−1.53	−1.05	−4.60	4.38
1980–1989	0.06	0.10	0.10	0.10	0.07	0.05	−0.23	−0.30	−1.13	−1.61	1.67
t-Statistics	1.16	1.42	1.05	0.77	0.72	0.31	−1.79	−2.01	−6.72	−5.71	5.60
1990–1999	0.06	0.05	0.08	0.02	0.01	0.01	−0.25	−0.06	0.06	−0.83	0.89
t-Statistics	1.12	0.53	0.60	0.11	0.08	0.06	−1.17	−0.21	0.15	−1.82	1.82
2000–2009	0.09	0.13	0.08	0.17	−0.14	0.06	0.15	−0.45	−0.65	−1.14	1.23
t-Statistics	0.97	0.93	0.46	0.95	−0.78	0.23	0.50	−1.38	−1.87	−2.52	2.64

Panel C: Different definitions of JACKPOT

	1	2	3	4	5	6	7	8	9	10	1–10
JACKPOT as 50%	0.05	0.15	0.13	0.05	0.03	−0.08	−0.19	−0.39	−0.67	−1.07	1.12
t-Statistics	1.45	2.65	1.63	0.53	0.33	−0.76	−1.82	−3.31	−4.42	−5.02	5.05
JACKPOT as 75%	0.04	0.17	0.05	0.05	0.12	−0.06	−0.17	−0.30	−0.69	−1.03	1.08
t-Statistics	1.27	2.55	0.73	0.65	1.12	−0.55	−1.38	−1.93	−4.61	−4.68	4.63
JACKPOT as 100%	0.05	0.10	0.18	0.00	0.01	0.09	−0.12	−0.36	−0.62	−1.02	1.07
t-Statistics	1.33	1.65	2.71	0.02	0.11	0.72	−0.91	−2.17	−3.60	−4.45	4.40

Jackpot is one if firm has continuously compounded returns >100% over months $t+1$ to $t+12$ and zero 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.

JACKPOTP is predicted probability of jackpot return from out-of-sample regressions (specification as in Table 3, baseline model)

DEATHP is predicted probability of distress from the main model in Campbell, Hilscher, and Szilagyi (2008) (Table 4, 12-month lag, *p*. 2913). This is in-sample and computed based on quarterly Compustat data.

The next set of variables are used to predict jackpots in our main specification.

SKEW is skewness of log daily returns over the last three months, centered around zero.

RET12 is log return over the past year.

SALEG is sales growth in year *y* Ln ($Sales_y/Sales_{y-1}$).

AGE is time (in years) since appearance on CRSP.

TANG is gross PPE/total assets.

TURN is detrended stock turnover. Computed as in Chen, Hong, and Stein (2001), as average past six-month turnover minus average past 18-month turnover.

STDEV is standard deviation of daily returns over the past three months, centered around zero.

SIZE is log (market capitalization in thousands).

The following variables are used to predict jackpots in Model 3 and are defined in a similar manner as CHS (except we use annual instead of quarterly Compustat data).

ROMA is return on market assets = net profits/(market equity + total liabilities).

MLEV is (short-term debt + long-term debt)/(market equity + short term debt + long term debt).

RELSIZE is log (firm market cap/market cap of S&P 500).

CASH is cash/(market cap + book value of total liabilities).

PRC15 is log of stock price, truncated at $15.

EXRAVG is excess returns of the stock over the S&P 500 over the last 12 months with geometrically declining weights.

MB is market-to-book. Book value of equity is computed as in CHS, based on the procedure in Cohen, Polk, and Vuolteenaho (2003).

All accounting data are lagged by six months, to ensure they are known by investors.

Appendix B. The accuracy ratio

The accuracy ratio is used to assess the predictive ability of a model that ranks elements. It has been used extensively in the credit risk literature in assessing the performance of credit rating models (e.g., Vassalou and Xing, 2004).

Suppose that a model ranks firms according to a measure of predicted jackpot probability. There are N firms in total in our sample, and M of those realize a jackpot return in the next one year. Let $\theta = M/N$ be the percentage of firms that realize a jackpot return. For every integer λ between zero and one hundred, K_λ is the number of firms that realize a jackpot return within λ% of firms with the highest jackpot probability. K_λ cannot be more than M. $f(\lambda)$ is defined as K_λ/M. Then $f(\lambda)$ takes values between zero and one, and it is an increasing function of λ. Moreover, $f(0)=0$ and $f(100)=0$.

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

$$f(\lambda) = \frac{\lambda}{\theta} \quad \text{for } \lambda < \theta \tag{2}$$

and

$$f(\lambda) = 1 \quad \text{for } \lambda \geq \theta \tag{3}$$

The graph of average $f(\lambda)$ over all months in the sample for this perfect measure is shown as the kinked line in the right-hand-side panel of Fig. A1. At the other extreme, suppose we had zero information about future jackpot probability, and we were ranking the stocks randomly. If we did that a large number of times, $f(\lambda)$ would be equal to λ. The average $f(\lambda)$ would correspond to the 45 degree line in the graphs of Fig. A1.

We measure the amount of information in a model by how far the graph of the average $f(\lambda)$ for a given model lies above the 45 degree line. Specifically, we measure it by the area between the 45-degree line and the graph of average $f(\lambda)$. This is depicted as the area A in Fig. A1. The accuracy ratio of a model is then defined as the ratio between the area associated with that model's average $f(\lambda)$ function and the one associated with the perfect model's average $f(\lambda)$ function (area B in Fig. A1). Under this definition, the perfect model has accuracy ratio of one and the zero-information model has an accuracy ratio of zero.

Appendix C. Correlated independent variables in Fama and MacBeth regressions

We simulate the cross section of returns to understand the impact of adding correlated variables into Fama and Macbeth specifications. We consider two correlated variables: the probability of default (*DEATHP)* and the probability of jackpot returns (*JACKPOTP)*. Expected returns are related to *JACKPOTP* but not to *DEATHP*. Both *DEATHP* and *JACKPOTP* are measured with error, and these observed values are used as explanatory variables in Fama and Macbeth regressions. We present results for calibrations with different degrees of correlation between *DEATHP* and *JACKPOTP* and different degrees of measurement error.

The specification is as follows

1. True *DEATHP* and *JACKPOTP* are bivariate normal with unit variance and correlation (or covariance) ρ:

$$\begin{pmatrix} DEATHP_{i,t} \\ JACKPOTP_{i,t} \end{pmatrix} \sim N\begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$$

2. These are both observed with error:

$$\widehat{DEATHP}_{i,t} = DEATHP_{i,t} + u_{i,t}$$

and

$$\widehat{JACKPOTP} = JACKPOTP_{i,t} + v_{i,t}$$

where $u_{i,t} \sim N(0, \sigma_u^2)$ and $v_{i,t} \sim N(0, \sigma_v^2)$ are measurement errors in *DEATHP* and *JACKPOTP*, respectively.

3. The data generating process for returns is

$$r_{i,t} = r_{m,t} + \lambda_t JACKPOTP_{i,t} + \varepsilon_{i,t},$$

and $r_{m,t} \sim N(0.01,\ 0.057735)$ is the monthly return on the average stock, with standard deviation chosen to be 20% per year.

$\varepsilon_{i,t} \sim N(0,\ \sigma^2_{ivol,i,t})$ is an idiosyncratic shock, whose log variance is distributed normally across firms, with parameters calibrated to data (mean $=-4.17$ and variance $=1.38$).

$\lambda_t \sim N(\mu_\lambda,\ \sigma_\lambda^2)$ is a time-varying premium for *JACKPOTP*.

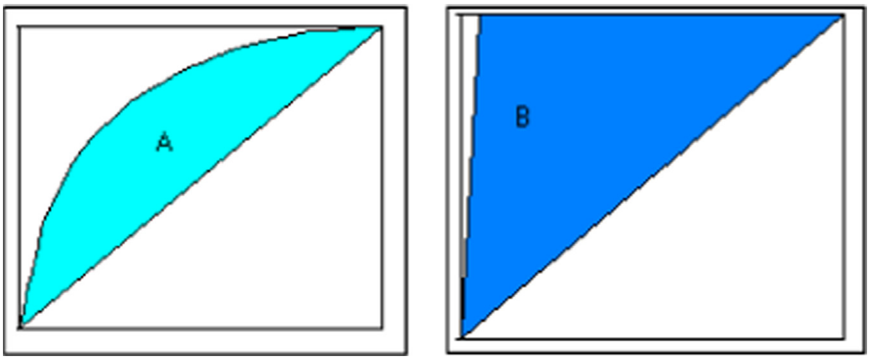

Fig. A1. Illustrating the accuracy ratio.

Table A1
The impact of correlated variables on Fama and Macbeth regressions.

This table presents simulations of Fama and Macbeth regressions with correlated independent variables measured with error. The simulations are described in Appendix C and are run for different values for measurement error in death (σ_u=0.1, 0.3, 0.5, and 0.7) and the true correlation between jackpot probability and default probability (ρ=0.5, 0.6, 0.7, and 0.8). Panel A reports average coefficients across five hundred simulations for a regression with both observed jackpot probability (Jackpothat) and observed default probability (Deathhat). Panel B has only Jackpothat and Panel C has only Deathhat. All three panels include an intercept. Panel D reports measurement error in JACKPOTP that is used in each simulation. This is backed out from the measurement error in DEATHP and true correlation so that the observed correlation between Deathhat and Jackpothat is 0.4.

	Intercept	Jackpothat	Deathhat	Intercept	Jackpothat	Deathhat	Intercept	Jackpothat	Deathhat	Intercept	Jackpothat	Deathhat
	σ_u=0.1			σ_u=0.3			σ_u=0.5			σ_u=0.7		
Panel A: Specification with intercept, Jackpothat and deathhat												
ρ=0.5												
Coefficient	0.99%	−0.57%	−0.17%	1.00%	−0.61%	−0.14%	1.00%	−0.68%	−0.09%	1.00%	−0.77%	−0.02%
t-Statistics	3.82	−5.44	−5.03	3.86	−5.48	−4.84	3.86	−5.56	−4.21	3.85	−5.50	−1.27
ρ=0.6												
Coefficient	1.00%	−0.40%	−0.31%	1.00%	−0.44%	−0.28%	1.02%	−0.51%	−0.23%	1.00%	−0.58%	0.16%
t-Statistics	3.85	−5.36	−5.31	3.86	−5.42	−5.35	3.92	−5.50	−5.29	3.86	−5.41	−4.93
ρ=0.7												
Coefficient	1.00%	−0.28%	−0.45%	1.00%	−0.31%	−0.41%	1.00%	−0.37%	−0.35%	1.02%	−0.45%	−0.28%
t-Statistics	3.85	−5.34	−5.48	3.84	−5.42	−5.46	3.83	−5.37	−5.35	3.92	−5.48	−5.37
ρ=0.8												
Coefficient	1.02%	−0.18%	−0.57%	1.03%	−0.20%	−0.53%	0.98%	−0.26%	−0.46%	1.00%	−0.33%	−0.39%
t-Statistics	3.92	−5.16	−5.53	3.95	−5.14	−5.45	3.80	−5.29	−5.41	3.84	−5.43	−5.45
Panel B: Specification with intercept and Jackpothat												
ρ=0.5												
Coefficient	0.99%	−0.63%		1.00%	−0.66%		1.00%	−0.72%		1.00%	−0.78%	
t-Statistics	3.82	−5.46		3.85	−5.49		3.86	−5.57		3.85	−5.50	
ρ=0.6												
Coefficient	1.00%	−0.53%		1.00%	−0.55%		1.02%	−0.60%		1.00%	−0.64%	
t-Statistics	3.85	−5.41		3.86	−5.46		3.92	−5.52		3.85	−5.43	
ρ=0.7												
Coefficient	1.00%	−0.46%		1.00%	−0.48%		1.00%	−0.50%		1.02%	−0.56%	
t-Statistics	3.85	−5.48		3.84	−5.51		3.83	−5.43		3.92	−5.52	
ρ=0.8												
Coefficient	1.02%	−0.41%		1.03%	−0.41%		0.98%	−0.44%		1.00%	−0.49%	
t-Statistics	3.92	−5.52		3.95	−5.42		3.80	−5.43		3.84	−5.51	
Panel C: Specification with intercept and deathhat												
ρ=0.5												
Coefficient	0.99%		−0.39%	1.00%		−0.38%	1.00%		−0.36%	0.99%		−0.35%
t-Statistics	3.82		−5.42	3.86		−5.43	3.86		−5.49	3.86		−5.40
ρ=0.6												
Coefficient	1.00%		−0.47%	1.00%		−0.46%	1.02%		−0.43%	1.00%		−0.39%
t-Statistics	3.92		−5.49	3.86		−5.46	3.85		−5.40	3.85		−5.38
ρ=0.7												
Coefficient	1.00%		−0.56%	1.00%		−0.54%	1.00%		−0.49%	1.02%		−0.46%
t-Statistics	3.83		−5.42	3.84		−5.51	3.85		−5.51	3.92		−5.50
ρ=0.8												
Coefficient	1.02%		−0.64%	1.03%		−0.61%	0.98%		−0.57%	1.00%		−0.52%
t-Statistics	3.80		−5.45	3.95		−5.47	3.92		−5.55	3.84		−5.51

***Panel D:** Measurement error for Jackpot (σ_v)*

ρ	σ_u=0.1	σ_u=0.3	σ_u=0.5	σ_u=0.7
0.5	0.74	0.66	0.50	0.22
0.6	1.11	1.10	0.89	0.71
0.7	1.43	1.35	1.20	1.03
0.8	1.72	1.63	1.48	1.30

We use this data generating process to simulate a panel of returns with two thousand firms and T=400 months. For each panel we run Fama and Macbeth regressions of returns on observed *DEATHP* and observed *JACKPOTP*. We report statistics over five hundred such simulations.

Although we have several free parameters, these are restricted by observed data.

1. We tune μ_λ, σ_λ^2 such that we match mean coefficients and *t*-statistics observed in the data in Fama and MacBeth regressions of returns on *JACKPOTP* (approximately −0.5 for the mean and −5 for the *t*-statistic).
2. Because we can observe r_m, we use the average measured variance of market returns. It is comforting that the *t*-statistics for the intercept in our calibration are reasonably close to the data.

3. We have three free parameters left: ρ, the true correlation between *DEATHP* and *JACKPOTP*, and σ_u and σ_v, the standard deviations of measurement errors in *DEATHP* and *JACKPOTP*, respectively. However, the measured correlation between *DEATHP* and *JACKPOTP* ties down one degree of freedom for these three. Therefore, we present results for a range of true ρ and true σ_u and back out the value of σ_v that gives a measured correlation between *DEATHP* and *JACKPOTP* of 0.4. Also, given the lower R^2s in predicting jackpot returns as compared with those in predicting default in the data, the measurement error in *JACKPOTP* likely is greater than that in *DEATHP*.

Table A1 reports results of these simulations for σ_u taking on values 0.1, 0.3, 0.5, and 0.7 and ρ taking values 0.5, 0.6, 0.7, and 0.8. We report three specifications: returns on both *DEATHP* and *JACKPOTP*, on only *DEATHP*, and on only *JACKPOTP*. All specifications include a constant as well.

The table shows that parameter values exist for which a high correlation between *DEATHP* and *JACKPOTP*, coupled with measurement error, results in significant *t*-statistics for both variables in Fama and MacBeth regressions. In many specifications (particularly those with higher measurement error for *JACKPOTP* than for *DEATHP*), the magnitudes of the coefficients for both *DEATHP* and *JACKPOTP* are roughly similar. Thus, Fama and MacBeth regressions might not have sufficient power to distinguish between the effects of jackpot probability and default probability on expected returns.

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