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Downside Risk and Stock Returns: The Case of Amman Stock Exchange

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ABSTRACT

This study investigates the effect of downside risk on stock return. In specific, we augment downside risk mimicking factor into both the Capital Assets Pricing Model (CAPM) and the three factor model of Fama and French (1993). The study uses daily data over the period (2013-2017) for a sample consisting of 92 companies listed in Amman Stock Exchange (ASE). Using panel regressions, results show that there is a statistically significant positive effect of downside risk on stock returns in ASE, thus the downside risk represents a source of systematic risk. In contrast, results indicate that there is no statistically significant effect of upside risk on stock returns. Moreover, a statistically significant effect of market risk premium, Small Minus Big (SMB) and High Minus Low (HML) is found on the stock return.

Keywords: Downside risk, Upside risk, Stock return, Systematic risk, Fama and French (1993), CAPM, SMB, HML, Amman Stock Exchange.

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مخاطر هبوط الأسعار العام وعوائد الأسهم: حالة بورصة عمان للأوراق المالية

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ملخص

تهدف هذه الدراسة إلى اختبار أثر مخاطر هبوط الأسعار العام على عوائد الأسهم. بالتحديد، فقد تمت إضافة عامل خطورة هبوط الأسعار العام إلى نماذج تسعير الأصول الرأسمالية، وهي: نموذج تسعير الأصول الرأسمالية (CAPM) ونموذج فاما وفرينش ثلاثي العوامل. استخدمت الدراسة بيانات يومية للفترة (2013–2017) لعينة تتكون من 92 شركة مدرجة في بورصة عمان للأوراق المالية، باستخدام تحليل الانحدار للبيانات المقطعية ذات السلاسل الزمنية. وبينت نتائج الدراسة أن هناك أثراً إيجابياً ذا دلالة إحصائية لخطر هبوط الأسعار العام على عوائد الأسهم في بورصة عمان للأوراق المالية. كما بينت النتائج أن خطر هبوط الأسعار العام يعتبر مصدراً من مصادر الخطر النظامي. في المقابل، بينت الدراسة أنه ليس هناك أثر ذو دلالة إحصائية لخطر ارتفاع الأسعار العام على عوائد الأسهم خلال نفس الفترة في بورصة عمان للأوراق المالية. لذلك فإن خطر ارتفاع الأسعار العام لا يعتبر مصدراً من مصادر الخطر النظامي. كذلك بينت الدراسة أن هناك أثراً ايجابياً ذا دلالة إحصائية لِ (HML, SMB, MKT) على عوائد الأسهم في بورصة عمان للأوراق المالية.

الكلمات الدالة: خطر هبوط الأسعار العام، خطر ارتفاع الأسعار، الخطر النظامي، عامل الحجم، نموذج فاما وفرينش ثلاثي العوامل، عامل القيمة، نموذج تسعير الأصول الرأسمالية، عوائد الأسهم، بورصة عمان للأوراق المالية.

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1. INTRODUCTION

Assets Pricing Models describe the relationship between risk and expected return. Markowitz (1952) is the first who studied the relationship between risk and expected return for any financial asset, then Capital Asset Pricing Model (CAPM) was developed by Sharpe (1964), Lintner (1965) and Mossin (1966). However, Ross (1976) and Roll (1977) in their papers stated that the CAPM is not testable, because it depends only on one factor. They developed the Arbitrage Pricing Theory (APT), where the APT model is a multi-factor model. This theory indicates that expected return must be related to risk in such a way that no single investor could create unlimited wealth through arbitrage. Fama and French (1992) developed the CAPM by adding two factors, size risk premium (measured by market capitalization) and value risk premium (measured by book-to-market ratio). Carhart (1997) added the momentum factor to the Fama and French three-factor model. Researchers suggested many variables that may determine the rate of return on investment in ASE, such as liquidity risk (Bani Hani and Al-Mwalla, 2017) and volatility risk (Alrabadi, 2019).

In this study, we test the effect of downside risk on stock return. Downside risk refers to the risk of an asset or portfolio in case of an adverse economic scenario (Farago and Tedongap, 2018). Downside risk also refers to the risk that assets tend to move downward in a declining market. Upside risk refers to the tendency of assets to move upward in a rising market (Ang *et al.,* 2005).

Researchers have long recognized that they care differently about downside losses *versus* upside gains. Agents place greater weight on downside risk demand additional compensation for holding stocks with high sensitivities to downside market movements. They show that the cross-section of stock returns reflects a premium for downside risk. Specifically, stocks that co-vary strongly with the market when the market declines have higher average returns than other stocks. This study investigates the effect of both downside and upside risks on the cross-section of stock returns in Amman Stock Exchange. Research is conducted to test two main null hypotheses:

H0.1: There is no statistically significant effect of downside risk on the cross-section of stock returns over the period (2013-2017) in ASE.

H0.2: There is no statistically significant effect of upside risk on the cross-section of stock returns over the period (2013-2017) in ASE.

The remainder of this study is organized as follows: Section 2 reviews the literature, Section 3 describes data and methodology, Section 4 presents the results of analysis and Section 5 concludes the paper.

2. Literature Review

Researchers have investigated the effect of downside risk on stock returns in many capital markets around the world. In a pioneering work, Ang *et al.* (2002) demonstrated that a part of the factor structure in stock returns reflects variations in downside risk, measured by downside correlations. Researchers find that while the Fama-French (1993) three-factor model cannot explain the variations in expected returns of stocks sorted by downside correlations, a factor reflecting the spread in expected returns induced by downside correlations explains these variations. They construct a downside correlation factor that captures the return premium between stocks with high downside correlations and stocks with low downside correlations, which they term the “CMC” factor for “high Correlations Minus Low Correlations”. The CMC factor goes with long stocks with high downside correlations, which have high expected returns and shorts stocks with low downside correlations, which have low expected returns. The study uses data from the Center for Research in Security Prices (CRSP) to construct portfolios of stocks sorted by various characteristics of returns and uses daily returns from CRSP for the period covering January 1st, 1964 to December 31st, 1999, including NASDAQ data which is only available post-1972. The results of this study show that stocks with high downside correlations have higher expected returns than stocks with low downside correlations. The portfolio of stocks with the greatest downside correlations outperforms the portfolio of stocks with the lowest downside correlations by 4.91% *per annum*. Downside correlation is distinct from market risk and liquidity risk and is not mechanically linked to past returns.

Post *et al.* (2012) investigated the role of downside risk in explaining the cross-section of US stock returns. They used monthly stock data from 1951 to 1969. Using the multivariate regression approach of Fama and Macbeth (1973) based on single sorted and double sorted portfolio, the results of this study suggest that downside risk, when properly defined and estimated, is a driving force behind stock prices.

Galasband (2012) investigated the downside risk exposure of international stock returns. The researcher used monthly international value-weight dollar returns of value and growth portfolios in fourteen industrialized economies: the G7 countries plus Australia, Belgium, Hong Kong, the Netherlands, Singapore, Sweden and Switzerland. For the period 1975–2010, this study found that differences in returns on value and growth portfolios can be rationalized by assets' reactions to market's downside shocks. International value stocks are particularly sensitive to market's permanent downside shocks, while international growth stocks are particularly sensitive to market's temporary downside shocks.

Atilgan and Demirtas (2013) investigated the relationship between downside risk and expected returns on the aggregate stock market in an international context. Non-parametric and parametric Value at Risk (VaR) were used as measures of downside risk to determine the existence and significance of a risk-return trade-off using daily market returns data from 27 emerging countries. Fixed-effects panel data regressions provide evidence for a significantly positive relationship between monthly expected market returns and downside risk. This result is robust after controlling for aggregate dividend yield, price-to-earnings ratio and price-to-cash flow ratio. The relationship between expected returns and downside risk is much weaker for developed markets. Indeed, it vanishes when control variables are included in the downside risk-return specification.

Sevi (2013) considered the downside-risk aversion of investors as an explanation for the risk-return trade-off. The researcher empirically tested this hypothesis using intraday data along with a measure of downside risk called realized semi-variance developed by Barndorff-Nielsen *et al.* (2010). The data consisted of daily observations over the period (1996–2008). The results provided evidence of a significant relationship between semi-variance and excess returns at the daily frequency.

Alles and Murray (2013) used individual equities in a range of emerging Asian markets and investigated the potential contribution of downside risk measures to explain assets' prices in these markets. Realized returns were used as proxy for expected returns. The researchers separately examined conditional returns in upturn and downturn periods, in order to successfully identify risk and return relationships. The data was obtained from eight emerging national equity markets in the Asia Pacific region. These are China, India, Indonesia, Malaysia, Pakistan, Taiwan, Thailand and South Korea. The sample period was from 1999 to 2009. The researchers showed that the shares which co-vary strongly with the market during market downturns have higher average returns.

Moore *et al.* (2013) investigated the cross-sectional difference in the downside tail risks of stock returns. By modeling the heavy-tailed feature in the left tail region of stock return distributions, the downside tail risk was determined jointly by the tail index and scale. The sample included daily equity return data of non-financial US companies listed in both the NYSE and the NASDAQ from 2000 to 2011. The researchers split their sample into 9 overlapping periods with 4 years of data in each period. They showed that under the safety-first asset pricing framework, if investors have a sufficiently low tail risk tolerance, then stocks traded in the same market share a homogeneous tail index. In addition, given the homogeneous tail indices, the equilibrium prices of assets are differentiated by the scales. To empirically test such theoretical predictions, they established two statistical procedures on testing the homogeneity of tail indices and scales in stock returns, accounting for the potential cross-sectional tail dependence. Empirical results supported the theoretical prediction that tail index is homogeneous across equity returns, while tail scales are heterogeneous. The study further showed that the differences in tail scales are driven by firm characteristics, such as size, growth, leverage, bid-ask spread and market beta.

Chen and Chiang (2016) investigated the intertemporal relationship between downside risks and expected stock returns for five major advanced markets; the Canadian S&P/TSX Composite Index (CA), the French CAC40 (FR), Germany's DAX30 (GM), the United Kingdom's FTSE 100 (UK) and the US S&P500 (US). The data consisted of the stocks from the five advanced markets. The sample period was from January 1, 1975 to June 30, 2015. The researchers used Value-at-Risk (VaR) as a measure of downside risk. They found a positive and significant relationship between VaR and the expected return before the world financial crisis (September 2008). However, when they estimated the model using a sample after this date, the results showed a negative risk–return relationship. Evidence from a two-state Markov regime-switching model indicated that as uncertainty rises, the sign of the risk–return relationship turns negative. Evidence suggests that the Markov regime switching model helps resolve the conflicting signs in the risk–return relationship.

Fargo and Tedongap (2018) provided an analysis of downside risk and US assets' prices using monthly returns over the period (July 1964 to December 2016). The researchers used the generalized method of moments (GMM) to empirically investigate the performance of their three-and five-factor models. Their benchmark test assets were various portfolio formed from US stocks, index option portfolios sorted by type and maturity and currency portfolios sorted based on their respective interest rate.

The results of the study showed that besides market returns and market volatility, downside factor and volatility downside factor are also priced. The researchers found that expected returns on various assets' classes reflect premium for bearing undesirable exposures to these factors. In addition to fall in the market return, downside risk maybe associated with a rise in market volatility. The empirical tests confirmed that these factors are priced in the cross-section of various assets' classes, including stocks, options, currencies, treasury bills, corporate bonds and commodity future.

To the best of the authors' knowledge, this is the first study in Jordan that discusses the effect of downside risk on the cross-section of stock returns.

3. Data and Methodology

3.1 Data

The dataset of this study consists of the daily observations of all the companies listed in Amman Stock Exchange over the period (2013-2017), inclusive. However, a filtering process is performed in order to avoid the thinly traded stocks. In order for the company to be included in our sample, 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 with mergers or split are excluded.

The filtering process resulted in a sample of 92 companies.

3.2 Methodology

Research Design

Daily stock return is calculated as follows:

$$R_{it} = Ln(\frac{P_{it}}{Pi,t-1}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(1)$$

where:

R_{it}: is the return of stock i on day t.

P_{it}: is the closing price of company i on day t.

$Pi,t\text{-}1$: is the closing price of company i on day t-1.

To achieve research objectives at the beginning of each year, we sort stocks into five quintiles based on their realized β^{+} (for upside risk) and realized β^{-} (for downside risk). In specific, each year sample stocks are ranked according to their beta values, from the lowest beta to the highest. Thereafter, they are divided into five groups (portfolios), portfolio one consisting of stocks with lowest beta values, while portfolio five consisting of stocks with highest beta values. We calculate downside risk factor and upside risk factor as follows (Ang *et al.*, 2005):

Downside Risk Beta

$$\beta^{-}{}_{0} = cov(r_i, r_m; r_m < 0) / var(r_m; r_m < 0) \quad \ldots\ldots\ldots(2)$$

Upside Risk Beta

$$\beta^{+}{}_{0} = cov(r_i, r_m; r_m > 0) / var(r_m; r_m > 0) \quad \ldots\ldots\ldots (3)$$

where:

Cov: is the covariance between stock return and market return.

Var: is the variance of market return.

After we construct two portfolios; portfolio one with the lowest downside risk beta and portfolio five with the highest downside risk beta; the downside risk mimicking factor is constructed as the difference between the two portfolios' daily returns. Thereafter, the downside risk mimicking factor is added to both the CAPM and Fama and French (1993), respectively, as follows:

$$R_{it} - Rf_t = \beta_0 + \beta_1(Rm_t - Rf_t) + \beta_2 Down_t + \varepsilon_{it} \ldots\ldots (4)$$

$$R_{it} - Rf_t = \beta_0 + \beta_1(Rm_t - Rf_t) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 Down_t + \varepsilon_{it} \quad (5)$$

where:

R_{it}: is the rate of return on stock i on day t.

R_{ft}: is the risk-free rate of return on day t.

R_{mt}: is the market rate of return on day t.

SMB_t: (small minus big): is the difference between the average rates of return on small and large stock portfolios on day t.

HML_t (high minus low): is the difference between the average rates of return on high and low book-to-market equity stock portfolios on day t.

$Down_t$: is the mimicking factor of downside risk on day t.

On the other hand, we construct two portfolios; portfolio one with the lowest upside risk beta and portfolio five with the highest upside risk beta; the upside risk mimicking factor is constructed as the difference between the two portfolios' daily returns. The upside risk mimicking factor is augmented to both the CAPM and Fama and French (1993), respectively, as follows:

$$R_{it} - Rf_t = \beta_0 + \beta_1(Rm_t - Rf_t) + \beta_{i2}Up_t + \varepsilon_{it} \qquad \text{……..….(6)}$$

$$R_{it} - Rf_t = \beta_0 + \beta_1(Rm_t - Rf_t) + \beta_2 SMB_t + \beta_3 HML_t + \beta_{i2}Up_t + \varepsilon_{it} \qquad (7)$$

where:

UP_t: is the mimicking factor of upside risk on day t.

Thereafter, Equations (4), (5), (6) and (7) are estimated using panel regression analysis. Fixed effect panel regressions are used based on the significant values of both Lm and Hausman tests. All the common risk factors are calculated by dividing the sample stocks into five groups according to a certain criterion, thereafter calculating the difference in daily returns between the two portfolios of the first and fifth quintiles. The portfolios are reconstructed on a yearly basis.

4. Results of Analysis

4.1 Descriptive Statistics

4.1.1 Descriptive Statistics of Stock Return

Table (1) shows the descriptive statistics of return of the sample stock with a mean of (-0.0003). In a bullish market (when rm> 0), the market return has a mean of (0.0032), while in a bearish market (when rm< 0), the market return has a mean of (-0.0030). The downside risk beta has a mean of (0.9755), a maximum value of (2.4535) and a minimum value of (0.2277). The upside risk beta has a mean of (0.9849), a maximum value of (2.6192) and a minimum value of (-0.0738).

Table (1) shows the descriptive statistics of the variables of the study. Return denotes the sample stock returns; MKT denotes the market return. MKTPOS denotes the market return when the market is bullish (rm>0). MKTNEG denotes the market return when the market is bearish (rm<0). β^+ denotes the upside risk betas. β^- denotes the downside risk betas.

Table (1)

Descriptive statistics of the study variables

	RETURN	MKTPOS	MKTNEG	MKT	β^+	β^-
Mean	-0.0003	0.0032	-0.0030	0.0001	0.9755	0.9849
Median	0.0000	0.0024	-0.0024	0.0000	1.0015	0.7309
Maximum	3.6490	0.0209	0.0000	0.0209	2.4535	2.6192
Minimum	-2.4400	0.0000	-0.0198	-0.0198	0.2277	-0.0738
Std. Dev.	0.0704	0.0032	0.0028	0.0043	0.5612	0.6951

Figures (1), (2) and (3) show the MKT, MKTNEG and MKTPOS, respectively, over the study period (2013-2017).

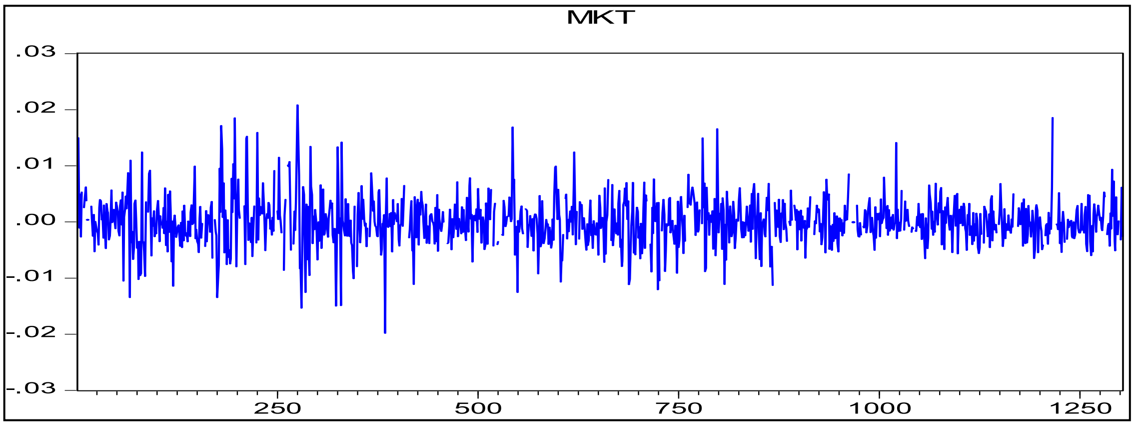

Figure (1)

MKT over the study period (2013-2017)

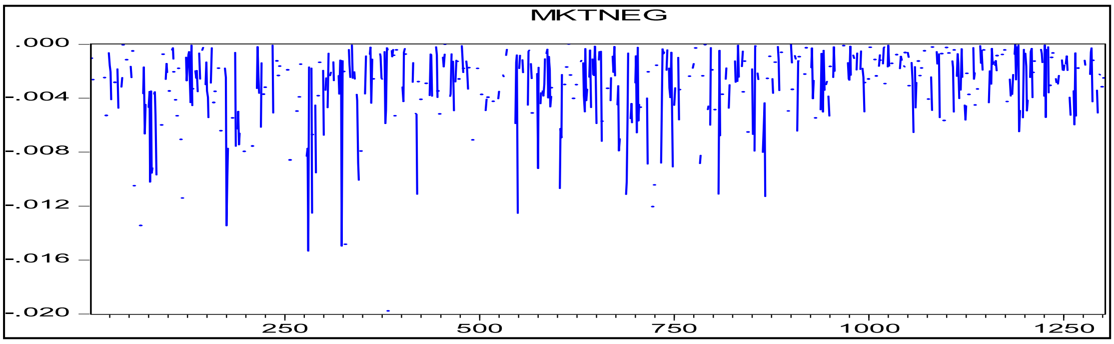

Figure (2)

MKTNEG over the study period (2013-2017)

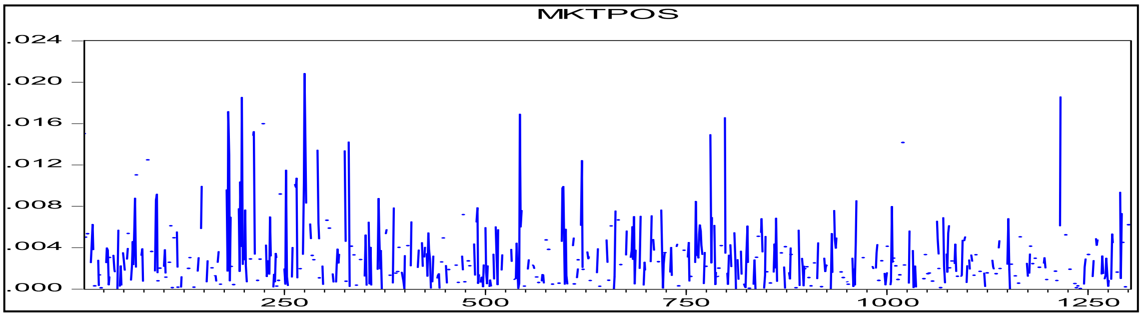

Figure (3)

MKTPOS over the study period (2013-2017)

4.1.2 Descriptive Statistics of the Risk Factors

Table (2) reports the descriptive statistics of risk factors and the results show that market risk premium has a mean of (0.0001). The means of all other risk factors are negative over the period of the study.

Table (2) shows the descriptive statistics of the risk factors of the study. (rm-rf) denotes the market risk premium. SMB denotes the small minus big factor. HML denotes the high minus low factor. DOWN denotes the downside risk factor. UP denotes the upside risk factor.

Table (2)

Descriptive statistics of risk factors

	(rm-rf)	**SMB**	**HML**	**DOWN**	**UPS**
Mean	0.0001	-0.0067	-0.0117	-0.0005	-0.0042
Median	0.0000	-0.0013	-0.0021	-0.0015	-0.0005
Maximum	0.0209	0.2009	0.2201	0.3712	0.2158
Minimum	-0.0198	-0.3009	-0.5737	-0.2488	-0.3012
Std. Dev.	0.0043	0.0426	0.0709	0.0577	0.0479

4.2 Correlation Coefficients

Table (3) shows the correlation between the risk factors. The results show that all the correlation coefficient values between the risk factors are low (less than 70%), which indicates that there is no multicollinearity problem (Gujarati, 2004).

Table (3) shows correlation coefficients between risk factors. (rm-rf) denotes the market risk premium. SMB denotes the small minus big factor. HML denotes the high minus low factor. DOWN denotes the downside risk factor. UP denotes the upside risk factor.

Table (3)

Correlation coefficients between risk factors

	(rm-rf)	HML	SMB	UP	DOWN
(rm-rf)	1.0000	-0.0921	-0.0890	0.1642	0.0986
HML	-0.0921	1.0000	0.1738	0.0748	-0.1216
SMB	-0.0890	0.1738	1.0000	0.0666	-0.2680
UP	0.1642	0.0748	0.0666	1.0000	0.0363
DOWN	0.0986	-0.1216	-0.2680	0.0363	1.0000

4.3 Estimation Results

Table (4) shows the estimation results of the CAPM augmented with the downside risk factor. Results show that there is a statistically significant positive effect of the market risk premium on the stock returns in ASE over the period (2013-2017).

The market risk premium coefficient is (89%). Results also show that there is a statistically significant positive effect of the downside risk on the stock returns. These results indicate that the downside risk represents a statistically significant source of systematic risk in ASE over the period (2013-2017). The adjusted (R^2) of the model equals 11.95%, which indicates that the CAPM augmented with downside risk explains 11.95% of the cross-section of stock returns in ASE over the period (2013-2017).

Table (4) shows the estimation results of the CAPM augmented with downside risk factor. (rm-rf) denotes the market risk premium. DOWN denotes the downside risk betas augmented to the CAPM.

Table (4)
The estimation results of the CAPM augmented with downside risk factor

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.0010	0.0004	-2.4495	0.0143
(rm-rf)	0.8904	0.0862	10.3338	0.0000
DOWN	0.0207	0.0072	2.8526	0.0043
Adjusted R^2 = 0.1195				

Table (5) shows the estimation results of the CAPM augmented with the upside risk factor. Results show that there is a statistically significant positive effect of the market risk premium on the stock returns in ASE over the study period (2013-2017). The market risk premium coefficient is (98%). However, the results show that there is no statistically significant effect of the upside risk on the stock returns in ASE over the study period (2013-2017). These results indicate that the upside risk does not represent a source of systematic risk in ASE over the period (2013-2017). The adjusted (R^2) of the model equals 11.86%, which indicates that the CAPM augmented with upside risk factor explains 11.86% of the cross-section of stock returns in ASE over the period (2013-2017).

Table (5) shows the estimation results of CAPM augmented with upside risk factor. (rm-rf) denotes the market risk premium. UP denotes the upside risk factor.

Table (5)
The estimation results of CAPM augmented with upside risk factor

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.0006	0.0003	-2.0600	0.0394
(rm-rf)	0.9824	0.0682	14.3954	0.0000
UP	-0.0043	0.0066	-0.6511	0.5150
Adjusted R^2 =0.1186				

Table (6) shows the estimation results of the three – factor model of Fama and French (1993) augmented with the downside risk factor. The results show that there is a statistically significant positive effect of the market risk premium on the stock returns in ASE over the study period (2013-2017). The market risk premium coefficient is (99%). The results also show that there is a statistically significant positive effect of small minus big (SMB) factor on the stock return, (prob $\leq$ *10%)*; the high minus low (HML) factor has also a statistically significant positive effect on the stock returns. On other hand, there is a statistically significant positive effect of the downside risk on the stock returns. These results indicate that the downside represents a source of systematic risk over the period (2013-2017). The adjusted (R^2) of the model equals 13.69%, which indicates that Fama and French (1993) three- factor model augmented with the downside risk factor explains 13.69% of the cross-section of stock returns in ASE over the period (2013-2017). The intercept of the model is statistically insignificant, indicating that the risk factors in this model explain the returns in ASE.

Table (6) shows the estimation results of Fama and French three- factor model augmented with downside risk mimicking factor. (rm-rf) denotes the market risk premium. SMB denotes the small minus big factor. HML denotes the high minus low factor. DOWN denotes the downside risk factor.

Table (6)

The estimation results of Fama and French three- factor model augmented with downside risk mimicking factor

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.0007	0.0005	-1.4239	0.1545
(rm-rf)	0.9986	0.0927	10.7723	0.0000
SMB	0.0259	0.0154	1.6875	0.0916
HML	0.0442	0.0090	4.9362	0.0000
DOWN	0.0399	0.0081	4.9035	0.0000
Adjusted R^2 = 0.1369				

Table (7) shows the estimation results of Fama and French (1993) model augmented with the upside risk factor. The results show that there is a statistically significant positive effect of the market risk premium on the stock returns in ASE over the period (2013-2017). The market risk premium coefficient is (99%).The results also show that there is a statistically significant positive effect of small minus big (SMB) factor on the stock return, (prob $\leq$ *10%)*; the high minus low (HML) factor has also a statistically significant positive effect on the stock return. However, the results show that there is no statistically significant effect of the upside risk on the stock returns. These results indicate that the upside risk does not represent a statistically significant source of systematic risk over the period (2013-2017).The adjusted (R^2) of the model equals 13.32%, which indicates that Fama and French (1993) model augmented with upside risk factor explains 13.32% of the cross-section of stock returns in ASE over the period (2013-2017). The intercept of the model is statistically insignificant, indicating that the risk factors in this model explain the returns in ASE.

Table (7) shows correlation coefficients of risk factors. (rm-rf) denotes the market risk premium.

SMB denotes the small minus big factor. HML denotes the high minus low factor. UP denotes the upside risk factor.

Table (7)
The estimation results of Fama and French three-factor model augmented with upside mimicking factor

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.0005	0.0003	-1.3083	0.1908
(rm-rf)	1.0700	0.0690	15.5032	0.0000
SMB	0.0203	0.0112	1.8102	0.0703
HML	0.0357	0.0067	5.3150	0.0000
UP	-0.0048	0.0076	-0.6263	0.5312
Adjusted R^2 =0.1332				

Overall, based on our results, we reject H0.1, while we accept H0.2. Our results are consistent with (Ang *et al.*, 2002; Alles and Murray, 2013; Atilgan and Demirtas, 2013; Chen and Chiang, 2015; Fargo and Tedongap, 2018).

5. Conclusions

The main aim of this study is to investigate the effect of downside risk on stock returns in ASE over the period (2013-2017). We also investigate the effect of upside risk on stock returns by default. We augmented the downside and upside risk factors to CAPM model and three-factor model of Fama and French (1993). The study uses daily data over the period (2013-2017). The sample consists of 92 companies listed in ASE and uses panel data regression analysis. Results show that there is a statistically significant positive effect of downside risk on stock returns in ASE. On the other hand, there is no statistically significant effect of upside risk on the stock returns. Thus, the downside risk represents a source of systematic risk in ASE.

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