경영학석사학위논문

Why Do Individual Investors Hold Overpriced Stocks? Evidence from Korean market

무엇이 개인투자자들이 고평가된 주식들을 보유하게 하는가? 한국 주식시장 데이터를 통한 분석

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이 논문을 경영학 석사학위논문으로 제출함

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윤석인의 석사학위논문을 인준함

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Abstract

Why Do Individual Investors Hold Overpriced Stocks? :Evidence from Korean market

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Campbell, Hilscher, and Szilagyi(2008) reports that firms with a high probability of default risk earn low subsequent returns. This result turns out to be puzzling. Then, Conrad, Kapadia, and Xing(2014, henceforth; CKX) find that stocks with a high probability of default tend to generate extremely high returns (over 100%) over the next year. A feature that those stocks possessing lottery-like (extremely positive skewed) payoffs allow investors to desire to hold them, leading to high valuation and low exante returns.

This paper examines whether distress risk puzzle is also present in Korean market by following methodologies from CHS and CKX. I find that a high probability of jackpot returns have low average future returns in Korean market. Also, there exists a strong correlation between the predicted probability of a jackpot return and the probability of default from the CHS model within Korean market, along with a high correlation between returns of a jackpot and distress strategy.

Therefore, I can conclude that a high probability of jackpot payoffs is a plausible explanation for at least a portion of the low average future returns of stocks with a high probability of default. Also, this explanation can be applied to distress risk puzzle present in Korea.

Key words: distress risk puzzle, skewness.
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Ⅰ. Introduction

Conrad, Kapadia, and Xing (2014; henceforth CKX) show that a high likelihood of jackpot payoffs (over 100% over the next year) have low subsequent returns. Investors bid up the price of securities if the securities offer a lottery-like payoff framework. Investors with prospect theory based utility functions desire positively skewed securities, leading to over-valuation and negative average exante excess returns. As shown by Boyer, Mitton, and Vorkink (2010), Bali, Cakici, and Whitelaw (2011), Conrad, Dittmar, and Ghysels (2013), and others, positive skewness or a high probability of extremely positive outcomes (jackpots) have low subsequent returns.

Campbell, Hilscher, and Silagyi (2008; CHS) show securities with a high probability of default have low subsequent future returns. The result is inexplicable if the direction of the effect that risk has on average returns is considered. Fama and French (1996) claim that distress risk holds a positive risk premium. Also, Vassalou and Xing (2004), and Kapadia (2011) assert that distress risk results in positive expected returns. One possible explanation, suggested by CHS, is that individual securities with high default probabilities, as well as portfolios derived from distressed stocks, possess positive skewness. It infers investors who strongly prefer positive skewness could bid up the prices of securities, resulting in low average future returns.

Chava and Purnanandam (2010), George and Hwang (2010), and Garlappi and Yan (2011) explain the results of CHS. Their recent explanations comprise small-sample effects, the cost of financial distress, and differences in creditor protection system, in particular, shareholder recovery. They assert that those factors are respectively in charge of low subsequent returns of high default probability stocks. However, Gao, Parsons, and Shen (2012) respectively discover that the distress effect still remains within a sample of 39 countries and is not related to the matter of creditor protection.

CKX show the probability of jackpot returns propels the default risk effect, by examining the link between default probability and the probability of earing jackpot returns. This paper examines; 1) Korean firms with a high probability of default risk also possess similar features of high probability default firms in US stock market 2) whether a high probability of jackpot payoffs calibrated with Korean market data also shows low subsequent average returns of securities of Korean firms with a high default probability.

My paper is arranged as follows. Section 2 displays that high default probability stocks have lottery-like payoffs. Section 3 outlines the model for estimating the probability of a jackpot payoff, a logit model. In section4, I examine whether a possibility for a jackpot return can explain the low average return of stock. Section 5 implements further robustness check. I infer the conclusion in section 6.

2. Motivation

In this section, I examines the relation between default probability and the possibility of earning jackpot returns. The surmise CKX embeded is that the probability of jackpot returns incur the default risk effect. To test, I scrutinize by examining whether sorts on default probability also result in sorting on jackpot returns.

The first operation is to construct a measure of default probability (DEATHP) of each stock from the model from CHS (Table 4, 12-month lag, p.2913). I follow procedures described in CHS, requiring monthly data from 1987 and 1997. I sort stocks into deciles based on DEATHP. Table 1 shows the characteristics of decile portfolios based on DEATHP. I skip a month between computing DEATHP and measuring returns to assure that the results are not impelled by short-term reversals. 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 be default decile is about -1% per month for both returns and four factor alphas. Therefore, stocks with a high default probability seem unattractive to investors. A attractive feature is that these stocks also have high probabilities for earning jackpot returns. For example, the fraction of stocks in the safest portfolio that has log returns greater than 100% over the next year is 1.7%. This fraction almost triples to 4.8% for the portfolio with the highest default probability. The average skewness of daily returs in the safest portfolio decile over the next year is 0.76, and the one observed in the portfolio with the highest default probability increases to 1.40.

Table 1

Motivation.

This table shows results for portfolios formed from sorts on DEATHP, the probability of default from the model in Campbell, Hilscher, and Sizlagyi (2008). Portfolios are value weighted and formed monthly. A month between portfolio formation and measuring returns. The table 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 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. The sample period is 1998-2013.

Key statistics of DEATH sorted portfolios											
	1	2	3	4	5	6	7	8	9	10	1-10
Excess return	1.52	1.47	1.49	1.45	1.36	0.53	0.37	0.42	0.04	-0.71	0.92
t-statistics	2.73	2.70	2.32	1.67	1.25	1.09	1.21	0.79	0.01	-0.12	2.79
Four-factor alpha	0.19	0.01	0.21	0.03	-0.57	0.03	0.04	-0.13	-0.23	-1.31	1.51
t-statistics	1.20	0.0	1.83	0.34	-1.37	2.12	1..73	-1.56	-0.55	-3.39	3.29
Logreturns > 100%	1.7%	1,7%	1.9%	1.9%	2.1%	2.0%	2.0%	2.3%	2.5%	4.8%	-2.4%
Arithmetic returns > 100%	4.2%	4.3%	4.2%	4.8%	5.0%	5.1%	5.3%	6.2%	8.1%	8.9%	-4.5%
Arithmetic returns > 75%	9.1%	9.1%	9.1%	9.2%	9.1%	8.9%	9.0%	11.2%	-12,0 %	14.5%	-5.1%
Skewness (t+1, t+12)	0.76	0.79	0.81	0.86	0.88	0.92	0.94	1.03	1.36	1.40	-0.64

3. A logit model for jackpot returns

The model to forecast the exante probability of jackpot returns comes from CHS. In this section, I examine whether a correlation between jackpot and distress provides an explanation of why individual investors hold these stocks. Section 3.1 defines jackpot returns and describes the model to predict the future likelihood of exante jackpot payoffs. Section 3.2 examines key determinants of jackpot probabilities. Section 3.3 analyzes the out of sample forecasting power of the model.

3.1 Definition of jackpots and a logit model

I define jackpot returns as log returns greater than 100% over the next 12 months. I model the probability of a firm achieving a jackpot return in the next year as a continuous probability distribution given by

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

where $Jackpot_{i,t,t+12}$ is a dummy variable that equals one if the firm's log return in the next year 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 $a+b^{*}X_{I,t-1}$ refers the likelihood of achieving a jackpot return in the next 12 moths is higher. For each firm, I first estimate the parameters of a logit model using 10 years of historical data (1987-1997) and then construct out-of-sample estimates of jackpot probabilities. I reestimate this model once a year (in June) to avoid overlapping returns. I use variables utilized by Chen, Hong, and Stein (2001); Campbell, Hilscher, and Silagyi (2008); Boyer, Mitton, and Vorkink (2010) to predict jackpot returns. Variables are described as follow: the stock's (log) return over the

Table 2

Summary statistics

This table provides summary statistics for key variables used in this paper. These variables are described in Appendix A. Panel A shows statistics for all firm months when data are available for all variable. Panel B informs 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 1987-2013.

	SKEW	RET12	AGE	TANG	SALESGRTH	TURN	STDEV	SIZE
Panel A: Summary statistics for key variables								
Mean	2.781	0.200	20.658	0.292	0.069	0.00017	3.607	10.911
Standard deviation	0.917	0.795	11.154	0.195	0.482	0.021	2.068	1.572
Minimum	-7.950	-7.635	0.500	0.000	-7.387	-0.486	0.000	1.792
Maximum	8.150	16.025	57.750	0.995	12.780	0.757	394.377	19.334
Number of observation	324564							
Panel B. Summary statistics for jackpot subsample								
Mean	2.912	0.038	20.265	0.309	0.045	0.00097	4.537	9.878
Standard deviation	1.097	1.175	10.234	0.202	0.497	0.020	2.048	1.460
Minimum	-6.981	-3.189	0.500	0.000	-4.118	-0.151	0.000	3.638
Maximum	7.781	13.330	57.750	0.981	5.518	0.349	10.418	16.831
Number of observation	2539							

last year (RET12), volatility (STDEV) and skewness (SKEW) of daily returns over the past three months, detrended stock turnover((TURN:(six-month volume/shares outstanding) minus (19-month volume/shares outstanding)), and size(SIZE: log market capitalization), asset tangibility (TANG:gross property plant and equipment (PPE)/total assets), and sales growth (SALESGRTH) over the prior year. Appendix A offers further details on the construction of these variables. All variables are winsorized at 5% and 95%, following CHS. Variables that I use to predict a jackpot return are constructed from DataGuide. All securities either listed in Kosdaq or Kospi are included. Beginning my sample construction in 1987 enables me to have 10 years of data to estimate my first set of out-of-sample jackpot probabilities in 1998. In the CKX, they use a 20 year data span. However, it is not possible in Korean stock market due to the restriction in collecting data. Therefore, I use a 10 year data, which is the best and longest data span within accessible data access with accuracy. I afterwards can expand the data span to 20 years for better estimation.

Panel A of table 2 offers summery statistics for these variables over the 1987-2013 sample period. Panel B peruses these variables for firms that subsequently realized jackpot returns over the next year. Jackpot firms are likely to be smaller, younger, and more volatile and have lower prior returns than firms on overage.

3.2 What predicts jackpot returns?

Table 3 reports results from the model to predict jackpot returns. SKEW, SALESGRTH, STDEV, and SIZE are statistically significant. Stocks with higher past skewness, higher sales growth rate, and higher volatility and smaller size are associated with a higher likelihood for jackpots. Percent change in the odds ratio for 1 standard deviation change in the independent variable. The odd ratio is calculated by

Table 3

In-sample predictions 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 1987 to 2013.

Variable	Coefficient	t-Statistic	Percent change in odds ratio for a 1 δ change in X	R2
Intercept	-2.175	-10.72		16.42%
SKEW	0.195	4.69	19.58	
RET12	-0.313	-2.68	-22.04	
AGE	0.002	0.85	2.70	
TANG	0.073	0.81	1.43	
SALESGRTH	0.170	12.80	8.52	
TURN	2.166	0.61	4.58	
STDEV	0.273	5.32	75.97	
SIZE	-0.509	-31.38	-55.06	

$$\ln \frac{\Pr(a\,jackpot\,return)}{\Pr(ahceiving\,a\,jackpot\,return)} \qquad (2)$$

It is the log of the ratio of the probability of a jackpot return divided by the probability of not achieving a jackpot return. For all variables, SIZE, STDEV, and SKEW have the largest impact on the odds ratio of the logistic regression. A 1 standard deviation increase in firm size reduces the odds ratio for jackpots by 55.06%, a 1 standard deviation increase in STDEV increases the odds ratio by 75.97%, and a 1 standard deviation increase in SKEW increases the odds ratio by 19.58%.

3.3 Predictive power

The logit model obtains 16.42% of a pseudo R-square. It is relatively low because extreme events are hard to predict. Therefore, I test whether the low R-square generates reliable measures of jackpot returns out-of-sample. Beginning from 1987, I use all available data (expanding annual rolling windows) to reestimate the model and then create out-of-sample forecasts for the probability of jackpot returns with each set of estimated parameters. The first out-of-sample forecast is estimated 1998, and the last out-of-sample prediction is calculated in 2013. To reckon the effectiveness of the out-of-sample predictability, the accuracy ratio from Vassalou and Xing (2004) are used. The accuracy ratio displays the capability of a model to forecast actual jackpot returns over a one-year horizon. The perfect model yields 100%of an accuracy ratio, and extremely uninformative model yields 0% of an accuracy ration. The out-of-sample forecasted jackpot likelihood from the model has an accuracy ratio of 72.39% in predicting realized jackpot returns. Particularly, 59% of stocks that realized an future jackpot returns are in the top 1% of future forecasted jackpot probability. 65% of stocks that realize a jackpot return are in the top 10% of forecasted jackpot.

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

In section 4, I test whether a high probability of achieving jackpot returns can explain the low subsequent average returns of high distress risk stocks. To do so, section 4.1 examines whether stocks with a high likelihood of jackpot returns have the low average returns. Section 4.2 compares both characteristics and factor loadings of distress-sorted portfolios and predicted jackpot sorted portfolios. In section 4.3, I analyze the correlation between the probability of jackpots and the probability of distress and examine how the distress strategy and jackpot strategy are correlated to each other.

4.1 Average returns for strategies based on predicted jackpot probability

I examine whether trading strategies based on the probability of jackpot returns create comparable patterns of returns to those based on CHS default potentiality. At moment t, I use the out-of-sample forecasted jackpot likelihood computed using available information to sort all stocks into ten deciles and compute value-weighted portfolio returns for month t+2. I skip a month between portfolio formation and measuring returns to reduce apprehension regarding to the possibly confounding microstructure effects such as bid-ask bound. Portfolios are rebalanced every each month. Out-of-sample forecasted jackpot feasibility measures starts in 1998, allowing at least 10 years of data for the initial estimation.

Table 4 provides the results from tests on value-weighted decile portfolios formed from sorts on out-of-sample forecasted jackpot probability. Panel A reports average excess returns over the risk-free rate for these portfolios as well as the alphas calculated 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. The sharp drop in excess returns comes in Decile 10 (-.67% 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 1.82% per month.

Turning to risk-adjusted returns, I find that conrolling for risk using 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. The alpha on the long-short portfolio increases to 1.97% for the CAPM, 2.77% for Fama and French three-factor model, and 2.60% for Carhart four-factor model. The alpha of each model is significant. Panel B, I show the lodaings on MKT (market), SMB (small minus big), HML (high minus low), and WML (winner minus losers) in the four-factor model for the ten jackpot portfolios. The SMB loading across the ten jackpot portfolios increases monotonically from -.06 in Decile 1 to 1.33 in Decile 10. High jackpot probability stocks also tend to be loser stocks as they load negatively on the momentum factor WML. The fist seven deciles of jackpot-sorted portfolios have negatively skewed portfolio returns, whileas Decile 8, 9 and 10 have respectively positive skewness of 0.15, 0.52 and 1.93.

Table 4

Portfolios formed a sort on out-of-sample predicted jackpot probability. This table shows statistics of portfolios formed from decile sorts on predicted jackpot probability (JACKPOTP), from out-of-sample, expanding window, logit regressions of the model. Panel A shows excess returns and alphas of these portfolios from Capita asset pricing model, Fama and French, and four-factor (Fama-French and momentum) regressions. Panel B portfolio loadings in the four factor regressions, and Panel C shows the characteristics of these portfolios. The sample period is 1998 to 2013.

	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	1.30	1.46	1.03	1.07	0.69	0.53	0.33	0.40	1.01	-0.67	1.82
t-Statistics	2.22	2.13	1.51	1.40	0.78	0.67	0.42	0.49	1.14	-1.58	2.63
CAPM alpha	0.18	0.14	-0.32	-0.15	-0.70	-0.63	-0.86	-0.73	-0.15	-1.64	1.97
t-Statistics	1.23	0.39	-0.83	-0.34	-1.31	-1.17	-1.64	-1.23	-0.22	-1.55	2.49
Three-factor Alpha	0.35	-0.13	-0.50	-0.57	-1.04	-0.82	-0.95	-1.01	-0.63	-2.58	2.77
t-Statistics	2.53	-0.38	-1.39	-1.56	-2.15	-1.80	-2.47	-2.82	-1.41	-3.37	3.42
Four-factor Alpha	0.36	-0.17	-0.58	-0.56	-0.91	-0.72	-0.95	-1.02	-0.42	-2.39	2.60
t-Statistics	2.60	-0.51	-1.62	-1.53	-1.92	-1.60	-2.44	-2.80	-1.01	-3.17	3.24
Panel B: Factor Loadings in the four-factor Model											
Market	0.93	1.17	1.20	1.13	1.28	1.10	1.14	1.14	1.19	1.11	-0.18
t-Statistics	54.93	28.90	27.34	25.01	22.00	19.70	23.95	25.41	23.32	11.94	-1.80
SMB	-0.06	0.26	0.32	0.49	0.44	0.56	0.69	0.91	0.92	1.33	-1.39
t-Statistics	-3.15	5.67	6.43	9.40	6.62	8.69	12.66	17.77	15.70	12.49	-12.30
HML	-0.11	0.17	0.10	0.24	0.17	0.05	-0.02	0.10	0.20	0.48	-0.60
t-Statistics	-5.69	3.45	1.99	4.50	2.43	0.80	-0.34	1.80	3.36	4.41	-5.13
WML	0.01	0.06	0.10	-0.01	-0.08	-0.13	-0.17	-.20	-0.29	-0.25	0.24
t-Statistics	2.90	2.51	2.46	-0.18	-3.21	-2.45	-0.07	-2.08	-6.02	-2.89	2.56
Panel C: Portfolio characteristics											
Portfolio standard deviation	7.86	10.17	10.54	10.23	11.87	10.63	10.64	10.98	11.94	15.52	14.91
Portfolio skew	-.17	-0.14	-0.76	-0.51	-.42	-.55	-.60	0.15	0.52	1.93	-1.32

4.2 Similarities and differences between high predicted jackpot probabilities and high predicted distress firms

Table 5 reports characteristics of firms that are in portfolios formed from sorts on DEATHP, which is the default measure from CHS, and those formed from sorts on JACKPOTP, which is the out-of-sample predicted jackpot measure. The fraction of firms in the top decile portfolio that realized jackpot return is higher (4.5%) for the highest DEATHP portfolio that for the highest JACKPOTP sorted returns (2.1%). Both DEATHP and JACKPOTP rise; size and past 12 month- returns shrink but within different magnitudes. Also, there exists a pattern in JACKPOTP portfolios. Sales growth and skewness increase. In this table, skewness is computed in daily log returns over the past three months. However, note that the skewness in table 1 is calculated in returns over the next year, whileas there is no such pattern in slaes growth and skewnes for DEEATHP portfolios.

4.3 Relation between distress and jackpots

Section 4.3 examines the link between exante distress and jackpot probability. It is important to see whether jackpot returns to be a plausible explanation for the low subsequent returns of high distress stocks. To be so, exante measure of these two variables, exante distress and jackpot probability, should be significantly correlated with each other. In Table 6, Panel A shows pair-wise Spearman correlations between forecasted distress from the CHS model (DEATHP) and another measure of the out-of-sample likelihood of a jackpot return from the model, turing out that there is a correlation of 38.9% with the probability of distress.

I also examines the relation between returns of a long-short strategy devised to test the CHS distress effect and one devised to test the jackpot effect. First, distress strategy, DEATHPLS, is long stocks in the bottom DEATHP decile and short stocks in the top DEATHP decile, whereas JACKPOTLS is long the bottom decile of JACKPOTP and short stocks in the top decile JACKPOTP. All portfolios are value-weighted. Longing the safest stocks, in other words, least likely to achieve a jackpot return allows positive average returns for DEATHPLS and JACKPOTLS. Panel B and C examines the correlation in the returns of the jackpot and distress strategies. Then, I compare their exposures to the four standard factors in specification 2. The result is to show how returns of the two strategies, DEATHPLS and JACKPOTLS, are correlated to each other. There exists a strong relation of 29.38% of the times series variation in the jackpot (distress) strategy returns explained by the distress (jackpot) strategy returns. In specification 2, the right-hand column of Panel B and C, I add other risk factors such as MKT, SMB, HML, and WML in the analysis. After controlling for these risks, the jackpot strategy repletively has significant alphas of 0.68%

Table 5

Firm characteristics

This table reports average individual firm characteristics for portfolios sorted forecasted default probability according to the Campbell, Hilscher, and Szilagyi (2008) model in Panel A and for portforlios sorted on out-of-sample predicted jackpot probability in Panel B. The bariables 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 1998-2013.

	Decile									
	1	2	3	4	5	6	7	8	9	10
Panel A: Individual stock chracteristics of DEATHP sorted portfolios										
JACKPOTP	0.8%	0.9%	1.0%	1.1%	1.2%	1.3%	1.6%	1.9%	2.0%	3.8%
Realized jackpot	1.2%	1.3%	1.3%	1.3%	1.5%	1.9%	2.0%	2.0%	2.3%	4.5%
RET12	18.3%	17.6%	17.2%	12.9%	11.5%	4.1%	1.4%	-1.7%	-11.3%	-19.0%
SIZEZ	6.95	6.91	6.88	6.34	6.17	5.96	5.21	5.15	4.89	3.27
SALESGRTH	7.1%	7.3%	7.4%	7.9%	8.1%	8.0%	7.9%	7.8%	7.8%	6.9%
SKEW	0.92	0.89	0.83	0.78	0.73	0.71	0.69	0.65	0.64	0.57
Panel B : Individual stock characteristics of JACKPOTP sorted portfolios										
JACKPOTP	0.2%	0.4%	0.7%	1.1%	1.5%	2.1%	2.8%	3.7%	5.5%	10.1%
Realized jackpot	0.7%	0.8%	0.9%	0.9%	1.0%	1.2%	1.3%	1.4%	1.6%	2.1%
RET12	6.2%	4.5%	3.8%	3.2%	2.7%	2.3%	2.1%	1.7%	1.0%	-0.1%
SIZEZ	13.81	12.12	11.43	11.02	10.71	10.44	10.20	9.96	9.68	9.19
SALESGRTH	3.3%	3.8%	4.7%	5.5%	5.2%	6.7%	7.7%	8.1%	9.2%	10.0%
SKEW	-0.37	0.50	0.47	0.49	0.46	0.44	0.45	0.42	0.43	0.50

and 0.73%. These result presents 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. Therefore, I can conclude that a high probability of a jackpot return is a playsible explanation for the low subsequent average returns of stocks with

Table 6

The link between returns of distress and jackpot strategies

Spearman correlations examines the relation between forecasted jackpot probability (JACKPOTP) and predicted default probability (DEATHP). JACKPOTP is from the model in Table 3 and ones with different cutoffs used in describing jackpot (arithmetic returns of 50%, 70%, and 100% over the next year). In Panel B, time-series of regressions of returns of the distress strategy on different portfolios. The distress strategy, DEATHLS, refers to long the top decile of stocks (lowest default probability) and short the top decile of stocks (highest default probability) based on Campbell, Hilscher, and Szilagyi (2008). In specification 1, I regress the distress strategy on JACKPOTLS. JACKPOTLS is a portfolio of stocks which is long the bottom decile to have jackpot returns, based on the model out-of sample jackpot prediction model. Specification 2 utilizes time-series regressions of returns of JACKPOTLS on different portfolios. I first regress JACKPOTLS on DEATHLS, and adds in the four factors. The sample period is 1998 to 2013. All portfolios are value-weighted and skip a month between portfolio formation and measuring returns.

Variable	Correlation			
Panel A : Spearman correlations with		DEATHP		
JACKPOT	39.80%			
JACKPOT50	42.34%			
JACKPOT75	42.38%			
JACKPOT100	42.89%			
	(1)		(2)	
	Coefficient	t-Value	Coefficient	t-Value
Panel B: Explaining the returns of the distress strategy				
Intercept	0.49	1.25	0.68	2.56
JACKPOTLS	0.50	4.67	0.21	6.03
R^2	29.38%			59.24%
Panel C: Explaining the returns of tthe jackpot strategy				
Intercept	0.31	1.03	0.73	2.67
DEATHPLS	0.52	9.13	0.24	5.61
R^2	29.38%			59.24%

high default probability.

Ⅴ. Conclusion

Campbell, Hilscher, and Szilagyi(2008) find that firms with a high probability of default risk earn low subsequent returns. This phenomena is puzzling when the effect of risk on average returns is considered. The direction infers an idea; we rational investors ask for premium to bear such risks, particularly default risks in this case. Then, there's eventually little payoff in our hard which is considerably small to what we endure for default risk. Conrad, Kapadia, and Xing(2014, henceforth; CKX) report that stocks with a high probability of default by the CHS model tend to generate extremely high returns (over 100%) over the next year. CKX present a feature that those stocks have lottery-like(extremely positive skewed) payoffs, allowing investors to desire to hold them, leading to high valuation. This high valuation of investors bid up the prices and lead to low exante returns. As stated in CHS paper, it is consistent with prospect theory based utility functions in Barberis and Huang (2008). A strong inclination for such stocks brings on low average returns in equilibrium. This paper aims to examine whether distress risk puzzle shown in CKX is also present within Korean market by following methodologies in CKX (jackpots) and CHS (death).

To predict which stocks posses lottery like returns (jackpot payoffs), I used a logit model from CKX. I estimate this model on an expanding out-of-sample window with a sample period from 1998 to 2013 and find that a high probability of jackpot returns have low average future returns in Korean market. I also find that there exists a strong relation between the predicted probability of a jackpot return and the probability of default from the CHS mode with Korean market data. Therefore, I can conclude that a high probability of jackpot return is a plausible explanation for distress risk puzzle in Korean market as shown in CHS with the US market data. As what CKX does in their paper, I run a set of tests to see whether there exists a strong link between the effects of jackpot payoffs and expected returns on default. The returns of jackpot and distress strategy returns are significantly correlated

My results report that a high likelihood of jackpot payoffs is a plausible explanation for at least a portion of the low average exante returns of stocks with a high default probability. A feature of lottery-like payoff structure enables investors to bid up the prices of stocks with a high probability of default. This distress risk puzzling phenomena is also present in Korea. Therefore, I can conclude that at least investors in US market and Korean market do appreciate securities which possess the feature of highly positive skewed payoffs. This preference is an plausible explanation to gives a reason for distress risk puzzle and low exante returns of high default probability securities. For a logit model, due to the restriction of data availability, I use 10 years. I afterwards can expand a data span to 20 years, which is used in the CKX for better accuracy. Also, other variables which can represent a feature resulting in jackpot returns such as an institutional ownership ratio can be added to the baseline model.

Appendix

A. Definitions of key variables

Key variables are defined as follow.

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

JACKPOTP is predicted probability of jackpot return from out-of-sample regressions.

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

The next set of variables are used to forecast jackpots in my model.

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

RET12 is log returns over the past year.

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

TANG is gross PPE/total assets.

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

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

SIZE is log (market capitalization)

SALESG is sales growth in year y LN ($_{SALES_y/SALES_{y-1}}$).

References

Barberis, N., Huang, M., 2008. Stocks as lotteries: the implications of probability weighting for security prices. American Economic Review 98, 2066-2100.

Campbell, J.Y., Hilscher, J., Szilagyi, J., 2008. In search of distress risk. Journal of Finance 63, 2899-2939.

Chava, S., Purnanandam, A., 2010. Is default risk negatively related to stock returns? Review of Financial Studies 23, 2523-2559.

Chen, J., Hong, H., Stein, J., 2001. Forecasting crashes: trading volume, past returns, and conditional skewness in stock prices. Journal of Financial Economics 61, 345-381.

Conrad, J., Dittmar, R., Ghysels, E., 2013. Exante skewness and expected stock returns. Journal of Finance 68, 85–124.

Fama, E. F., French, K. R., 1996. Multi factor explanations of asset pricinganomalies. Journal of Finance 51,55–84.

Vassalou, M., Xing, Y., 2004. Default risk in equity returns. Journal of Finance 59, 831–868.

국 문 초 록

개인 투자자들이 왜 고평가된 주식을 보유하는가에 대한 연구
: 한국 주식시장을 통한 검증

서울대학교 대학원
재무금융 석사전공
윤석인

본 논문은 default 확률이 높은 주식들이 다음년도에 100%가 넘는 수익을 실현하게 되는 강한 성향이 있으며 이는 투자자들의 lottery-like payoffs에 대한 선호를 야기한다. 위와 같은 주식들은 차후에 오히려 낮은 평균 수익을 제공한다는 Conrad, Kapadia, and Xing(2014)의 distress risk puzzle에 관한 연구의 결과가 한국 시장에서도 관찰되는지를 살펴보았다.

본 연구는 Campbell, Hilscher, and Silagyi (2008)와 Kapadia, and Xing (2014) 의 방법론을 따랐으며, 그 결과 한국시장에서도 default 확률이 높은 주식들이 차후에 낮은 평균 수익을 갖는 distress risk puzzle이 관찰되었다. 또한, exante distress 와 jackpot returns이 강한 상관관계가 있으며 jackpot strategy와 distress strategy의 수익 또한 강한 상관관계가 있음을 보여줬다. 이로서, 한국시장에서도 jackpot payoffs에 대한 높은 확률이 default확률이 높은 주식의 낮은 평균 수익을 설명할 수 있다.

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