Low-Volatility Puzzle: Evidence from Amman Stock Exchange

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ABSTRACT

This study investigates the low -volatility puzzle in Amman Stock Exchange (ASE) using daily trading data over the period (2006-2015). Stocks are sorted according to their idiosyncratic volatility. Thereafter, high- and low-volatility portfolios are constructed and basic asset pricing models are estimated. The results of this study confirm the existence of low-volatility effect in ASE over the study period. Specifically, there are statistically significant differences in the rate of return between lowest-volatility portfolios and highest- volatility portfolios. The annual average of these differences amounts to 32.5%. However, this return is totally explained by the capital asset pricing model (CAPM) and Fama and French (1993) three- factor model. Moreover, the findings indicate that the aggregate low-high volatility risk factor is priced in the cross-section of stock returns. The findings of this study are vital to both academics and practitioners.

Keywords: Low-volatility puzzle, Anomaly, Asset pricing, CAPM, Fama and French, Stock return, Amman Stock Exchange.

INTRODUCTION

The classical financial theory asserts a positive relationship between the expected risk of an investment and its required rate of return. The basic capital asset pricing model (CAPM) expresses the required rate of return on an investment as a function of its systematic risk measured by beta (Sharpe, 1964; Lintner, 1965; and Mossin, 1966). Fama and French (1993) have added two systematic risk factors to the CAPM that positively affect investment return, the small minus big (SMB) and high minus low (HML). Similarly, Carhart (1997) argue that momentum risk factor does positively affect stock returns. Overall, from both theoretical and practical points of view, investors are rewarded for bearing aggregate risks.

On the individual stock level, Malkiel and Xu (2001), Spiegel and Wang (2005) and Fu (2009) find that idiosyncratic volatility positively affects expected returns, which in turn, supports the risk aversion rule that investments with greater risk are expected to achieve higher rates of return. However, a well-documented evidence that low volatility stocks outperform high volatility stocks has beaten this rule. In academic literature, this phenomenon has become known as the "low volatility puzzle". Baker *et al*. (2011) argue that this puzzle is the greatest anomaly in finance because it challenges the basic risk-return trade-off. Ang *et al.* (2006) measure idiosyncratic volatility using the Fama and French (1993) model and show that U.S. stocks with high idiosyncratic volatility earn very low average returns. They find a large difference in average returns across stocks with low and high idiosyncratic volatility. The existence of this puzzle has also been confirmed by several authors (see for example, Ang *et*

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al., (2009; Stambaugh *et al.*, 2015; Schneider *et al.*, 2016).

Literature has suggested many rationalizations to the low-volatility anomaly. Some of them are based on behavioral finance (Blitz and Vliet, 2007; Blitz *et al.*, 2014; Baker *et al.*, 2011), while other rationalizations are linked to the firms' own characteristics such as operating performance. Dutt and Humphery-Jenner (2013) argue that low volatility stocks achieve larger operating returns than high volatility stocks. Constraints on short-selling and leverage are also proposed as possible explanations for the low volatility anomaly. Frazzini and Pedersen (2014) reveal that investors who are constrained to use leverage will purchase more volatile stocks or they will have a fewer number of low-volatile stocks in their portfolios. On the other hand, Stambaugh *et al.* (2015) state that high idiosyncratic volatility stocks are more susceptible to mispricing and that this creates the negative relationship between idiosyncratic volatility and expected returns due to arbitrage asymmetry.

This study investigates the low volatility puzzle in Amman Stock Exchange (ASE) using daily trading data over the period (2006-2015). ASE is a frontier stock market that has lower market capitalization and liquidity and higher volatility levels than emerging and developed stock exchanges. Such a market could plausibly be more vulnerable to the price anomalies and specifically the low volatility puzzle. This study is important for several reasons: first, the findings of this study may have vital insights to the efficient market hypothesis. Second, if the low volatility puzzle exists in ASE, then investors may formulate investment strategies and achieve abnormal returns accordingly. Finally, more evidence on this topic will challenge the basic risk-return trade off in finance. The remainder of this study is organized as follows: Section two reviews the related literature. Section three describes data and methodology. Section four reports the results of provided analysis, concluding with section five.

1. Literature Review

Ang *et al.* (2006) investigate whether aggregate volatility risk and individual stock liquidity are priced in the cross-section of expected stock returns in USA over the period (1986-2000). Their findings present the low-volatility puzzle. Indeed, they find that stocks with high idiosyncratic volatility earn very low returns. The quintile portfolio with the highest idiosyncratic volatility does not even earn an average positive total return, and the difference in Fama and French (1993) alpha's between quintile portfolios with the lowest and highest idiosyncratic risk is -1.31% per month. Moreover, they estimate a significantly negative cross-sectional price of risk for systematic volatility, with a cross-sectional volatility factor earning -0.87% per month.

Ang *et al.* (2009) reexamines the low volatility puzzle in 23 developed markets around the world over the period (1980-2003). They measure the idiosyncratic volatility of a firm using local, regional, and global versions of the Fama and French (1993) three-factor model. Their findings present an international evidence of the negative relation between idiosyncratic volatility and expected returns. They find that across the investigated markets, the difference in average returns between the extreme quintile portfolios sorted on idiosyncratic volatility (high minus low) is –1.31% per month, after controlling for world market, size, and value factors.

Blitz and Vliet (2007) investigate the low volatility anomaly within the US, European and Japanese markets in isolation over the period (1986-2006). They provide empirical evidence that stocks with low volatility earn high risk-adjusted returns. The annual alpha spread of global low versus high volatility decile portfolios amounts to 12%. Moreover, they argue that the volatility effect cannot be explained by other well-known effects such as value and size. Blitz and Vliet (2012) extend the evidence of a negative volatility-return relationship over 30 different emerging markets using monthly data over the period (1988-2010). They state that this evidence is robust to the basic size, value and momentum effects.

Schneider *et al.* (2016) show that beta- and volatility-based low risk anomalies are driven by return skewness. They argue that the returns to betting against beta or volatility do not necessarily pose asset pricing puzzles but rather that such strategies collect premia that compensate for skew risk. Thus, the profitability of betting against beta/volatility increases with firms' downside risk, and the risk-adjusted return differential of betting against beta/volatility among low skew firms compared to high skew firms is economically large. Bali *et al.* (2011, 2016) document that controlling for the lottery characteristics of stocks reverses the relation between idiosyncratic volatility and equity returns. Baker *et al.* (2011) and Frazzini and Pedersen (2010) relate the low volatility effect to benchmark driven institutional investors. Boheme *et al.* (2009) find that for firms with low visibility, the relationship between idiosyncratic volatility and expected returns turns positive in the absence of short selling constraints.

To the best of my knowledge, this is the first conducted study in Jordan that examines the low volatility puzzle, whether there is a significant difference between the lowest and highest volatile portfolios' returns or not, whether this anomaly is explained by the basic asset pricing models or not, and whether it represents an aggregate risk factor that affects the cross-section of stock returns or not.

2. Data and Methodology

Data set consists of the daily observations of all firms listed in Amman Stock Exchange over the period (2006-2015). However, the firms that were thinly traded during the period of the study are excluded. For the firm to be included in the sample of the study, the stock should meet the following criteria:

- It should be listed over the study period.
- It should be traded at least once every 10 days.
- Stocks that had mergers or splits are excluded.

62 firms have been sampled after applying the filtering procedures. The effect of survivorship bias in the sample of the study is expected to be minimal because of the selection criteria which only exclude thinly traded stocks. Thus, the study sample consists of the same 62 firms over the study period. Usually the survivorship bias exists in samples of performance studies that include only the surviving companies and exclude companies that have been failed. The construction of lowest and highest volatile portfolios is executed following Ang *et al.* (2006). The Fama and French (1993) three factor model is estimated for each stock. The idiosyncratic volatility for each stock is calculated as the standard deviation of the residuals of the estimated model using daily excess returns over the past month. At the end of each month, stocks are sorted into deciles according to their idiosyncratic volatility. Three portfolios are selected for proceeding in analysis, the least volatile portfolio (PORTL), the most volatile portfolio (PORTM) and a zero-cost portfolio of holding the least volatile decile stocks and short selling the most volatile decile stocks (PORT(L-M)). The portfolios are rebalanced monthly. Thereafter, the capital asset pricing model (CAPM) and the Fama and French (1993) three-factor model are estimated for the three portfolios.

The Capital Asset Pricing Model (CAPM)

$$R_{it} - Rf_t = \alpha_0 + \alpha_1(Rm_t - Rf_t) + e_{it}$$

Where:

R_{it} is the daily return on portfolio i on day t.

Rf_t is the daily risk free rate on day t. It is obtained from the statistics of the central bank of Jordan and it represents the return on (12-months) treasury bills divided by 365.

Rm_t is the daily rate of return on the free float market index on day t.

The Fama and French Three-Factor Model

$$R_{it} - Rf_t = \beta_0 + \beta_1(Rm_t - Rf_t) + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_{it}$$

Where:

$[SMB_t]$: is the (small minus big) common risk factor on day t that had been introduced by Fama and

French (1993). It represents the difference in return between the portfolio of smallest size stocks and the portfolio of biggest size stocks in the market. Portfolios are formed in June of year *t* based on the market capitalization (a proxy for size) measured with accounting data for the fiscal year ending in *t*-1).

HML_t : is the (high minus low) common risk factor on day t that had been introduced by Fama and French (1993). It represents the difference in return between the portfolio of highest book to market ratio stocks and the portfolio of lowest book to market ratio stocks in the market. Portfolios are formed in June of year *t* based on the book to market ratio measured with accounting data for the fiscal year ending in *t*-1).

Following Fama and French (1993), we construct the two factors as follows:

We rank all the stocks in the sample according to their market capitalization at the end of June of each year over the period (2006-2015).The stocks are then separated into two groups according to the median value of the market capitalization, the small market capitalization group (S) and the big market capitalization group (B). After that, we calculate the ratio of book-to-market value for each stock at the end of year t-1. After excluding the stocks with negative book-to-market value ratio, we rank all the remaining sample stocks according to their ratios and construct three groups. The first group consists of the 30% of stocks with the highest ratios (H), the second group contains 30% of the stocks with the lowest ratios (L) and the last group includes the remaining 40% of the stocks whose book to market values are around the middle (M). Each year, we construct six portfolios from the combinations of the two market capitalization-based groups and the three book-to-market value ratio-based groups. These portfolios are S/L, S/M, S/H, B/L, B/M and B/H. The S/L portfolio contains the stocks in both the small size and the low book to market ratio groups at the same time. S/M portfolio contains the stocks in both the small size and the medium book to market ratio groups at the same time and so on. We calculate the daily returns on each of the six portfolios starting 1st July year t-1 to 30th June year t. The portfolios are reformed on a yearly basis. The High minus Low factor (HML) is calculated as the difference between the equally weighted average daily return on the two high book-to-market value ratio portfolios (S/H and B/H) and on the two low book-to-market value ratio portfolios (S/L and B/L). Similarly, the Small minus Big factor (SMB) is calculated as the difference between the equally weighted average daily return on the three small portfolios (S/L, S/M and S/H) and on the three big portfolios (B/L, B/M and B/H). All the preceding procedures are repeated annually.

Thereafter, the mimicking common risk factor of volatility, which represents the difference in daily return between the lowest volatile portfolio and the highest volatile portfolio, is augmented to the Fama and French three-factor model. The resulted four-factor model is estimated for the sample stocks as follows:

$$R_{it} - Rf_t = \beta_0 + \beta_1(Rm_t - Rf_t) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 VOL_t + \varepsilon_{it}$$

Where:

VOL_t **:** is the mimicking common risk factor of volatility.

3. Results of Analysis

Table 1 reports the descriptive statistics of the variables of the study. The daily mean returns of both the least volatile portfolio (PORTL) and the most volatile portfolio (PORTM) are negative over the study period. However, the least minus most volatile portfolio (PORT(L-M)) achieves a daily mean return of 0.0013 which is approximately equivalent to 32.5% annually. The maximum daily return for the PORTL, PORTM, PORT(L-M) are 7%, 5% and 200.3%, respectively. On the other hand, the minimum values of the daily returns of the three portfolios are -14%, -200.3% and -16%, respectively. The test for equality of means between the returns of PORTL and PORTM which is reported in Table 2 is statistically significant which indicates the rejection of the null hypothesis of equal means. The low volatility effect seems to be more dominant in frontier markets comparing to the developed stock exchanges. Ang *et al.* (2009) finds that the difference in monthly average returns between the least and most quintile portfolios is 1.31% in 23 developed markets around the world, which is equivalent to 15.72% annually.

Table 1: Descriptive Statistics

Mean, median, maximum, minimum and standard deviation values of the variables of the study in ASE over the period (2006-2015) are reported. PORTL denotes the least volatile portfolio, PORTM denotes the most volatile portfolio and PORT(L-M) denotes the least minus most volatile portfolio. HML refers to the high minus low common risk factor of Fama and French (1993), MKT refers to the excess market return common risk factor and SMB refers to the small minus big common risk factor of Fama and French (1993).

	PORTL	**PORTM**	**PORT(L-M)**	**HML**	**MKT**	**SMB**
Mean	-0.0002	-0.0014	0.0013	-0.0007	0.0001	0.0012
Median	0.0000	0.0000	0.0000	-0.0002	0.0003	0.0000
Maximum	0.0699	0.0488	2.3189	0.1765	0.0469	2.3583
Minimum	-0.1411	-2.3120	-0.1574	-0.2933	-0.0453	-0.3941
Std. Dev.	0.0160	0.0535	0.0572	0.0271	0.0101	0.0624

Table 2: Test for Equality of Means Between Series

This table reports the t-test results of the equality of means between the returns of the least and most volatile portfolios in ASE over the period (2006-2015).

Method	Value	Probability
t-test	15.4614	0.0000

The capital asset pricing model (CAPM) and the Fama and French (1993) are estimated for the three portfolios. Table 3 presents the correlation matrix between the study variables. It shows that all correlation values are less than 70% indicating no multicollinearity problem between the independent variables (Gujarati, 2004). Table 4 displays the results of the augmented Dickey-Fuller test. The test statistics show that all the study variables are stationary. The significant test values indicating a rejection of the null hypothesis of a unit root. The stationary of time series is an important condition to estimate time series regressions. Tables 5 and 6 show the estimation of time series regressions of the CAPM and Fama and French (1993) for the PORTL, PORTM and PORT(L-M). Overall, the common risk factors and specifically the excess market return (MKT) and the size factor (SMB) significantly affect portfolios' returns. Moreover, the results illustrate that the intercept and all GRS values in the estimated regressions are statistically insignificant indicating that the returns of the three portfolios are fully explained by both the CAPM and the Fama and French three-factor model. These results are contrasting with Blitz and Vliet (2012) who study the low volatility puzzle in 30 different emerging markets and find that its effect is anomalous and robust to the basic size, value and momentum effects. Ang *et al.* (2006, 2009) find similar results to those of (Blitz and Vliet, 2012) in the developed markets.

Table 3: Correlation Matrix

This table reports the correlation coefficient values between the variables of the study in ASE over the period (2006-2015). MKT denotes the excess market return common risk factor. SMB denotes the small minus big common risk factor of Fama and French (1993). HML denotes the high minus low common risk factor of Fama and French (1993). VOL denotes the mimicking common risk factor of volatility.

	MKT	SMB	HML	VOL
MKT	1.0000	-0.0543	-0.2572	-0.0889
SMB	-0.0543	1.0000	-0.0118	0.1758
HML	-0.2572	-0.0118	1.0000	-0.0066
VOL	-0.0889	0.1758	-0.0066	1.0000

Table 4: Augmented Dickey-Fuller test

This table reports the results of the Augmented Dickey-Fuller test of the variables of the study in ASE over the period (2006-2015). HML refers to the high minus low common risk factor of Fama and French (1993), MKT refers to the excess market return common risk factor and SMB refers to the small minus big common risk factor of Fama and French (1993). PORTL denotes the least volatile portfolio, PORTM denotes the most volatile portfolio and PORT(L-M) denotes the least minus most volatile portfolio.

HML	t-Statistic	Prob.*
test statistic	-40.9313	0.0000
MKT	t-Statistic	Prob.*
test statistic	-33.7504	0.0000
SMB	t-Statistic	Prob.*
test statistic	-43.3191	0.0000
PORTL	t-Statistic	Prob.*
test statistic	-47.3930	0.0001
PORTM	t-Statistic	Prob.*
test statistic	-47.7269	0.0001
PORT(L-M)	t-Statistic	Prob.*
test statistic	-45.8505	0.0001

Table 5: Capital Asset Pricing Model

The capital asset pricing model is estimated on a daily basis for the least volatile portfolio (PORTL), the most volatile portfolio (PORTM) and the least minus most volatile portfolio in ASE over the period (2006-2015). C denotes the intercept and MKT denotes the excess market return common risk factor. The R-squared and Adjusted R-squared values are also reported.

PORTL			
Variable	Coefficient	t-Statistic	Prob.
C	-0.0002	-0.7548	0.4504
MKT	0.4916	10.4069	0.0000
R-squared	0.1507		
Adjusted R-squared	0.1503		
GRS statistic[1]	1.0675		
PORTM			
Variable	Coefficient	t-Statistic	Prob.
C	-0.0015	-1.4087	0.1591
MKT	1.0110	14.5582	0.0000
R-squared	0.1066		
Adjusted R-squared	0.1062		
GRS statistic	1.4398		
PORT(L-M)			
Variable	Coefficient	t-Statistic	Prob.
C	0.0013	1.1159	0.2646
MKT	-0.5320	-6.3179	0.0000
R-squared	0.0892		
Adjusted R-squared	0.0888		
GRS statistic	1.2173		

[1] GRS statistic is F-statistic of Gibbons et al. (1989). It tests the null hypothesis that intercepts of the portfolios are jointly equal to zero. It is described as $GRS = (\frac{T}{N})(\frac{T-N-L}{T-L-1})\left[\frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1+\bar{\mu}'\hat{\Omega}^{-1}\bar{\mu}}\right] \sim F(N, T-N-L)$

Table 6: Fama and French Three-Factor Model

The Fama and French (1993) three-factor model is estimated on a daily basis for the least volatile portfolio (PORTL), the most volatile portfolio (PORTM) and the least minus most volatile portfolio in ASE over the period (2006-2015). C denotes the intercept, MKT denotes the excess market return common risk factor, SMB denotes the small minus big common risk factor and HML denotes the high minus low common risk factor. The R-squared and Adjusted R-squared values are also reported.

PORTL			
Variable	Coefficient	t-Statistic	Prob.
C	-0.0005	-1.6825	0.0926
MKT	0.5100	9.0554	0.0000
SMB	0.0041	1.3109	0.1901
HML	0.0075	0.4183	0.6758
R-squared	0.1096		
Adjusted R-squared	0.1081		
GRS statistic	1.5641		
PORTM			
Variable	Coefficient	t-Statistic	Prob.
C	-0.0010	-1.5720	0.1161
MKT	0.7574	9.9793	0.0000
SMB	-0.7890	-5.8280	0.0000
HML	0.0137	0.6456	0.5186
R-squared	0.7061		
Adjusted R-squared	0.7058		
GRS statistic	1.3815		
PORT(L-M)			
Variable	Coefficient	t-Statistic	Prob.
C	0.0006	0.8234	0.4104
MKT	-0.2507	-3.0550	0.0023
SMB	0.8064	6.3316	0.0000
HML	-0.0162	-0.5418	0.5880
R-squared	0.6687		
Adjusted R-squared	0.6683		
GRS statistic	1.0516		

Finally, we regress the individual stock returns of all sample stocks on the three common risk factors (MKT, SMB and HML) and a mimicking volatility common risk factor (VOL) which represents the difference in daily returns between the lowest volatile portfolio and the highest volatile portfolio (the daily return of the PORT (L-M)). Table 7 reports the pooled, fixed and random effect estimation results of the volatility augmented four-factor model. The results demonstrate that VOL significantly negatively affects the cross-section of stock returns. Thus, the volatility risk represents an aggregate risk factor that is priced in the cross-section of stock returns. Moreover, the volatility common risk factor seems to be more important than the HML in describing the cross-section of stock returns. These results are consistent with Ang *et al.* (2006) who estimate a significantly negative cross-sectional price of risk for systematic volatility.

Table 7: The Volatility Augmented Four-Factor model

Individual stock returns of all sample stocks are regressed on a daily basis on the three common risk factors of Fama and French (1993) (MKT, SMB and HML) and a mimicking volatility common risk factor (VOL) which represents the difference in daily returns between the lowest volatile portfolio and the highest volatile portfolio (the daily return of the PORT(L-M)). The sample includes 62 stocks listed in ASE over the period (2006-2015). The results of three estimation methods are reported; the pooled estimation, the fixed effects panel data model and the random effects panel data model. R-squared and adjusted R-squared values are also reported.

	Pooled	Fixed	Random
Variable	Coefficient	Coefficient	Coefficient
C	-0.0003	-0.0003	-0.0003
Prob.	0.0179	0.0179	0.0179
MKT	0.8359	0.8359	0.8359
Prob.	0.0000	0.0000	0.0000
SMB	0.0329	0.0329	0.0329
Prob.	0.0027	0.0027	0.0027
HML	-0.0024	-0.0024	-0.0024
Prob.	0.7094	0.7124	0.7094
VOL	-0.0757	-0.0758	-0.0757
Prob.	0.0114	0.0114	0.0114
R-squared	0.1342	0.1345	0.1342
Adjusted R-squared	0.1341	0.1339	0.1341

4. Conclusion

The low volatility puzzle is examined in Amman Stock Exchange using daily data over the period (2006-2015). A strategy of buying previously low-volatility stocks and selling previously high volatility stocks is found to generate an annual rate of return of 32.5%. However, this return is fully explained by the asset pricing models. Thus, the low volatility puzzle is driven by a systematic risk factor that is priced in the cross-section of stock returns rather than a mispricing effect. Our findings provide vital insights to both researchers and investors with respect to asset pricing, stock returns, portfolio construction and the idiosyncratic volatility risk.

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لغز التذبذب المنخفض: دليل من بورصة عمان للأوراق المالية

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ملخص

تختبر هذه الدراسة لغز التذبذب المنخفض باستخدام بيانات يومية على الفترة (2006–2015) في بورصة عمان للأوراق المالية. تم تصنيف الأسهم تبعاً لدرجة التذبذب في عوائدها وتشكيل محافظ استثمارية مرتفعة التذبذب وأخرى منخفضة التذبذب وتقدير نماذج تسعير الأصول. تؤكد نتائج الدراسة وجود أثر التذبذب المنخفض في بورصة عمان للأوراق المالية حيث أن الفرق في العائد بين المحفظة الأقل تقلباً والمحفظة الأعلى تقلباً دال إحصائياً ويبلغ 32% سنوياً، ولكن هذا العائد مفسر كلياً في نماذج تسعير الأصول مثل نموذج تسعير الأصول الرأسمالية ونموذج فاما وفرينش ثلاثي العوامل. تشير النتائج أيضاً إلى أن عامل الخطورة الكلية الذي يمثل الفرق في العائد بين الأسهم الأقل والأعلى تذبذباً مسعر في العوائد المقطعية. تعتبر نتائج هذه الدراسة ذات أهمية بالغة للأكاديميين والمستثمرين في البورصة.

الكلمات الدالة: لغز التذبذب المنخفض، الانحراف، تسعير الأصول، نموذج تسعير الأصول الرأسمالية، نموذج فاما وفرينش، عوائد الأسهم، بورصة عمان للأوراق المالية.

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