行政院國家科學委員會專題研究計畫 成果報告

從相關結構評估下方風險—以美國股市為例
研究成果報告(精簡版)

計 畫 類 別 ：個別型
計 畫 編 號 ：NSC 95-2416-H-004-046-
執 行 期 間 ：95 年 08 月 01 日至 96 年 07 月 31 日
執 行 單 位 ：國立政治大學財務管理學系

計畫主持人：盧敬植

計畫參與人員：碩士班研究生-兼任助理：葉柏良、翁筱雯

處 理 方 式 ：本計畫可公開查詢

中 華 民 國 96 年 10 月 31 日

附件一

行政院國家科學委員會補助專題研究計畫 X 成果報告 □期中進度報告

從相關結構評估下方風險—以美國股市為例

計畫類別：X 個別型計畫 □ 整合型計畫
計畫編號：NSC 95－2416－H－004－046 －
執行期間： 2006 年 08 月 01 日至 2007 年 07 月 31 日

計畫主持人：盧敬植
共同主持人：
計畫參與人員： 葉柏良、翁筱雯

成果報告類型(依經費核定清單規定繳交)：X 精簡報告 □完整報告

本成果報告包括以下應繳交之附件：
□赴國外出差或研習心得報告一份
□赴大陸地區出差或研習心得報告一份
□出席國際學術會議心得報告及發表之論文各一份
□國際合作研究計畫國外研究報告書一份

處理方式：除產學合作研究計畫、提升產業技術及人才培育研究計畫、列管計畫及下列情形者外，得立即公開查詢
□涉及專利或其他智慧財產權，□一年□二年後可公開查詢

執行單位：國立政治大學財務管理學系

中 華 民 國 96 年 10 月 31 日

附件二

可供推廣之研發成果資料表

中文摘要

研究者和實務界早已認知投資者並非用同樣的心態去看待同樣大小但反向的意外獲益和損失。一般人對於趨避損失，也就是避免承擔所謂的『下方風險』(downside risk) 看得要比獲益更為重要。在這個研究中我們發現接近左尾的相關係數才會對橫斷面的股票預期收益發生影響，換句話說唯有資產或資產組合包含的下方風險才會真正影響收益。從相關結構來看在同一群擁有相近的市場 beta 值的股票中，真正影響到價格的只是該股票自己的波動值，以及與市場資產組合的有較高的左尾相關係數。我們利用這種特性組合新的風險因子並加以檢定，並使用 H-J bound 來證明它的確優於資本資產定價模型。

關鍵詞：下方風險, 關聯結構, 資產定價

Abstract

Economists and practitioners have long recognized that investors treat downside and upside risks differently. People put higher weights on the downside risks will usually demand higher compensation for bearing them. In this research we found that only correlation coefficient close to the left tail can explain the return behavior in cross section, not the full sample correlation. In other words, only the downside correlation between a stock/portfolio and the market return matters in asset pricing. The assets with higher returns among the class with similar market betas are usually those assets with higher volatility. We use these finding to sort stocks and form new risk factors, and use H-J bound to test they are in fact superior to the CAPM.

Keywords: Downside risk; Copula; Asset Pricing; Dependence Structure

Downside Risk Final Report: Brief Version

Ching-Chih Lu

October 31, 2007

1 Introduction

It has been recognized that investors react differently to the market gain or loss. The securities co-moves with the market heavily in the downside should acquire higher return to compensate this un-welcoming characteristic.

Various approaches have been proposed to deal with this stylized fact. Harvey and Siddique (2000) incorporate conditional skewness in the pricing model as a risk factor, while Ang, Chen, and Xing (2006) uses a downside beta to show that extra risk premium can be obtained.

In this research, we first apply a through anatomy on the traditional market beta to see if the mis-pricing exists and how it behaves in order to incorporate the downside measures. Ang, Chen, and Xing (2006) are the first to use all individual stocks to examine the cross sectional behavior of the downside risk, and they find an approximately 6% per annum premium on the downside risk. We take a step further to see where the mis-pricing comes from by dissecting the beta into several components, that is

$$\beta_i = \frac{\rho(r_i^e, r_m^e)\sqrt{\mathrm{Var}(r_i^e)}}{\sqrt{\mathrm{Var}(r_m^e)}}$$

For each beta, we can decompose it into three parts: the correlation between the excess returns of the stock and the market portfolio, the standard deviation of the excess return of the stock, and the market portfolio.

If the market portfolio is efficient and the CAPM holds for all stocks, the risk-return trade-off can be perfectly depicted by the following equation:

$$(\mathrm{E}[R_i] - R_f) = \beta_i(\mathrm{E}[R_m] - R_f) \tag{1}$$

Therefore, the excess return of the stock in the cross section should be proportional to its correlation to the excess market return or its own standard deviation.

We take log on the both sides of the equation (1),

$$\log(\mathrm{E}[R_i] - R_f) = \gamma_{0t} + \gamma_{1t}\log(\rho_{i,m}) + \gamma_{2t}\log(\sigma_i) + \varepsilon_i \tag{2}$$

and conduct a Fama and MacBeth (1973) regression on limited samples, where the correlation is positive and both $(\mathrm{E}[R_i] - R_f)$ and $(\mathrm{E}[R_m] - R_f)$ are with the same sign. If They are both negative, then we take absolute value of both excess returns. To estimate the correlation coefficient and the standard deviation of the expected excess return of the individual stock, we use two year weekly data in each time series regression then run the cross-sectional regressions. If the individual stock does not have full observations during the whole two-year sample period, we also leave them out of the samples.

If CAPM holds true for each and every security in cross section all the time, then $\gamma_1 = \gamma_2 = 1$ and $\gamma_0 = -\log(\mathrm{E}[R_m] - R_f)$. Therefore we can test whether

$$\begin{aligned}\hat{\gamma}_1 &= \frac{1}{T}\sum_{t=1}^{T}\gamma_{1t} \\ \hat{\gamma}_2 &= \frac{1}{T}\sum_{t=1}^{T}\gamma_{2t}\end{aligned}$$

are both insignificantly different from 1.

The estimation results are 0.0837 (0.1958) for γ_1 and 1.0753 (0.4414) for γ_2. This apparently shows that the correlation does a very poor job on explaining excess returns of security in cross section, while the standard deviation of individual stocks still has certain explanatory power cross-sectionally, though not perfect.

In light of Ang, Chen, and Xing (2006)'s finding on the downside beta being able to explain part of the expected stock returns, we go a step further so show the effect is mainly the downside correlation. That is, the full sample correlation does not provide the risk to be compensated for. Investors loathe strong comovement between their investment with the market only when the market moves downward, not when both of them work well. The same thing can be said to the individual stock volatility, but we can show that this characteristic of a stock or a portfolio is more symmetric, so a sub-sample volatility does not provide extra information of the risk a stock carries. This is different from the downside beta Ang, Chen, and Xing (2006) propose since it can provide a more detailed idea of what really affects the cross-sectional behavior of the stock returns. Our strategy of showing downside correlation is a source of downside risk as follows.

First we discuss portfolios sorted by realized risk characteristics. For these risk measure being able to explain part of the cross-sectional behavior, we should see significant returns spread between portfolios. We first divide beta into six categories: the full sample beta (β), the downside beta (β^-), and four quartile betas (β_1 to β_4, where β_1 represents the beta when the market portfolio return is below its first quartile, β_2 is calculated using the sub-sample where the market return is between its first and second quartiles, and so on). We also form portfolios basis on the standard deviation or the correlation with the market portfolio of individual stocks. Second, we examine if these contemporaneous relationship between risk measure and expected returns could also be correlation to other widely discussed phenomena, such as book-to-market ratio and firm size, to determine if the downside risks we discuss are only another facet of existing risk loading.

Third, we check if the risk characteristics in the past can predict future expected returns. The return spread for portfolios sorted with different risk characteristics shows mixed message because its high volatility. The regressions of sorted portfolio on the excess market return (CAPM) and size, B/M factors (FF-3) show the existence of significant $alpha$ is most cases, which means the needs for another risk factor to explain the downside risk and the failure to predict future with current risk measures.

2 Pre-Ranking Results

We include all the stocks traded in the NYSE, AMSE and NASDAQ from 1963 to 2005 with share code 10 or 11 in the CRSP database.[1] Unlike the Fama and French (1992) or

[1] We only include common stocks in the study. All other domestic traded assets, like ADRs, closed-end funds or REITs are excluded.

their later works, the finance sector is included in our samples because the leverage effect is not our biggest concern.

From Table 1 Panel A we see a very clear pattern on either β or downside β, β^-. For the quartile cases only β_1 [2] works well, which further suggests that people care more about their losses than potential gain or any tranquil period comovement. This effect is not a coincidence because the only quartile portfolio with any clear pattern or significant difference between the returns of the portfolios with the highest and lowest risk measures is the first one, which is estimated with r_m less than its first quartile.

As suggested earlier we separate the effects of individual stock volatility and correlation to the market from a single statistic, β, and see if they tell a different story. Portfolios sorted by individual stock's standard deviation display a unanimous pattern in cross section no matter how we dissect the sample. It always shows bigger standard deviation will bring bigger expected return, which is consistent the the traditional wisdom on the return/risk tradeoff. The correlation does not fare so well as traditional wisdom imply. One might assume a stock moves more often to the same direction as the market will be less adored and demand a higher compensation in return. We find that only downside correlation plays such a significant role in determining the cross-sectional difference of average stock returns. The evidence is that the full sample correlation or the correlation determined by sub-samples other than the lowest quartile do not have any influence on cross-sectional expected returns.

We further examine if the risk measures we examined are influenced by other well-known risk characteristics, such as book-to-market ratio or size. Table 2 shows the average book-to-market ratio from the aforementioned sorted portfolios. Although we can see a pattern in portfolios sorted by some of the risk characteristics,for example, the lower the beta or correlation, the higher the B/M ratio, the difference is not significant because the variability of the B/M ratios is quite large.

Unlike the book-to-market ratios, the size factor might play a more significant role in determining the cross-sectional return behavior of the sorted portfolios here. As suggested by Fama and French (1992), the size factor is almost independent to the market beta, and thus constitute another risk source. However, it is not the case for the portfolios sorted by the volatility or the correlation alone. In both Panel B and C, we see the difference in size

[2]
$$\beta_1 = \frac{\text{cov}(r_i, r_m | r_m < F_{rm}^{-1}(0.25))}{\text{var}(r_m | r_m < F_{rm}^{-1}(0.25))}$$

are significant for high-low return difference in all volatility based portfolios and two cases in correlation based portfolios. The direction of the average returns are exactly opposite for these two risk characteristics. The explanation could be that smaller firms tend to have higher volatility, while bigger firms takes higher weights in the market and usually comove with the market more closely.

We also conduct a two-way sorting with standard deviation and correlation as two sorting criteria. The table is not presented in this brief report, but the results are consistent with Table 1. For each σ_i-sorted portfolio, average returns go up with the correlation except for the portfolios ranked in the highest volatility group. Also for each correlation-sorted portfolio, averages returns increase as the volatilities increase.

We also ranked the portfolios with its tail dependence derived from the dependence of a rotated copula model to see if it has a similar effect of the downside correlation. The results are not so promising until we exclude the negative correlated securities from the sample. Such models work much better in the portfolio level, not on the security level.

3 Post-Ranking Results

In an asset pricing model we care not only about the contemporaneous connection between variables but also the ability to predict the future. At the end of June of each year, we sort stocks with their risk characteristic (β's, σ_i's, and ρ_{im}'s in Table 1) from their past two year weekly returns. We then calculate equal-weighted portfolio's weekly return from July of the same year to June of the next year, and then reform the portfolio for the following year. The procedure is very similar to the Fama and French (1992) portfolios, only we use two year weekly data instead of five year monthly data. We need a larger sample size to accommodate the downside and quartile betas since they are using only a fraction (one-half or one-quarter) of the total observations. On the other hand, the risk measures are hardly persistent over time, we can not freely extend our pre-ranking period way back to the past. Between tradeoff of the number of observations and a shorter, stationary sample period, we decide to work on two year weekly data.

The portfolios formed on the basis of the rank of risk characteristics in Table 4 show mixed results in the return patterns. The average returns gradually decrease with the increasing beta or increasing downside beta, which is opposite to the direction in Table 1, but the difference is not significant and can be assumed no changes. The relationship between the return changes and other two risk measures are in the same direction but also insignificant. The different behavior between the post- and pre-ranking portfolios is that the returns of these post-ranking portfolios are too volatile over time, which lead to huge standard deviations and thus very low t-stat. This may need more scrutiny because the risk exposure or the price of risk itself can be time-varying and it might be overlooked in this scenario.

Ang, Chen, and Xing (2006) shows that there is a premium of the downside beta (β^-) after controlling for the past volatility. This and the magnitude of the effect from downside beta are consistent with our findings.

In an unreported table, we show that the aforementioned sorted portfolios all have large alphas in either CAPM or FF-3 left unexplained, which also imply there are risk factors regarding downside risks not account for in these models.

We also use the post-ranking portfolio to establish a mimic zero cost portfolio in order to track the effect of these risk measures on security returns. Only marginal improvement has been achieved over the dynamic CAPM with market return as the lone risk factor. We use the Fama-French 5-by-5 portfolios as testing portfolios and the H-J bound in Hansen and Jagannathan (1997).

4 Conclusion

When we sort stocks with contemporaneous risk characteristics, we find that the standard deviation of individual stocks is the most important component in the traditional market beta to drive the cross-sectional return difference. The correlation between stocks and market returns does not have pronounced effect as we expect, however, the downside correlation does, especially the correlation conditional on the first quartile market returns. It implies that investors only care about the correlation when the market performs poorly, and do not consider the correlation between individual stocks and the market a “risk” when the market is doing well. The pattern of volatility changes in cross section is very similar for the whole sample or in each sub-sample, so we do not see a difference on the downside only The downside risk defined by the downside beta in Ang, Chen, and Xing (2006) is likely be the effect of downside correlation.

The post-ranking portfolios do not preserve the full effect of the contemporaneously sorted portfolios. However, the ones sorted by the correlation and the standard deviation basically display the same pattern.

It is widely discussed that low stock returns are usually associated with increased volatility, as in Bae, Kim, and Nelson (2007),this time-series phenomenon could be the driving force of the inconsistency in our model. To improve the post-ranking portfolio behavior, we probably should change the trading strategy from 104/0/52 strategy[3] to a shorter holding strategy. As in Fama and French (2007) discussion, the securities may change their characteristic and move across portfolios over time.

Note: The reference listed are those included in this brief report. Please see the research proposal for more detailed reference list.

[3] We use 104 week window to estimate the risk characteristic, wait for 0 week, then hold the stock in the portfolio for another 52 weeks. See Ang, Hodrick, Xing, and Zhang (2005) for details.

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Table 1: **Returns of Stocks Sorted by Realized Risk Characteristics**

Panel A: Returns of Stocks Sorted by realized β

Portfolio	β	β^-	β_1	β_2	β_3	β_4
Low-1	8.11	7.86	8.31	13.56	14.51	12.98
2	8.37	8.11	8.11	9.60	10.65	9.81
3	10.15	10.18	9.95	9.50	9.91	9.98
4	12.92	12.89	12.84	10.99	10.04	11.03
High-5	19.24	19.75	19.58	15.14	13.66	14.98
High-Low	11.13	11.89	11.27	1.58	-0.85	2.00
t-stat	3.62	4.34	4.31	1.74	-0.73	1.15

Panel B: Returns of Stocks Sorted by realized σ_i

Portfolio	σ	σ^-	σ_1	σ_2	σ_3	σ_4
Low-1	6.63	6.96	7.03	7.15	7.15	7.29
2	8.96	8.85	8.87	9.26	9.24	9.22
3	10.35	10.16	10.11	10.39	10.32	10.38
4	11.03	11.24	12.04	11.56	11.75	12.15
High-5	21.82	21.58	20.75	20.42	20.34	19.74
High-Low	15.19	14.63	13.72	13.28	13.19	12.46
t-stat	3.85	4.02	3.91	3.85	3.65	3.42

Panel C: Returns of Stocks Sorted by realized ρ_{im}

Portfolio	ρ	ρ^-	ρ_1	ρ_2	ρ_3	ρ_4
Low-1	12.04	9.83	9.38	11.63	12.70	12.08
2	11.13	10.54	10.29	11.55	12.32	11.79
3	10.59	11.19	11.75	11.41	11.86	11.72
4	11.45	12.28	12.37	11.73	11.16	11.44
High-5	13.57	14.93	14.99	12.47	10.72	11.75
High-Low	1.53	5.10	5.61	0.84	-1.98	-0.33
t-stat	0.75	2.51	2.84	1.11	-1.84	-0.21

All the numbers except the t-statistics are in percentage per annum. This table lists the equal-weighted average returns of the portfolios ranked by realized risk characteristics. The second column which is labeled by β, σ and ρ report portfolio returns sorted by respective risk characteristics with full sample estimation. The third column is using only downside sample ($r_m \leq \mu_m$), while the characteristics used in the last four columns are estimated with the first to the fourth quartile of the r_m. The t-stat in the last row of each panel is calculated with Newey and West (1987) standard error with 1 lag for the high-low difference.

Table 2: **Average Book-to-Market Ratio for Realized Risk Characteristics**

Panel A: Stocks Sorted by realized β

Portfolio	β	β^-	β_1	β_2	β_3	β_4
Low-1	1.14	1.10	1.07	1.05	1.03	1.08
2	1.03	1.00	0.99	0.96	0.95	1.01
3	0.97	0.96	0.95	0.94	0.94	0.95
4	0.89	0.92	0.93	0.94	0.94	0.90
High-5	0.81	0.86	0.90	0.95	0.98	0.89
High-Low	-0.33	-0.23	-0.17	-0.10	-0.06	-0.19
t-stat	-1.44	-1.56	-1.15	-0.49	-0.32	-0.85

Panel B: Stocks Sorted by realized σ_i

Portfolio	σ	σ^-	σ_1	σ_2	σ_3	σ_4
Low-1	0.91	0.91	0.92	0.90	0.90	0.91
2	0.90	0.90	0.91	0.89	0.90	0.90
3	0.96	0.96	0.95	0.96	0.96	0.94
4	1.00	1.00	0.99	1.00	1.00	0.99
High-5	1.07	1.08	1.07	1.09	1.09	1.09
High-Low	0.16	0.17	0.15	0.20	0.19	0.18
t-stat	0.30	0.34	0.32	0.39	0.38	0.34

Panel C: Stocks Sorted by realized ρ_{im}

Portfolio	ρ	ρ^-	ρ_1	ρ_2	ρ_3	ρ_4
Low-1	1.21	1.14	1.08	1.02	1.02	1.08
2	1.09	1.06	1.03	0.99	0.98	1.04
3	0.97	0.98	0.98	0.98	0.97	0.98
4	0.86	0.90	0.92	0.95	0.95	0.92
High-5	0.71	0.77	0.82	0.90	0.92	0.82
High-Low	-0.50	-0.37	-0.26	-0.13	-0.09	-0.26
t-stat	-1.37	-1.28	-1.16	-0.60	-0.64	-0.94

Numbers reported in the table are average book-to-market ratios for portfolios sorted by a specific risk characteristic. The definition of the risk characteristics to constitute each portfolio follows the same rule in Table 1.

Table 3: **Average Size for Portfolios Formed by Realized Risk Characteristics**

Panel A: Stocks Sorted by realized β

Portfolio	β	β^{-}	β_1	β_2	β_3	β_4
Low-1	3.76	4.08	4.17	3.90	3.97	3.62
2	4.58	4.83	4.87	4.84	4.85	4.53
3	4.89	4.94	4.97	5.08	5.05	5.02
4	4.95	4.80	4.77	4.93	4.97	5.16
High-5	4.76	4.29	4.16	4.18	4.10	4.61
High-Low	1.00	0.21	-0.01	0.28	0.13	0.99
t-stat	0.77	0.21	-0.01	0.44	0.25	1.91

Panel B: Stocks Sorted by realized σ_i

Portfolio	σ	σ^{-}	σ_1	σ_2	σ_3	σ_4
Low-1	5.92	5.99	5.90	6.01	6.03	5.89
2	5.49	5.43	5.37	5.41	5.40	5.43
3	4.67	4.65	4.66	4.64	4.63	4.67
4	3.92	3.91	3.96	3.89	3.91	3.93
High-5	2.94	2.95	3.05	2.98	2.97	3.02
High-Low	-2.98	-3.04	-2.85	-3.03	-3.06	-2.87
t-stat	-4.19	-4.48	-4.46	-4.58	-4.83	-4.56

Panel C: Stocks Sorted by realized ρ_{im}

Portfolio	ρ	ρ^{-}	ρ_1	ρ_2	ρ_3	ρ_4
Low-1	3.04	3.61	3.95	4.20	4.31	3.76
2	3.77	4.10	4.28	4.44	4.47	4.11
3	4.46	4.52	4.52	4.57	4.56	4.49
4	5.22	4.97	4.83	4.72	4.70	4.95
High-5	6.44	5.75	5.37	5.01	4.90	5.62
High-Low	3.40	2.14	1.42	0.81	0.59	1.87
t-stat	3.48	1.97	1.43	1.24	1.44	3.09

Numbers reported in the table are average log(Size) for portfolios sorted by a specific risk characteristic. The definition of the risk characteristics to constitute each portfolio follows the same rule in Table 1.

Table 4: **Returns of Portfolios Formed on Pre-Ranking Risk Characteristics**

Panel A: Portfolios Formed on Pre-Ranking β

Portfolio	β	β^-	β_1	β_2	β_3	β_4
Low-1	13.14	13.14	12.16	13.21	13.21	13.89
2	11.06	10.82	10.61	10.25	10.12	10.89
3	11.59	11.48	11.04	10.23	10.21	10.33
4	10.95	10.93	11.63	10.62	10.61	10.63
High-5	10.52	10.87	11.77	13.05	13.16	11.63
High-Low	-2.61	-2.27	-0.39	-0.16	-0.05	-2.25
t-stat	-0.15	-0.16	-0.03	-0.02	-0.01	-0.27

Panel B: Portfolios Formed on Pre-Ranking σ_i

Portfolio	σ	σ^-	σ_1	σ_2	σ_3	σ_4
Low-1	7.92	7.77	7.78	7.81	7.80	7.92
2	9.04	8.95	9.18	9.06	9.09	9.23
3	10.11	10.40	9.96	10.21	10.48	10.15
4	12.49	12.14	12.56	12.27	11.99	12.37
High-5	18.45	18.80	18.51	18.59	18.55	18.21
High-Low	10.53	11.03	10.74	10.78	10.75	10.28
t-stat	0.53	0.58	0.60	0.59	0.59	0.55

Panel C: Portfolios Formed on Pre-Ranking ρ_{im}

Portfolio	ρ	ρ^-	ρ_1	ρ_2	ρ_3	ρ_4
Low-1	16.74	15.76	13.47	11.87	11.84	12.94
2	13.25	13.07	13.11	12.00	11.25	12.30
3	11.14	11.70	11.81	11.59	11.65	11.95
4	9.19	10.07	10.91	11.42	11.41	10.78
High-5	7.26	6.79	7.98	10.40	11.06	9.32
High-Low	-9.49	-8.97	-5.49	-1.47	-0.78	-3.61
t-stat	-0.71	-0.81	-0.60	-0.27	-0.15	-0.48

The average return is the time-series average of the weekly equal-weighted portfolio returns in percentage per annum. We include all the stocks which have complete two year data in the pre-sorting period without considering if they ceased to exist during the post-ranking period. Therefore we are immune from survivor bias. The definition of the risk characteristics to constitute each portfolio follows the same rule in Table 1.

Self-Evaluation

Although there are a few setbacks in the application of copula dependence parameters, this research has still achieved its original goal. We still need to do more robustness tests to finish this paper, but it is plausible at time being.