Diversification benefits of investments in emerging markets – A Swedish perspective

Gustav Berg* Pontus Zetterberg†

Stockholm School of Economics

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Abstract

This paper evaluates the possibilities for Swedish investors to diversify their portfolios through investments in emerging market equities. Two different investor profiles are considered, where one seeks to minimize the risk in her portfolio and the other seeks to maximize her risk-adjusted return. We start off by analyzing the return characteristics of a Swedish stock index and an emerging markets index. A set of portfolios are then created based on, and evaluated with, the volatility estimated by the DCC MGARCH model and the Conditional Value-at-Risk. Our findings suggest that the investor seeking to minimize her portfolio risk can enjoy diversification benefits from investments in emerging markets. Conversely, the investor seeking to maximize her risk-adjusted return cannot improve her base portfolio by investing in emerging markets. This implies that investors should consider their ultimate purpose before investing in emerging market equities.

Keywords: Emerging markets, diversification, risk, portfolio management

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* 23271@student.hhs.se

† 23238@student.hhs.se

Table of Contents

1. Introduction

Portfolio diversification is considered to be one of the most central and important pillars of modern finance (Asness et al., 2011). Portfolio management originates from the seemingly simple framework of Modern Portfolio Theory (MPT) laid out by Harry Markowitz in 1959 (Markowitz, 1959). He argues that rational investors will choose the portfolio that maximizes their return for a given level of risk. MPT also states that investors can reduce their exposure to risk by holding a diversified portfolio. This means that investors hold a portfolio consisting of several different assets in order to minimize its idiosyncratic risk. In this study, we examine the diversification benefits Swedish investors can enjoy by allocating resources in emerging market equities.

During the 90's, emerging market equities became an increasingly attractive asset class for investors in developed countries. These equities showcased a relatively low correlation with developed markets' returns in combination with having the potential of offering high returns. Thus, this new type of asset provided significant diversification benefits (Bekaert and Harvey, 1995).

Today, the use of emerging markets equities as a diversification asset is more disputed, and some argue that the benefits have evaporated. The main reason for this is that globalization has led to increased integration between emerging and developed markets, which in turn has increased the correlation between them. In fact, Garza-Gómez and Metghalchi (2006) found no statistically significant diversification benefits from investing in emerging market equity indices, mainly due to an increasing correlation with S&P 500. Christoffersen et al. (2012) also noticed an increasing correlation between emerging and developed markets, but argue that the emerging market equities still offer significant diversification benefits for investors in developed countries.

A central concept of portfolio management is the choice of risk measurement. The mean-variance framework laid out by Markowitz assumes that returns are normally distributed. In this framework the portfolio variance is deemed to be the suitable measurement of risk. However, Bekaert and Harvey (2002) highlights the problematic nature of emerging markets when it comes to risk assessment. They argue that emerging market equities exhibit non-normality in returns, with higher values to both skewness and kurtosis, which makes the variance an inadequate technique of measuring portfolio risk.

Further, another common feature in emerging markets when it comes to risk assessment is the existence of volatility clusters (Harvey, 1995). This means that volatility is time-varying, i.e. periods of high volatility are likely to be followed by periods of high volatility and vice versa. This necessitates alternative ways of measuring risk that incorporates the time-variety of variance to appropriately capture the risk in a portfolio optimization problem including emerging market equities. A commonly used method to deal with this issue is to use extensions of the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model.

This study aims to add to the ongoing debate of whether emerging markets offer diversification benefits by taking the perspective of a Swedish investor. These benefits might be different from those of investors from other countries due to the differences in size and nature between markets. Furthermore, the research devoted to the diversification benefits from a Swedish perspective is currently limited.

To get a thorough understanding of the diversification benefits, the topic is analyzed from the perspective of two different investor profiles. The first investor only seeks to minimize her risk, while the second investor aims to maximize her risk-adjusted return. Two hypotheses are formulated in relation to the different investor profiles. The first null hypothesis is that the portfolios that include investments in the emerging markets index will have the same risk as the base portfolio. This is tested against the alternative that the portfolio risks will differ. The second null hypothesis is that the risk-adjusted return in the portfolios that include investments in the emerging markets index will be the same as in the base portfolio. This hypothesis is tested against the alternative that the risk-adjusted returns will differ from the base portfolios. To avoid the pitfalls of commonly used risk measures when it comes to emerging market returns, we adopt two alternative measures that are deemed more suitable to capture the economic reality of the investment. The DCC MGARCH model is used to estimate volatility, and the Conditional Value-at-Risk is used to specifically capture the downside risk. These risk-measures are applied in the portfolio optimization problem and later on used to test the risk in the portfolios created.

The results showed that both null hypotheses could be rejected, meaning that the portfolios created had different risks and risk-adjusted returns than the base portfolio. More specifically, the findings suggest that Swedish investors can lower their portfolio risk, but that they cannot increase their risk-adjusted return by investing in emerging market equities.

2. Literature Review

Many studies have examined the possibilities for international portfolio diversification. Levy and Sarnat (1970) provided early research about the diversification benefits one could enjoy by investing internationally due to the relatively low correlation between different markets. Focusing specifically on emerging markets, Harvey (1995) found that investments in these could reduce portfolio volatility and increase expected returns. He also noted that these markets showcased higher predictability in returns than developed markets, and highlighted the inadequacy of using standard asset pricing models due to their assumption of complete market integration.

Bekaert et al. (1998) analyzed the characteristics of emerging market returns, and found not only that the return distributions exhibit high values for skewness and kurtosis, but also that these factors changed over time. The authors also note that this has implications for asset allocation, which the mean-variance framework developed by Markowitz is unable to take into account. Ghysels et al. (2016) further investigated these implications for portfolio allocation. Their findings suggest that investors can increase their returns by allocating resources to emerging markets in order to capture the positive skewness these exhibit.

A characteristic of emerging market returns that complicates the analysis is the prevalence of time-varying correlation, as shown by Christoffersen et al. (2012). When evaluating the diversification benefits from investments in emerging markets, it is therefore important to apply a model that captures the effect of dynamic correlation. Another feature of the correlation that they noted was that it not only changed over time, but that there was a clear trend of it increasing gradually. This is a well-documented aspect which also has been noted by Gupta and Donleavy (2009) as well as Garza-Gómez and Metghalchi (2006). Studies by Longin and Solnik (1995) amongst many others have also shown that the correlation increases during times of financial distress.

A number of methods have been suggested to cope with the non-normality of emerging market returns when measuring risk. Christoffersen et al. (2012) proposes tail dependence as a measure of diversification benefits in addition to more conventional measures. Borokova (2011) takes a similar approach and investigates tail dependence in South-East Asia during the financial crisis of 2008-2010, where she finds that diversification benefits from investments in emerging markets decrease heavily during periods of financial turmoil. Dimitrakopoulus et al. (2009) instead try to quantify the risk in emerging markets by using and evaluating Value-at-Risk (VaR) models.

Much research in the field of emerging markets finance and international diversification has relied on the GARCH model and its extensions to estimate time-varying variances and covariances between markets. Longin and Solnik (1995) use a multivariate GARCH (MGARCH) model with constant conditional correlations to model the correlations between different markets. Engle (2002), however, introduces an extension of the MGARCH model that captures dynamic conditional correlations (DCC). A version of this DCC MGARCH model is used by Gupta and Donleavy (2009) to evaluate co-movements between countries in order to determine the diversification possibilities from investments in emerging markets.

3. Data

The data in this study has been gathered from Thomson Reuters Datastream and the Swedish National Debt Office for the period 2004-2016. The time period has been selected in order to capture cyclicality in financial markets and the correlation dynamics between the Swedish and emerging market equities. By evaluating the years between 2004 and 2016, it is possible to examine both the diversification benefits during more stable financial conditions as well as under financial turmoil, such as the financial crisis in 2008 and the US credit rating crash in 2011. Given the changing correlation dynamics during financial downturns, it is important to capture this effect since it might have an effect on the diversification benefits.

The data consists of daily adjusted closing prices and contains 3196 observations for the OMX Stockholm 30 (OMXS30) and iShares MSCI Emerging Markets ETF (MSCI EEM). Data has also been gathered for historical exchange rates for the given time period for the Swedish Krona (SEK) to US Dollar (USD).

The adjusted closing price corresponds to the closing price with adjustments for both stock-splits and dividends in order to better reflect the true performance of the instruments. The reason for why index instruments are used in this study is because one could argue that a diversification oriented investor prefers to invest in indices rather than individual securities. The choice of index instruments when studying international diversification is also supported by Errunza et al. (1999). The OMXS30 index consists of the 30 most traded stocks on the Stockholm Stock Exchange, and is used as a proxy for the portfolio of Swedish investors. The MSCI EEM is a well-diversified index consisting of holdings in more than 20 emerging markets. An overview of the top ten largest holdings in the MSCI EEM is presented in Appendix A.

Data has also been collected for the two-year maturity Swedish Government Bond, which is used as a proxy for the risk-free rate. To match the daily returns of the data from the indices, it is transformed into a daily rate. The transformation into daily compounding is under the assumption that a year consists of 250 trading days.

3.1. Currency Risk

Benefits of international investment are generally reduced by institutional, political and psychological factors. More important, however, is the existence of exchange-rate risk or currency risk (Solnik, 1995). A Swedish investor that seeks to invest in the American stock market or foreign assets is clearly subject to currency risk which arises from the change in price of one currency in relation to the other. If not taken into consideration, investors that have assets in foreign countries are subject to currency risk that might cause unpredictable profits and losses. One way to remove the currency risk from an international investment is to hedge foreign holdings. Although currency hedging lowers the exchange-rate risk for a portfolio, it does not have the same rewards as an uncovered portfolio (Solnik, 1995). Thus, this study will adjust the underlying data for the MSCI EEM with historical exchange rates for the SEK to USD in order to capture the currency risk of unhedged portfolios.

It is also worth noting that any emerging markets index itself will be exposed to currency risk. This stems from the fact that the ETF consists of a number of holdings in countries with different currencies. However, seeing as this paper takes a practical approach and examines the diversification benefits one can enjoy from investing in an index rather than direct stock investments in emerging markets, we do not emphasize the effect from this risk any further.

4. Theory and Methodology

This chapter presents the theoretical concepts and the methodology used in this study. First, the hypotheses are developed and formulated. The two investor profiles are then presented, which is followed by a description of the methods used in the construction of the portfolios. We then give an overview of some necessary theoretical concepts, and present the methods used in relation to them. Lastly, the metrics used to evaluate the portfolios are presented.

4.1. Hypotheses

The purpose of this study is to examine the diversification benefits Swedish investor possibly can draw from investing in emerging market equities. The primary motivation for holding a diversified portfolio is to reduce risk (Solnik, 1995). A well diversified portfolio consists of several different assets that allows for diversification of the idiosyncratic risk. Another important concept is correlation, which is strongly associated with diversification. The less the assets are correlated, the higher the diversification possibilities will be. Historically, emerging markets have been an attractive diversification instrument due to their low correlation with world market returns, which has been shown in a number of previous studies (Bekaert and Harvey, 2002; Christoffersen et al., 2012). In order to test if there are diversification possibilities for Swedish investors, the first null hypothesis is postulated in the following way:

$\mathbf{H_{0;1}}$: The risk in the portfolio that includes the emerging markets index is the same as the risk in the base portfolio.

This null hypothesis is tested against the alternative hypothesis:

$\mathbf{H_1}$: The risk in the portfolio that includes the emerging markets index will be different from the risk in the base portfolio.

The volatility estimated by the DCC MGARCH model and the CVaR will be used as measurements of risk. A further more detailed description of the risk quantifiers is presented in section 4.5. To further assess the possible diversification benefits, the direction of the change in risk is also analysed. The existence of diversification benefits from a risk-minimizing perspective will be defined as a reduction in both risk measures compared to the base portfolio. However, looking only at the reduction in the portfolio risk in isolation might be unsuitable since many diversification oriented investors are likely to also be interested in their risk-adjusted return. Therefore, the second null hypothesis is postulated as:

$H_{0;2}$: The risk-adjusted return in the portfolio that includes the emerging markets index will be the same as the risk-adjusted return in the base portfolio.

In turn, this null hypothesis is tested against the following alternative hypothesis:

H_2: The risk-adjusted return in the portfolio that includes the emerging markets index will be different from the risk-adjusted return in the base portfolio.

For both of these hypotheses, the base portfolio is defined as the OMXS30. The risk-adjusted return is measured with an adjusted Sharpe ratio which is further presented in section 4.5.3. In order to further assess the diversification benefits, the direction of the change in the risk-adjusted return will also be analysed. From the perspective of the investor seeking to maximize her risk-adjusted return, diversification benefits are defined as an improvement of the adjusted Sharpe ratio with regards to both risk measures in comparison to the base portfolio.

4.2. Investor Profiles

This section introduces the two investor profiles examined, which allows the study to cover a broader spectrum of investment strategies. The portfolio optimization problem is under the assumption that the portfolios must sum to 1, which implies that no capital can be kept or allocated to other assets. In the following subsections, an in-depth description of the investors is presented.

4.2.1. Minimizing the Portfolio Risk

The first investor profile seeks to minimize her portfolio risk. In this paper, this will be equivalent to minimizing the volatility estimated by the DCC MGARCH model and the CVaR in the portfolio. Thus, the optimal portfolio allocation for this investor can determined by solving the following optimization problem:

$$Minimize\ \boldsymbol{w}^{\boldsymbol{T}} \sum \boldsymbol{w}$$
$$subject\ to\ \boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{1} = 1$$
$$w_i \geq 0$$

where $\boldsymbol{w}^{\boldsymbol{T}} = (w_{1,\dots,}w_n)$ i.e. a vector of the portfolio weights w_i. $\sum$ is the covariance matrix of the n portfolio assets.[1]

4.2.2. Maximizing the Risk-Adjusted Return

In order to find the optimal portfolio allocation for the investor seeking to maximize her risk-adjusted return, adjusted Sharpe ratios will be used for the risk-measures covered in this study, which is described in detail in section 4.5.3. By solving the following optimization problem, investors can be ensured to find the optimal Sharpe-maximizing portfolio:

$$\widetilde{\boldsymbol{w}} = t\boldsymbol{w}, \quad t = \frac{1}{\boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{\mu} - r_f}$$

$$Minimize\ \widetilde{\boldsymbol{w}}^{\boldsymbol{T}} \sum \widetilde{\boldsymbol{w}}$$

$$subject\ to\ (\boldsymbol{\mu} - r_f\boldsymbol{1})\widetilde{\boldsymbol{w}} = 1,$$
$$\widetilde{\boldsymbol{w}}^{\boldsymbol{T}} \geq 0.$$
$$\widetilde{w}_i \geq 0.$$

where $\boldsymbol{w}^{\boldsymbol{T}} = (w_{1,\dots,}w_n)$ i.e. a vector of the portfolio weights, w_i. $\boldsymbol{\mu}$ is a vector matrix of the expected return and $\sum$ is the covariance matrix of the portfolio assets. r_f corresponds to the two-year maturity Swedish Government Bond after being transformed into daily compounding.[2]

[1] Readers interested in the mathematical derivation for the optimization model are directed to Engels (2004).
[2] Readers should note that this is a convex reformulation of the more well-known optimization problem. Those interested in the mathematical derivation and proof for the optimization model are directed to Cornuejols and Tütüncü (2006).

4.3. Portfolio Construction

This section gives a description of how the optimal portfolios have been constructed. The portfolio optimization problems outlined in this study have been performed in Stata and MATLAB. The hypotheses are tested by constructing a set of portfolios without allowing for short selling. The short selling constraint is imposed in the portfolio optimization, as many emerging markets have direct or indirect constraints on short sales (Gupta and Donleavy, 2009). Furthermore, a study conducted by Charoenrook and Daouk (2005) highlights the feasibility of short selling constraints in emerging markets. They conclude that short selling is only feasible in twelve percent of the emerging markets, which can be compared to eighty six percent among the developed countries. The portfolios, in turn, consists of index instruments for equities and emerging markets. The selected instruments are:

- Swedish Equity Index: OMXS30
- Emerging Markets Index: MSCI EEM

OMXS30 is used as a proxy for the base portfolio of a Swedish investor. The optimal portfolios, in turn, are created by adding investments in the emerging markets index to the base portfolio. These optimal portfolios are allowed to be rebalanced on a yearly basis, assuming no transaction costs. Portfolio rebalancing is an important aspect of portfolio optimization since changes of conditions in financial markets or disclosure of more information might cause the portfolio allocation from the previous year to become ineffective. Active equity investing has also historically outperformed passive equity investing when it comes to the diversification possibilities (Grossman, 1998). Moreover, a feature of this study is that we take a practical approach and rebalance the portfolio based on historical data, meaning that investors are not able to perfectly predict the future returns of the assets. In other words, this means that we compute the optimal portfolio for one year, and use the results from the optimization when we construct the portfolio for the following year. For instance, the portfolio created for 2005 is based on what in hindsight would have been the optimal portfolio for 2004. Given that our data for the indices spans between 2004-2016, optimal portfolios are created for the years between 2005-2016.

The optimal portfolios, in turn, are constructed for the two different investor profiles covered in this study. In order to improve the robustness of our findings, two different scenarios are examined. First we consider an unrestricted scenario where the investors are allowed to rebalance their portfolio freely without weight constraints. The second scenario, however, imposes weight constraints such that the investor must keep a minimum weight of 50% in the OMXS30. In total, four portfolios are created for each investor.

The rationale behind adding the weight constraints is that one might argue that it is a more realistic scenario due to the home-bias puzzle. Sharpe (1964) argues that an investor will hold the market portfolio in a world with perfect markets. The home-bias puzzle, in contradiction, means that many investors are reluctant to invest a larger proportion of their wealth into foreign markets even though the investment opportunity looks attractive from a theoretical point of view (Berrill and Kearney, 2008). The main reason for this is that investors in general are afraid of international exposure due to their unfamiliarity with the markets (Gupta and Donleavy, 2009).

The optimal portfolio allocations for the two investors are determined by creating an efficient frontier for each year between 2005-2016. For the risk-minimizing investor, the optimal portfolio will be the portfolio that minimizes the risk on the frontier. For the investor that seeks to maximize her risk-adjusted return, the optimal portfolio allocation will be determined by the tangency portfolio. The portfolios are then tested with the evaluation metrics presented in section 4.5 to determine whether diversification benefits exist.

4.4. Return Characteristics

It is well-documented that emerging markets exhibit non-normality in returns. This section therefore presents an overview of some theoretical concepts and methods that relate to these irregularities.

4.4.1. Jarque-Bera Test

The Jarque-Bera test is a commonly used method to test for normality in returns for a certain asset. It is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution (McNeil et al., 2015). The Jarque-Bera test is based on sample skewness and sample kurtosis. The mathematical formulation of the Jarque-Bera test for normality is presented in Appendix B.

4.4.2. Serial Correlation

An important aspect of time series is the concept of serial correlation, which means that the returns in the present period is influenced by the return from the previous period. Many of the traditional asset allocation frameworks are based on an assumption of normality, as well as independent and identically distributed returns, which can problematic when the returns are serially correlated. If not taken into consideration, the presence of serial correlation might distort the true risk characteristics of an asset class and underestimate the overall risk of the portfolio.

4.4.2.1. Ljung-Box Test

In order to test for serial correlation in assets returns, a very popular formal numerical test is the Ljung-Box test, also known as the Q-test (McNeil et al., 2015). Under the null hypothesis, the statistic is derived as:

$$Q_{LB} = n(n+2)\sum_{j=1}^{h}\frac{\hat{\rho}(j)^2}{n-j}$$

The Ljung-Box test has an asymptotic chi-squared distribution with h degrees of freedom. If the Q-statistic has a significance at a 95% confidence level (i.e. a p-value less than 0,05), it is possible to conclude that there is sufficient evidence to reject the null hypothesis of no serial correlation. If the returns are serially correlated, this contradicts the popular random-walk hypothesis which states that it is very difficult to predict future period returns based on historical data alone. However, returns can sometimes exhibit serial correlation. In a study conducted by Harvey (1995), the author noticed that serial correlation was a common characteristic of emerging market returns.

4.4.3. The DCC MGARCH Model

In this study, we will use the Dynamic Conditional Correlation (DCC) model that was proposed by Engle (2002). Historically, data has shown that the correlation between developed markets and emerging markets tend to shift over time. Previous studies that has focused on the correlation between developed markets and emerging markets have emphasized that the correlation has increased during the recent years (Christoffersen et al., 2012). More interesting, the correlation is also said to be abnormally high during times of financial distress (Bekaert and Harvey, 2002). A commonly used method to estimate correlations over time is the moving average, that uses a moving window over time. However, the main weakness of this method is that it puts equal weight to all the observations used in the moving average calculation (Gupta and Donleavy, 2009). An alternative way of incorporating time-varying correlations is the use of multivariate GARCH models. In the DCC MGARCH model proposed by Engle (2002), the correlation is time-varying and is able to capture the changes over time.

Further, it allows for added flexibility since it separates the modeling of volatility dynamics from correlation dynamics. Further, this extension of the MGARCH model has frequently been used in similar studies (Yang, 2005; Jithendranathan, 2005; Dunis and Shannon, 2005). The mathematical formula for the DCC MGARCH model with two variables is presented in Appendix C.

4.5. Portfolio Evaluation

As mentioned in previous sections, the non-normality of emerging market returns has implications for the measurement of risk. This section therefore presents the evaluation metrics that have been chosen specifically to deal with these irregularities. Further, the portfolios are also evaluated based on their skewness and kurtosis, due to their superiority when it comes to capture tail-risk (Harvey et al., 2010).

4.5.1. DCC MGARCH-volatility

Emerging market equities tend to exhibit both non-normality and serial correlation in its returns. As previously mentioned, the DCC MGARCH model suggested by Engle (2002) provides a solution to this when estimating the volatility of assets returns. Consequently, this makes the volatility estimated by the DCC MGARCH model a more appropriate alternative when quantifying portfolio risk. This model was also used by Bouslama and Ben Ouda (2014) in their estimation of risk in a non-normal framework. From here on, any mention of volatility in our study will refer to the volatility estimated by the DCC MGARCH model.

4.5.2. Conditional Value-at-Risk

Conditional Value-at-Risk (CVaR) is a risk assessment technique that measures the probability that a portfolio will incur large losses. CVaR is performed by measuring the likelihood that a loss will exceed the value at risk for a specific confidence level (Rockafellar and Uryasev, 2002). In this study, it is calculated with a confidence interval of 95 percent.

In a framework based on non-normality, one could argue that CVaR is a more appropriate method of measuring portfolio risk. Firstly, it captures the increased tail-risk caused by the presence of leptokurtic distributions (Ergen, 2014). Secondly, it avoids the pitfalls of measures such as standard deviation by not punishing the desirable upward movements as hard as it punishes the undesirable downside movements. Further, it is also considered to be a better approximation of potential losses than its cousin Value-at-Risk (VaR) since it provides an average expected loss rather than a wide range of potential losses that is difficult to account for.

Moreover, VaR might lead to an under-approximation of the risk as it ignores all the returns that are worse than the given VaR level, and thus also the fat tails of the distribution of the returns. Mathematically, the CVaR expression is derived as:

$$CVaR_{\alpha} = \frac{1}{1-\alpha}\int_{-\infty}^{VaR_{\alpha}} xf(x)dx$$

Where α is the specified confidence level, and $f(x)$ is the probability density function of getting return x.

4.5.3. Adjusted Sharpe Ratio

The Sharpe ratio is an important concept within asset allocation and is the most widely used method for calculating risk-adjusted return of a portfolio. It measures the risk premium a portfolio earns in relation to the undertaken risk, where the risk premium is equal to the portfolio return less the risk-free rate (Bodie et al., 2013). Further, a negative Sharpe ratio implies that the risk-free asset yields a higher return than the portfolio which makes an investment in the risk-free asset more appealing. One major drawback with the Sharpe ratio is that it tends to be inaccurate and deceptive when applied to assets that exhibit non-normality in returns. This is due to the inadequacy of the standard deviation as a risk measure for these assets. In order to give a more accurate analysis, this paper will therefore use adjusted Sharpe ratios with either the volatility estimated by the DCC MGARCH model or the CVaR as the measure of risk in the denominator. Thus, the adjusted Sharpe ratio is defined as:

$$\frac{r_p - r_f}{x_p}$$

where r_p is the portfolio return, r_f the risk-free rate and x_p is the applied risk-measure (i.e., the volatility estimated by the DCC MGARCH model or CVaR). In our calculations, the risk-free rate is based on the two-year Swedish Government Bond, transformed into daily compounding. From here on, any mention of the volatility-Sharpe will refer to the adjusted Sharpe ratio computed with the volatility from the DCC MGARCH model. Similarly, any mention of the CVaR-Sharpe refers to the adjusted Sharpe ratio computed with CVaR in the denominator.

4.5.4. Skewness

Skewness describes the asymmetry of a distribution. Although a normal distribution has a skewness of zero, most asset return data have either a positive or negative skew (Bodie et al., 2013). In the former case, the right tail of the distribution is longer than the left tail, and the distribution appears to lean to the left. This implies that there is a higher probability that extreme outcomes will be positive rather than negative. The opposite holds for negative skewness. Sample skewness is defined in the following way (McNeil et al., 2015):

$$b = \frac{\frac{1}{n}\sum_{i=1}^{n}(X_i - \overline{X})^3}{(\sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \overline{X})^2})^{3/2}}$$

where n is the sample size, X_i and $\bar{X}$ is the portfolio return at time i and mean return of the portfolio respectively.

4.5.5. Kurtosis

Kurtosis is a statistical measure that is commonly used to describe the distribution of data around the mean, which is referred to as the volatility of volatility. However, it is a measure that should be used to describe the shape of a distribution's tails in relation to its overall shape. A normal distribution has a kurtosis coefficient of 3. When a distribution's kurtosis coefficient is greater than 3, the distribution is leptokurtic, and when it is less than 3, it is platykurtic. A leptokurtic distribution is characterized by fat tails, which indicates that the likelihood of extreme outcomes is higher. Implicitly, an investor that seeks to minimize the portfolio risk will favor a low value of kurtosis. Sample kurtosis is defined in the following way (McNeil et al., 2015):

$$k = \frac{\frac{1}{n}\sum_{i=1}^{n}(X_i - \overline{X})^4}{(\frac{1}{n}\sum_{i=1}^{n}(X_i - \overline{X})^2)^2}$$

where n is the sample size, X_i and $\bar{X}$ is the portfolio return at time i and mean return of the portfolio respectively.

5. Results and Analysis

This section discloses the results from the study. At first, the descriptive statistics are presented. This is followed by a presentation of the results and analysis with respect to the two investor profiles, as well as a robustness evaluation.

5.1. Descriptive Statistics

This section first presents the summary statistics of the study. This is followed by a presentation of the results of the correlation between Swedish and emerging market equities.

5.1.1. Summary Statistics

Tables 1 and 2 display how the return characteristics have changed over the time period for both equity indices. Considering OMXS30 at first, the average daily return has slightly decreased over time, reaching the highest numbers during 2005 and 2009. For the MSCI EEM, it is possible to spot a similar trend in the average daily return as for the OMXS30 index, where it slightly lowers over the time period, reaching its highest numbers during 2005 and 2009. The high returns in 2009 can likely be explained by the recovery from financial crisis in 2008. By considering the time span between 2004-2016 as a whole, it is possible to conclude that a higher return comes with a higher risk. Table 2 also indicates that the overall returns of emerging market equities have historically been riskier than the returns for the Swedish equities.

Furthermore, the Jarque-Bera test rejects normality in returns for both indices for the total period between 2004-2016. As shown in Tables D1 and D2 in Appendix D, the emerging markets index exhibits higher values for both the skewness and kurtosis compared to the OMXS30. The positive skewness indicates that investors can increase their likelihood of high returns. However, the kurtosis indicates that the investor is exposed to a higher risk that extreme events occur, which potentially could be undesirable. This implies that emerging market equities are significantly more exposed to tail-risk.

Table 1

OMXS30	Return	Volatility	CVaR	Volatility-Sharpe	CVaR-Sharpe	Observations
Year 2005	0,1071%	0,8462%	1,6687%	0,1190	0,0604	247
Year 2006	0,0813%	1,1507%	2,9606%	0,0630	0,0245	242
Year 2007	-0,0159%	1,2467%	3,1546%	-0,0216	-0,0086	243
Year 2008	-0,1677%	2,1549%	5,6629%	-0,0826	-0,0314	245
Year 2009	0,1662%	1,7852%	3,9122%	0,0914	0,0417	244
Year 2010	0,0871%	1,1921%	2,6695%	0,0696	0,0311	244
Year 2011	-0,0476%	1,5642%	4,2396%	-0,0335	-0,0124	247
Year 2012	0,0540%	1,2316%	2,8591%	0,0418	0,0180	241
Year 2013	0,0808%	0,9030%	1,9236%	0,0864	0,0406	243
Year 2014	0,0432%	0,9300%	1,8293%	0,0452	0,0230	239
Year 2015	0,0032%	1,2434%	2,7242%	0,0033	0,0015	243
Year 2016	0,0284%	1,2752%	3,1878%	0,0236	0,0094	247
Total period 2005-2016	**0,0350%**	**1,2936%**	**3,0660%**	**0,0338**	**0,0165**	**2925**

All values are calculated as daily averages

"Volatility" refers to the volatility estimated by the DCC MGARCH model

Table 1 gives an overview of the returns and risks in the base portfolio during the time period analyzed in this study.

Table 2

MSCI EEM	Return	Volatility	CVaR	Volatility-Sharpe	CVaR-Sharpe	Observations
Year 2005	0,1969%	1,3507%	2,9319%	0,1410	0,0650	247
Year 2006	0,0604%	1,6991%	3,7916%	0,0304	0,0136	242
Year 2007	0,1138%	1,8684%	4,7169%	0,0550	0,0218	243
Year 2008	-0,1159%	3,3868%	9,7110%	-0,0373	-0,0130	245
Year 2009	0,2053%	2,0884%	4,2393%	0,0969	0,0477	244
Year 2010	0,0403%	1,3906%	2,8824%	0,0261	0,0126	244
Year 2011	-0,0698%	1,5601%	3,8845%	-0,0479	-0,0192	247
Year 2012	0,0430%	1,2077%	2,2125%	0,0336	0,0183	241
Year 2013	-0,0198%	1,2568%	2,4144%	-0,0180	-0,0094	243
Year 2014	0,0613%	1,1877%	2,2457%	0,0506	0,0268	239
Year 2015	-0,0334%	1,5496%	3,5850%	-0,0210	-0,0091	243
Year 2016	0,0730%	1,4087%	3,0174%	0,0529	0,0247	247
Total period 2005-2016	**0,0462%**	**1,6629%**	**3,8027%**	**0,0302**	**0,0150**	**2925**

All values are calculated as daily averages

"Volatility" refers to the volatility estimated by the DCC MGARCH model

Table 2 gives an overview of the MSCI EEM, which is the emerging markets index used as the diversification asset in this paper.

Moreover, the results from the Ljung-Box test are presented in Table 3. It provides statistical evidence that both the OMXS30 and the MSCI EEM indices exhibit serial correlation in its returns with ten statistically significant lags. A plausible explanation as for why emerging markets exhibit serial correlation is mainly due to the difficulty in pricing and the illiquidity of these markets (Lesmond, 2005).

Table 3

Equity index	OMXS30	MSCI EEM
Test statistic (Q)	8,763	113,630
P-value*	0,003	0,000
Statisically significant lag**	10	10
Serial correlation	Yes	Yes
J-B Test Statistic	0,000	0,000
Reject normality in returns	Yes	Yes

*The null hypothesis of no serial correlation in returns is rejected if p-value<0,05.

**One lag corresponds to one day of returns.

Table 3 shows the results form the Ljung-Box and Jarque-Bera tests.

5.1.2. Correlation

Figure 1 displays the correlation between the returns for the OMXS30 and the MSCI EEM for the time period. The correlation slightly decreases just before the financial crisis in 2008, where it sharply increases and reaches a peak around 0,55. This result is in line with the notion that correlation between developed markets and emerging markets increases during times of financial turmoil. The increase in correlation during such events is also apparent in the case of the US credit rating crash in August 2011, where the correlation rapidly jumps from 0,35 to 0,55. Conversely, from the beginning of 2012 the correlation between the two indices started to slowly decrease. During the most recent years, however, the results show that the correlation gradually increased again, reaching a number of approximately 0,50 at the end of 2016.

The results support the theory that the correlation between emerging and developed markets has increased over time. However, this increase is marginal and could also be the attributed to a temporary change. Still, the relatively low correlation indicates that there are potential benefits to international diversification into emerging markets for a Swedish investor.

Figure 1

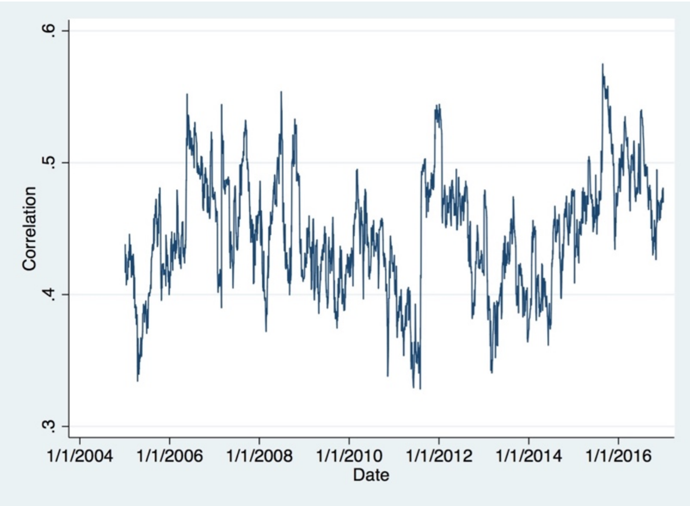

Figure 1 shows the correlation between OMXS30 and MSCI EEM. The correlation is computed using the variances and covariances from the DCC MGARCH model.

5.2. The Risk-Minimizing Investor

This section presents the results for the investor seeking to minimize her portfolio risk with the two approaches used in the study, which will be discussed in comparison to the base portfolio. The DCC approach implies that the portfolio optimization problem is solved by minimizing the volatility of the portfolio. The CVaR approach, in turn, solves the optimization problem by solely focusing on minimizing the portfolio CVaR. Recall that we in section 4.1 defined diversification benefits for the risk-minimizing investor as a reduction in both risk-measures used in the study.

5.2.1. GMV Portfolio with the DCC Approach

5.2.1.1. Unrestricted scenario

Table 6 illustrates the optimal portfolio between 2005-2016 for an investor that seeks to minimize her portfolio risk with the DCC approach. Recall that the unrestricted scenario is under the assumption that no weight constraints are imposed. On average, 71,05% of the portfolio weight is allocated to the OMXS30 and 28,95% to the MSCI EEM. This portfolio led to a reduction in the average daily volatility from 1,2936% in the base portfolio to 1,2554%, indicating a reduction of 2,950%.

Moreover, interesting trends can be identified when considering the results on a year-by-year basis as it appears that the reduction in volatility has increased during the later years of the time period. Hence, the results show some indications that portfolio has become increasingly efficient at minimizing risk.

Results suggesting greater reductions in risk came from CVaR, which was lowered by 6,409%. However, when considering each year for itself, it is important to emphasize the fact that although CVaR showed the greatest reduction in average risk, the CVaR increased in comparison to the base portfolio during the financial crisis in 2008. This highlights a problem in using emerging markets as a diversification instrument: when investors are in great need of diversification, i.e. under times of financial distress, emerging markets appear unable to provide them.

Furthermore, the portfolio also led to small increases in skewness and kurtosis compared to the base portfolio, indicating that investors will be subject to a higher tail-risk in this portfolio. Nevetheless, the reduction in both the volatility as well as CVaR suggests that a risk-minimizing investor can draw diversification benefits from investing in emerging market equities.

5.2.1.2. With weight constraints imposed

The weight constraints did not lead to any major differences in the results, as can be seen by comparing Tables 4 and 5. This portfolio is slightly more tilted towards the OMXS30, but the reductions in volatility and CVaR were 2,971% and 6,400% respectively, which is very similar to the unrestricted scenario. The same holds for the skewness and kurtosis, which did not result in any major changes. The negligible effect of the weight constraints is mainly due to the fact that the optimal portfolios during the time period barely changes. This indicates that weight constraints are of little importance in the case of minimizing the portfolio risk according to the DCC approach. Similar to the unrestricted scenario, the findings support the possibilities of diversification benefits from investments in emerging markets.

Table 4

GMV Portfolio - DCC Approach	Weight OMXS30	Weight MSCI EEM	Return	Volatility	CVaR	Volatility-Sharpe	CVaR-Sharpe
Year 2005	69,84%	30,16%	0,1342%	0,8935%	1,6050%	0,1430	0,0796
Year 2006	85,14%	14,86%	0,0782%	1,1656%	2,9121%	0,0595	0,0238
Year 2007	81,32%	18,68%	0,0083%	1,2530%	3,1361%	-0,0022	-0,0009
Year 2008	84,54%	15,46%	-0,1597%	2,1679%	5,6924%	-0,0784	-0,0298
Year 2009	91,97%	8,03%	0,1693%	1,7504%	3,7864%	0,0951	0,0439
Year 2010	65,51%	34,49%	0,0710%	1,1167%	2,3644%	0,0599	0,0283
Year 2011	61,98%	38,02%	-0,0561%	1,3965%	3,6963%	-0,0436	-0,0165
Year 2012	48,05%	51,95%	0,0483%	1,0626%	2,0808%	0,0431	0,0220
Year 2013	46,94%	53,06%	0,0274%	0,9255%	1,7391%	0,0266	0,0141
Year 2014	76,26%	23,74%	0,0475%	0,8951%	1,7426%	0,0517	0,0266
Year 2015	70,15%	29,85%	-0,0077%	1,2232%	2,9278%	-0,0055	-0,0023
Year 2016	70,94%	29,06%	0,0414%	1,2154%	2,7510%	0,0354	0,0156
Total period 2005-2016	**71,05%**	**28,95%**	**0,0335%**	**1,2554%**	**2,8695%**	**0,0320**	**0,0170**

All values are calculated as daily averages

"Volatility" refers to the volatility estimated by the DCC MGARCH model

Table 4 shows the risk, return, and the adjusted Sharpe ratios for the GMV (Global Minimum Variance) portfolio created with the DCC approach. In this case, GMV implies that the portfolio is optimized to minimize the volatility estimated by the DCC MGARCH model.

Table 5

GMV Portfolio - DCC Approach with weight constraints	Weight OMXS30	Weight MSCI EEM	Return	Volatility	CVaR	Volatility-Sharpe	CVaR-Sharpe
Year 2005	69,84%	30,16%	0,1342%	0,8938%	1,6050%	0,1430	0,0796
Year 2006	85,14%	14,86%	0,0782%	1,1660%	2,9171%	0,0595	0,0238
Year 2007	81,32%	18,68%	0,0083%	1,2533%	3,1388%	-0,0022	-0,0009
Year 2008	84,54%	15,46%	-0,1597%	2,1681%	5,6995%	-0,0784	-0,0298
Year 2009	91,97%	8,03%	0,1693%	1,7510%	3,7906%	0,0950	0,0439
Year 2010	65,51%	34,49%	0,0710%	1,1171%	2,3667%	0,0599	0,0283
Year 2011	61,98%	38,02%	-0,0561%	1,3968%	3,7001%	-0,0436	-0,0165
Year 2012	50,00%	50,00%	0,0485%	1,0653%	2,0981%	0,0432	0,0219
Year 2013	50,00%	50,00%	0,0305%	0,9159%	1,7202%	0,0302	0,0161
Year 2014	76,26%	23,74%	0,0475%	0,8954%	1,7442%	0,0517	0,0265
Year 2015	70,15%	29,85%	-0,0077%	1,2236%	2,7894%	-0,0055	-0,0024
Year 2016	70,94%	29,06%	0,0414%	1,2158%	2,8675%	0,0354	0,0150
Total period 2004-2016	**71,47%**	**28,53%**	**0,0338%**	**1,2552%**	**2,8698%**	**0,0324**	**0,0171**

All values are calculated as daily averages

"Volatility" refers to the volatility estimated by the DCC MGARCH model

Table 5 shows the risk, return, and the adjusted Sharpe ratios for the GMV (Global Minimum Variance) portfolio created with the DCC approach when weight constraints are imposed. In this case, GMV implies that the portfolio is optimized to minimize the volatility estimated by the DCC MGARCH model.

5.2.2. GMV Portfolio with the CVaR Approach

5.2.2.1. Unrestricted scenario

Table 6 presents the optimal portfolio between 2005-2016 for an investor that seeks to minimize her portfolio risk with the CVaR approach, assuming that no weight constraints are imposed. As the table shows, this portfolio was slightly more tilted towards the emerging markets index than the portfolio constructed with the DCC approach, and placed an average weight of 32,64% in the MSCI EEM.

The average daily volatility was reduced from 1,2936% to 1,2818%, which corresponds to a minor reduction of 0,913%. The CVaR is reduced to 2,9131% in the optimal portfolio from 3,0660% in the base portfolio, which corresponds to a reduction of 4,987%. By comparing the results on a year-by-year basis, this approach suggests that the overall diversification benefits have increased during the years after the financial crisis in 2008. Similar to the DCC approach, it also indicates that the diversification benefits disappear during times of financial distress.

The results also show that both the skewness and the kurtosis increases in comparison to the base portfolio. This implies that the investors are slightly more prone to large deviations from the mode, which is an unattractive characteristic for investors seeking to minimize the portfolio risk. However, since both the CVaR and the volatility are reduced, we argue that diversification benefits from investing in emerging markets exist for a risk-minimizing investor according to the CVaR approach in the unrestricted scenario.

5.2.2.2. With weight constraints imposed

Table 7 displays the results for the risk-minimizing investor according to the CVaR approach when weight constraints are imposed. This portfolio places more weight on the OMXS30, which in this case also resulted in greater risk reductions. More specifically, the reductions amounted to 2,763% and 5,541% for the volatility and CVaR respectively. The greater risk reductions compared to the DCC approach can be explained by the fact that this approach overall has greater shifts in weight allocations between the years. When the constraints are imposed, these shifts become less dramatic, which turns out to be a better performing strategy. Similar to the DCC approach, the weight constraints do not induce any major changes in the skewness and kurtosis of the portfolio.

Table 6

GMV Portfolio - CVaR Approach	Weight OMXS30	Weight MSCI EEM	Return	Volatility	CVaR	Volatility-Sharpe	CVaR-Sharpe
Year 2005	70,29%	29,71%	0,1338%	0,9010%	1,6026%	0,1414	0,0795
Year 2006	78,16%	21,84%	0,0767%	1,1849%	2,9089%	0,0573	0,0234
Year 2007	70,32%	29,68%	0,0226%	1,2877%	3,1783%	0,0089	0,0036
Year 2008	82,69%	17,31%	-0,1587%	2,1930%	5,7224%	-0,0770	-0,0295
Year 2009	92,40%	7,60%	0,1691%	1,7592%	3,7972%	0,0945	0,0438
Year 2010	41,44%	58,56%	0,0597%	1,1514%	2,4188%	0,0483	0,0230
Year 2011	62,71%	37,29%	-0,0559%	1,4127%	3,7064%	-0,0430	-0,0164
Year 2012	45,84%	54,16%	0,0480%	1,0677%	2,0669%	0,0427	0,0220
Year 2013	30,22%	69,78%	0,0106%	1,0072%	1,9274%	0,0077	0,0040
Year 2014	69,91%	30,09%	0,0487%	0,9042%	1,7448%	0,0525	0,0272
Year 2015	70,97%	29,03%	-0,0074%	1,2335%	2,7843%	-0,0053	-0,0023
Year 2016	93,40%	6,60%	0,0314%	1,2789%	3,0995%	0,0258	0,0106
Total period 2005-2016	**67,36%**	**32,64%**	**0,0315%**	**1,2818%**	**2,9131%**	**0,0295**	**0,0157**

All values are calculated as daily averages

"Volatility" refers to the volatility estimated by the DCC MGARCH model

Table 6 shows the risk, return, and the adjusted Sharpe ratios for the GMV (Global Minimum Variance) portfolio created with the CVaR approach. In this case, GMV implies that the portfolio is optimized to minimize the CVaR.

Table 7

GMV Portfolio - CVaR Approach with weight constraints	Weight OMXS30	Weight MSCI EEM	Return	Volatility	CVaR	Volatility-Sharpe	CVaR-Sharpe
Year 2005	70,29%	29,71%	0,1338%	0,9502%	1,6026%	0,1341	0,0795
Year 2006	78,16%	21,84%	0,0767%	1,1842%	2,9089%	0,0574	0,0234
Year 2007	70,32%	29,68%	0,0226%	1,2974%	3,1783%	0,0089	0,0036
Year 2008	82,69%	17,31%	-0,1587%	2,2074%	5,7224%	-0,0765	-0,0295
Year 2009	92,40%	7,60%	0,1691%	1,6535%	3,7971%	0,1005	0,0438
Year 2010	50,00%	50,00%	0,0637%	1,1172%	2,3910%	0,0534	0,0249
Year 2011	62,71%	37,29%	-0,0559%	1,3654%	3,7064%	-0,0445	-0,0164
Year 2012	50,00%	50,00%	0,0485%	1,0611%	2,0981%	0,0434	0,0219
Year 2013	50,00%	50,00%	0,0305%	0,9254%	1,7202%	0,0299	0,0161
Year 2014	69,91%	30,09%	0,0487%	0,9057%	1,7448%	0,0524	0,0272
Year 2015	70,97%	29,03%	-0,0074%	1,2293%	2,7843%	-0,0053	-0,0023
Year 2016	93,40%	6,60%	0,0314%	1,1976%	3,0995%	0,0276	0,0106
Total period 2005-2016	**70,07%**	**29,93%**	**0,0336%**	**1,2579%**	**2,8961%**	**0,0318**	**0,0169**

All values are calculated as daily averages

"Volatility" refers to the volatility estimated by the DCC MGARCH model

Table 7 shows the risk, return, and the adjusted Sharpe ratios for the GMV (Global Minimum Variance) portfolio created with the CVaR approach when weight constraints are imposed. In this case, GMV implies that the portfolio is optimized to minimize the CVaR.

5.3. The Maximum Risk-Adjusted Return Investor

This section presents the results for the investor that aims to maximize the risk-adjusted return of her portfolio. The DCC approach implies that the portfolio optimization problem is solved by maximizing the risk-adjusted return by using the volatility as the risk measure in the adjusted Sharpe ratio equation. The CVaR approach solves the portfolio optimization problem by using the CVaR as the measure of risk. Recall that we in section 4.1 defined diversification benefits for the investor seeking to maximize her risk-adjusted return as an improvement in both adjusted Sharpe ratios used in the study.

5.3.1. Maximum Risk-Adjusted Return with the DCC Approach

5.3.1.1. Unrestricted scenario

Table 8 presents the optimal portfolio between 2005-2016 for an investor that seeks to maximize her risk-adjusted return according to the DCC approach. The portfolio optimization problem is under the assumption that no weight constraints are in place. Compared to the GMV portfolios, this strategy places much more weight on the emerging markets index, with an average weight of 43,86% in the MSCI EEM. The volatility-Sharpe of this portfolio is 0,0330 which can be compared to 0,0338 in the base portfolio. This corresponds to a reduction of 2,479%. By considering the CVaR-Sharpe however, the ratio increases from 0,0165 to 0,0172, which corresponds to an increase of 4,510%. Even though this portfolio had a higher average CVaR-Sharpe, it is worth to notice that it has been outperformed by the base portfolio during the majority of the years after the financial crisis in 2008. It is also interesting to observe the portfolio's overall performance during times of financial distress. For instance, it is evident that the portfolio performs much worse during financial turmoil such as the financial crisis in 2008 and the US credit crash in 2011.

Moreover, by looking at the skewness and the kurtosis, one could note that they worsen in comparison to the base portfolio, and that the values are higher when compared to both GMV portfolios. Recall that our definition of diversification benefits for this investor required unison improvements for both ratios, and that the relative changes in adjusted Sharpe ratios were inconsistent. Because of this, the DCC approach suggest that investors seeking to maximize their risk-adjusted return cannot enjoy diversification benefits from investing in emerging market equities.

5.3.1.2. With weight constraints imposed

Table 9 presents the equivalent optimal portfolio when the weight constraints are imposed. This portfolio is slightly more tilted towards the OMXS30, and places an average weight of 40,18% in the MSCI EEM. When looking at the two adjusted Sharpe ratios, one can notice interesting results. Similar to the CVaR-Sharpe for the optimal portfolio in the unrestricted scenario, this ratio improves in comparison to the base portfolio by 10,180%. When considering the volatility-Sharpe, the ratio also improves when compared to the base portfolio, with an increase of 2,913%. This stands in contrast to the results suggested by the equivalent portfolio without weight constraints. Further, both the skewness and the kurtosis decrease marginally when the weight constraints are imposed.

To summarize, the DCC approach with weight constraints indicates that diversification benefits exist for an investor that aims to maximize her risk-adjusted return.

Table 8

Sharpe-maximizing Portfolio - DCC Approach	Weight OMXS30	Weight MSCI EEM	Return	Volatility	CVaR	Volatility-Sharpe	CVaR-Sharpe
Year 2005	55,03%	44,97%	0,1475%	0,9510%	1,7541%	0,1484	0,0804
Year 2006	73,10%	26,90%	0,0757%	1,1798%	2,9033%	0,0567	0,0230
Year 2007	63,25%	36,75%	0,0317%	1,2902%	3,2373%	0,0160	0,0064
Year 2008	67,46%	32,54%	-0,1509%	2,2044%	6,0973%	-0,0731	-0,0264
Year 2009	78,96%	21,04%	0,1744%	1,6377%	3,6063%	0,1047	0,0476
Year 2010	50,95%	49,05%	0,0642%	1,1143%	2,3885%	0,0539	0,0252
Year 2011	46,33%	53,67%	-0,0595%	1,3597%	3,6318%	-0,0474	-0,0177
Year 2012	31,55%	68,45%	0,0465%	1,0549%	2,0007%	0,0417	0,0220
Year 2013	31,29%	68,71%	0,0117%	0,9963%	1,9123%	0,0089	0,0046
Year 2014	63,16%	36,84%	0,0499%	0,9063%	1,7578%	0,0537	0,0277
Year 2015	56,68%	43,32%	-0,0127%	1,2276%	2,8852%	-0,0096	-0,0041
Year 2016	55,89%	44,11%	0,0481%	1,1948%	2,7496%	0,0416	0,0181
Total period 2005-2016	**56,14%**	**43,86%**	**0,0355%**	**1,2597%**	**2,9104%**	**0,0330**	**0,0172**

All values are calculated as daily averages

"Volatility" refers to the volatility estimated by the DCC MGARCH model

Table 8 shows the risk, return, and the adjusted Sharpe ratios for the portfolio that maximizes the risk-adjusted return with the DCC approach.

Table 9

Sharpe-maximizing Portfolio - CVaR Approach with weight constraints	Weight OMXS30	Weight MSCI EEM	Return	Volatility	CVaR	Volatility-Sharpe	CVaR-Sharpe
Year 2005	55,41%	44,59%	0,1472%	0,9502%	1,7487%	0,1481	0,0805
Year 2006	72,36%	27,64%	0,0755%	1,1842%	2,9025%	0,0564	0,0230
Year 2007	62,34%	37,66%	0,0329%	1,2974%	3,2472%	0,0169	0,0067
Year 2008	68,14%	31,86%	-0,1512%	2,2074%	6,0731%	-0,0731	-0,0266
Year 2009	81,37%	18,63%	0,1735%	1,6535%	3,6353%	0,1031	0,0469
Year 2010	50,78%	49,22%	0,0641%	1,1172%	2,3890%	0,0537	0,0251
Year 2011	50,12%	49,88%	-0,0587%	1,3654%	3,6437%	-0,0465	-0,0174
Year 2012	50,00%	50,00%	0,0485%	1,0611%	2,0981%	0,0434	0,0219
Year 2013	50,00%	50,00%	0,0305%	0,9254%	1,7202%	0,0299	0,0161
Year 2014	64,06%	35,94%	0,0497%	0,9057%	1,7555%	0,0535	0,0276
Year 2015	57,33%	42,67%	-0,0124%	1,2293%	2,8801%	-0,0093	-0,0040
Year 2016	55,92%	44,08%	0,0481%	1,1976%	2,7497%	0,0415	0,0181
Total period 2005-2016	**59,82%**	**40,18%**	**0,0373%**	**1,2579%**	**2,9036%**	**0,0348**	**0,0182**

All values are calculated as daily averages

"Volatility" refers to the volatility estimated by the DCC MGARCH model

Table 9 shows the risk, returns and adjusted Sharpe ratios for the portfolio that maximizes the risk-adjusted retun with the DCC approach when weight constraints were added to the optimization problem.

5.3.2. Maximum Risk-Adjusted Return with the CVaR Approach

5.3.2.1. Unrestricted scenario

Table 10 discloses the optimal portfolio between 2005-2016 for an investor that seeks to maximize her risk-adjusted return according to the CVaR approach under the assumption that no weight constraints are imposed. This portfolio places a slightly lower weight on the emerging markets index than the portfolio created with the DCC approach, with an average weight of 35,48% allocated to the MSCI EEM. The volatility-Sharpe of the optimal portfolio is 0,0251, which in comparison to the base portfolio, corresponds to a substantial decrease of 25,799%. The CVaR-Sharpe has an average value of 0,0144, which is a reduction of 12,357% compared to the base portfolio. The results are likely due to the extreme weight shifts between the two indices over time, which indicates that the investment strategy fails to capture the performance of previous periods. Similar to the portfolios presented previously, one can notice that the portfolio performs worse during times of financial distress. By looking at both adjusted Sharpe ratios in comparison to the base portfolio, it is also possible to observe that it has been performing even worse during the later years in the time period. Interesting to note is also the dramatic increase in the skewness and the kurtosis of the portfolio. This is due to substantial weight shifts of the portfolio, which during multiple years is fully allocated in the MSCI EEM.

Conclusively, the CVaR approach suggests that there are no diversification benefits from investing in emerging markets equities for an investor that seeks to maximize her risk-adjusted return.

Table 10

Sharpe-maximizing Portfolio - CVaR Approach	Weight OMXS30	Weight MSCI EEM	Return	Volatility	CVaR	Volatility-Sharpe	Sharpe-CVaR
Year 2005	100,00%	0,00%	0,1071%	0,9970%	1,6666%	0,1010	0,0604
Year 2006	61,70%	38,30%	0,0733%	1,3551%	2,9309%	0,0476	0,0220
Year 2007	100,00%	0,00%	-0,0159%	1,4087%	3,1546%	-0,0192	-0,0086
Year 2008	0,00%	100,00%	-0,1159%	3,7942%	9,7110%	-0,0333	-0,0130
Year 2009	0,00%	100,00%	0,2053%	2,2934%	4,2393%	0,0883	0,0477
Year 2010	41,44%	58,56%	0,0597%	1,2571%	2,4188%	0,0443	0,0230
Year 2011	100,00%	0,00%	-0,0476%	1,7677%	4,2396%	-0,0297	-0,0124
Year 2012	100,00%	0,00%	0,0540%	1,3730%	2,8591%	0,0375	0,0180
Year 2013	41,24%	58,76%	0,0217%	1,0571%	1,7958%	0,0178	0,0105
Year 2014	100,00%	0,00%	0,0432%	1,0482%	1,8293%	0,0401	0,0230
Year 2015	29,88%	70,12%	-0,0225%	1,4730%	3,1666%	-0,0146	-0,0068
Year 2016	100,00%	0,00%	0,0284%	1,4203%	3,1878%	0,0212	0,0094
Total period 2005-2016	**64,52%**	**35,48%**	**0,0326%**	**1,6037%**	**3,4333%**	**0,0251**	**0,0144**

All values are calculated as daily averages

"Volatility" refers to the volatility estimated by the DCC MGARCH model

Table 10 shows the risk, returns and adjusted Sharpe ratios for the portfolio that maximizes the risk-adjusted return with the CVaR approach.

Table 11

Sharpe-maximizing Portfolio - CVaR Approach with weight constraints	Weight OMXS30	Weight MSCI EEM	Return	Volatility	CVaR	Volatility-Sharpe	CVaR-Sharpe
Year 2005	100,00%	0,00%	0,1071%	1,0200%	1,6666%	0,0988	0,0604
Year 2006	61,86%	38,14%	0,0733%	1,3323%	2,9301%	0,0484	0,0220
Year 2007	100,00%	0,00%	-0,0159%	1,3763%	3,1546%	-0,0196	-0,0086
Year 2008	50,00%	50,00%	-0,1418%	2,5224%	6,7629%	-0,0603	-0,0225
Year 2009	50,00%	50,00%	0,1857%	1,7073%	3,4132%	0,1071	0,0536
Year 2010	50,00%	50,00%	0,0637%	1,2285%	2,3910%	0,0485	0,0249
Year 2011	98,04%	1,96%	-0,0481%	1,6804%	4,1995%	-0,0315	-0,0126
Year 2012	100,00%	0,00%	0,0540%	1,3396%	2,8591%	0,0384	0,0180
Year 2013	50,00%	50,00%	0,0305%	1,0553%	1,7202%	0,0262	0,0161
Year 2014	100,00%	0,00%	0,0432%	1,0768%	1,8293%	0,0390	0,0230
Year 2015	50,00%	50,00%	-0,0151%	1,3580%	2,9390%	-0,0104	-0,0048
Year 2016	100,00%	0,00%	0,0284%	1,3813%	3,1878%	0,0218	0,0094
Total period 2005-2016	**75,82%**	**24,18%**	**0,0304%**	**1,4232%**	**3,0878%**	**0,0255**	**0,0149**

All values are calculated as daily averages

"Volatility" refers to the volatility estimated by the DCC MGARCH model

Table 11 shows the risk, return, and the adjusted Sharpe ratios for the portfolio that maximized the risk-adjusted return with the CVaR approach when weight constraints are added in the optimization problem.

5.3.2.2. With weight constraints imposed

Table 11 presents the results for the equivalent portfolio when weight constraints are in place. As can be expected, the portfolio allocates less weight in the emerging markets index, with an average weight of 24,18% in the MSCI EEM. Analogously, both the adjusted Sharpe ratios improve compared to the unrestricted scenario, but the results still show a dramatic reduction compared to the base portfolio. Namely, the CVaR-Sharpe is reduced from 0,0165 to 0,0149 and the volatility-Sharpe decreases from 0,0338 to 0,0255. This corresponds to reductions of 9,508% and 24,455%, respectively. Moreover, the skewness and kurtosis are much lower than for the equivalent portfolio in the unrestricted scenario, but are still higher than in the base portfolio.

Similarly, the CVaR approach suggests that no benefits can be drawn from investing in emerging market equities for an investor that aims to maximize her risk-adjusted return. While the weight constraints lead to some improvements in the adjusted Sharpe ratios, this effect is negligible given how large the reductions are compared to the base portfolio.

5.4. Robustness Evaluation

In this section, an attempt is made to evaluate the robustness of the results in two steps. By analyzing different risk measures, investor profiles and scenarios it is possible to evaluate the robustness of our findings to some extent. At first, a comparison of the results from the different portfolios is made. This is followed by a discussion of our findings in the light of the results from similar previous research.

5.4.1. Comparison between Evaluation Metrics

This section will start with a discussion of the findings for the risk-minimizing investor. Recall that we in section 4.1 defined diversification benefits for the risk-minimizing investor as a reduction of both the volatility and the CVaR. It is therefore of interest to look at the direction and magnitude of the change of these measures in our risk-minimizing portfolios compared to the base portfolio.

As Table 12 shows, it is possible to conclude that both risk measures show consistent reductions in risk, both when the DCC and the CVaR approaches are used. These results also hold when weight constraints are imposed in the optimization problem. More specifically, in the case of the DCC approach, both the volatility and CVaR indicates that the weight constraints only have a minor impact on the risk of the portfolio. In the case of the CVaR approach however, the results suggest that investors can substantially reduce their portfolio risk when the weight constraints are added. In short, the coherence in the results suggests that the results are robust, and that diversification benefits exist for investors seeking to minimize their portfolio risk.

However, the robustness of the results for the investor seeking to maximize her risk-adjusted return are not as clear cut. Recall that we in section 4.1 defined diversification benefits for this investor as an improvement in both adjusted Sharpe ratios. With the DCC approach, the findings are mixed as to whether the portfolios improve the risk-adjusted return. The portfolio in the unrestricted scenario showed a reduction in the volatility-Sharpe, but an improvement in the CVaR-Sharpe. With the CVaR approach, both adjusted Sharpe ratios show a reduction compared to the base portfolio. These results also hold when the weight constraints are imposed. Thus, the findings suggest that no diversification benefits exists for this investor profile. However, the robustness of these results can be disputed due to the mixed evidence.

To further analyze the robustness of the findings, it is also important to look at the magnitudes of the results from the two risk measures. For the risk-minimizing investor, it is evident that the CVaR is more optimistic when it comes to the relative improvement in comparison to the base portfolio. For every portfolio, with and without weight constraints, the gain with CVaR is higher than with the volatility as the risk measure. This highlights the problematic nature of risk measurement in a portfolio optimization problem consisting of emerging market equities. One can also notice that relative changes across the different portfolios for both risk measures are coherent, averaging around 2,4% for the volatility and 5,8% for CVaR. This indicates that the findings are robust. In contrast, the results for the investor seeking to maximize her risk-adjusted return are much less coherent. The relative changes in the volatility-Sharpe ranges wildly between the different portfolios, from a reduction of 25,8% to an increase of 2,9%. Similarly, the CVaR-Sharpe ranges from a reduction of 12,4% to an increase of 10,2%. This puts to question the robustness of the findings for this investor profile.

Table 12

Portfolio	Return	Volatility	CVaR	Volatility-Sharpe	CVaR-Sharpe
GMV DCC	-4,299%	-2,950%	-6,409%	-5,201%	3,388%
GMV DCC WC	-3,513%	-2,971%	-6,400%	-4,312%	3,910%
GMV CVaR	-9,895%	-0,913%	-4,987%	-12,775%	-4,498%
GMV CVaR WC	-4,094%	-2,763%	-5,541%	-6,046%	2,525%
Sharpe DCC	1,521%	-2,617%	-5,076%	-2,479%	4,510%
Sharpe DCC WC	6,537%	-2,763%	-5,297%	2,913%	10,180%
Sharpe CVaR	-6,982%	23,974%	11,979%	-25,799%	-12,357%
Sharpe CVaR WC	-13,092%	10,017%	0,710%	-24,455%	-9,508%

"Volatility" refers to the volatility estimated by the DCC MGARCH model

Table 12 shows the relative changes in the evaluation metrics for the portfolios created in comparison to the base portfolio.

5.4.2. Comparison to Previous Literature

To further analyze the robustness of our findings, the results from this study will be compared to similar previous research. It should be noted however, that the results of diversification benefits will be affected by the methodology used. Differences in investment strategies and time periods, amongst many other factors, will have an impact on the results. Still, a comparison allows for further evaluation of the robustness of the findings.

Ergen (2014) analyzed the diversification benefits of investments in emerging markets by looking at the tail dependence between country pairs, and then analyzes these using VaR and CVaR. He finds that in the 99,9th quantile, the average diversification benefits amount to 4,479% and 13,081% for asymptotically dependent and independent pairs respectively. These results can be compared to the the reduction in CVaR in the GMV-portfolios in this study. Ignoring weight constraints, reductions in CVaR ranged from 5% to 6,4% in the risk-minimizing portfolios. The similarity in the risk reduction in this study compared to Ergen (2014) provides more robustness to our findings on the diversification benefits.

Gupta and Donleavy (2009) used an asymmetric DCC GARCH model to find correlation matrices, that consequently were used in their optimization problem. For their minimum-variance portfolio, they lowered their standard deviation from 13,99% to 13,09% which corresponds to a reduction of 6,88%. These results can be compared to the reductions of the volatility in the risk minimizing portfolios in this study, which ranged between 2,971% and 0,913%. However, it should be noted that this study not only adopts the DCC MGARCH model in the optimization problem, but also in the portfolio evaluation. The results in this study will therefore not be entirely comparable to theirs.

Gupta and Donleavy (2009) also found significant improvements in their Sharpe ratios, increasing their average annual Sharpe from 0,19 in the base portfolio to 0,33 in the minimum-variance portfolio, corresponding to a 74,47% increase. This paper found no similar improvements in the adjusted Sharpe ratios. Instead, a majority of the cases indicated large reductions in the risk-adjusted returns. As in section 5.4.1, this leads us to question the robustness of our findings for the investors seeking to maximize their risk-adjusted return. However, it is likely that part of the difference in the results in this study compared to Gupta and Donleavy's (2009) is related to different investment strategies, time periods analyzed and calculation methods used.

6. Discussion

The purpose of this thesis was to investigate whether emerging markets could offer diversification benefits to Swedish investors. In this section, an attempt is made to answer the hypotheses. This is followed by a discussion of the findings in light of the theoretical background as well as a comparison to previous research. Further, the implications and the limitations of this study are discussed.

6.1. Hypothesis Testing

By creating several different portfolios for different investor profiles, investment strategies and assumptions, the results of this study become multifaceted and are thus likely to give a true picture of the economic reality. These results will now be discussed in the light of the hypothesis presented in section 4.1. Recall that the first null hypothesis was that the optimal portfolios with the the emerging markets index included would have the same risk as the base portfolio. The results in section 5 showed that this null hypothesis can be rejected. More specifically, the portfolios created clearly had lower risk than the base portfolio, indicating that there are diversification benefits for this investor profile. Further, we argued that these results are robust.

The second null hypothesis was that the risk-adjusted returns would for the portfolios with the emerging markets index included would be the same as in the base portfolio. The results in section 5 showed that this null hypothesis can be rejected. By analyzing the findings, it was also apparent that the risk-adjusted returns of the optimal portfolios on average were lower than in the base portfolio. This indicates that the second investor profile cannot enjoy diversification benefits from investing in emerging market equities. However, the robustness of these findings can be questioned. For example, when considering the investor that aims to maximize her risk-adjusted return we could argue that an investor will enjoy diversification benefits from investing in emerging market equities with the CVaR approach, but not with the DCC approach. Further, using the DCC approach we could conclude that an investor would benefit from investing in emerging markets if weight constraints were imposed. Despite this, we argue that there are no diversification benefits seeing as the majority of the portfolios showed large reductions in the risk-adjusted returns.

6.2. Comparison to the Theoretical Background

Seeing as the main results of this study was compared to previous research in section 5.4.2, this section will instead only focus on comparing the results to the theoretical background.

The study showed that both indices exhibited similar characteristics as what has been noted in previous research. We found evidence of skewness and kurtosis in both indices, but the results were much stronger for the MSCI EEM than for OMXS30. These findings are clearly in line with what Bekaert and Harvey (1997), amongst many others, have found.

When comparing the correlation found in this paper to the findings in similar studies, one can notice some interesting results. Gupta and Donleavy (2009) investigated the correlation between the Australian market and a number of emerging markets by using an asymmetric DCC MGARCH model. The correlations, based on data from 1988 to 2005, ranged from 0,066 for Chile to 0,308 for Brazil, which is lower than what was found in this paper. One reason for could be that this study uses an emerging markets ETF consisting of holdings in multiple emerging markets, whereas Gupta and Donleavy used separate emerging market country indices. When looking at the holdings in the MSCI EEM it becomes evident that a large portion of the weight is distributed in countries such as Korea and Brazil, which Gupta and Donleavy also found had a relatively high correlation with the Australian market. Another plausible explanation stems from the fact that the Australian and Swedish economies naturally will have different correlations with emerging markets.

6.3. Implications and Limitations

The findings in this paper clearly has implications for Swedish investors' asset allocation decisions. While investments in emerging markets offer diversification benefits in terms of lowered risk, this also comes with a reduction in the risk-adjusted return. Therefore, when deciding whether to invest in emerging markets or not, investors need to put great considerations as to what their ultimate goal is.

This thesis has been subject to a number of limitations that one should be aware of. First, this study completely ignores transaction costs in the portfolio optimization problem. This might not reflect the real world conditions appropriately as emerging markets are considered to be relatively illiquid (Lesmond, 2005). Illiquid markets, in turn, tends to be strongly associated with high transaction costs compared to the developed markets. Therefore, it might be unrealistic to ignore the effect of transaction costs in the portfolio optimization problem.

Another limitation of this study is that it assumes that short selling constraints are in place. However, in a study by De Roon et al. (2001), the authors find that any diversification benefits disappear when investors face short selling constraints. If this study had considered a scenario with relaxed short selling constraints, the results might therefore have indicated greater diversification benefits. Yet, the assumption of short selling constraints is imposed in many of the previous studies conducted on similar topics (Ho et al., 2008; Moreno et al., 2005; Cain and Zumbruegg, 2010; Nawrocki, 1992; Rockafellar and Uryasev, 2000; Martin, 1955; Bouslama and Ben-Ouda, 2014).

One should also be aware of the limitation this study has been subject to with regards to the investment strategies tested. The strategies used in this thesis do not necessarily give an ultimate answer as to whether emerging markets offer diversification benefits or not. However, the strategies used were chosen based on what was deemed appropriate for normal investors. It is possible that more sophisticated investment strategies would show greater diversification benefits than what this study suggests.

7. Conclusion

This thesis examines if there are potential diversification benefits from investing in emerging market equities for a Swedish investor. Previous research has found mixed evidence of diversification benefits in emerging markets, and many argue that the increased correlation between emerging and developed markets implies that the benefits have disappeared. In this study, optimal portfolios are created for two investor profiles - one that seeks to minimize the portfolio risk, and one that seeks to maximize her risk-adjusted return. The portfolio optimization problem is solved by using two risk measures, the volatility estimated by the DCC MGARCH model and CVaR, to deal with the problematic nature of non-normality in the returns of emerging market equities.

The study finds that Swedish investors will be able to lower their portfolio risk by investing in emerging markets. The paper also suggests that Swedish investors are unable to increase their risk-adjusted return by investing in emerging market equities, although the robustness of these findings can be questioned. The implications of these results are that investors should consider their ultimate goal and be cautious with the investment and their investment strategy. An interesting finding was that CVaR consistently indicated better results in the form of lower risk and higher risk-adjusted return than the volatility estimated by the DCC MGARCH model. This highlights a key problem in risk management in asset allocation - there is no all-encompassing way of measuring risk, and different methods might yield different results.

To further clarify the implications of this study, future research could add comparisons with other commonly used diversification assets. When looked at in isolation, the diversification benefits from one investment are hard to assess. By including multiple assets, one would get a more thorough view on the benefits of investing in emerging markets. Future research could also test other investment strategies that complement those used in this paper. For instance, it would be interesting to examine a passive investment strategy. Another possible method would be to take the perspective of an investor that invests in individual emerging market country indices rather than the MSCI EEM. Given the discussion about short selling constraints and transaction costs above, future research could also continue to study the effects of international diversification from a Swedish perspective, but test a broader set of market frictions.

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Appendix A

Company	Sector	Country	Weight
SAMSUNG ELECTRONICS LTD	Information Technology	Korea (South)	4,32%
TENCENT HOLDINGS LTD	Information Technology	China	4,04%
TAIWAN SEMICONDUCTOR MANUFACTURI	Information Technology	Taiwan	3,68%
ALIBABA GROUP HOLDING ADR REPRESEN	Information Technology	China	2,94%
NASPERS LIMITED N LTD	Consumer Discretionary	South Africa	1,91%
CHINA CONSTRUCTION BANK CORP H	Financials	China	1,50%
CHINA MOBILE LTD	Telecommunication Services	China	1,46%
HON HAI PRECISION INDUSTRY LTD	Information Technology	Taiwan	1,17%
BAIDU ADR REPTG INC CLASS A	Information Technology	China	1,11%
INDUSTRIAL AND COMMERCIAL BANK OF	Financials	China	1,05%

Appendix A gives an overview of the top ten holdings in the iShares MSCI Emerging Markets ETF as of May 11th 2017.

Appendix B

The Jarque-Bera test for normality is presented in the following way:

$\mathbf{H_0}$: normal distribution, where skewness is zero and excess kurtosis is zero.

against the alternative hypothesis:

$\mathbf{H_1}$: non-normal distribution.

The Jarque-Bera test statistic is:

$$JB = n(\frac{(k_3)^2}{6} + \frac{(k_4)^2}{24})$$

where

$$k_3 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^{\ 3}}{ns^3}$$

and

$$k_4 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^{\ 4}}{ns^4} - 3$$

Appendix C

Mathematically, the DCC MGARCH model proposed by Engle (2002) with two variables, r_1 and r_2, with zero mean can be written as:

$$\rho_{12,t} = \frac{E_{t-1}(\varepsilon_{1,t}\varepsilon_{2,t})}{\sqrt{E_{t-1}\left(\varepsilon_{1,t}^2\right)E_{t-1}\left(\varepsilon_{2,t}^2\right)}} = E_{t-1}(\varepsilon_{1,t}\varepsilon_{2,t})$$

where $h_{i,t} = E_{t-1}\left(\varepsilon_{1,t}^2\right)$ and $r_{i,t} = \sqrt{h_{i,t}\varepsilon_{i,t}}$ for i=1,2, where $\varepsilon_{i,t}$ is a standardized disturbance that has a mean of zero and a variance of one.

Using the GARCH(1,1) specification, the covariance between the two variables can be formulated as:

$$q_{12,t} = \bar{\rho}_{12} + \alpha\left(\varepsilon_{1,t-1}\varepsilon_{2,t-1} - \bar{\rho}_{12}\right) + \beta(q_{12,t-1} - \bar{\rho}_{12})$$

where the unconditional expectation of the cross-product is $\bar{\rho}_{12}$, while for the variances:

$$\bar{\rho}_{12} = 1, \text{the correlation estimator is: } \rho_{12,t}\frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}}.$$

The model is mean-reverting if $\alpha + \beta < 1$. The matrix version of this model can be written as:

$$Q_t = S(1-\alpha-\beta) + \alpha(\varepsilon_{t-1}\varepsilon_{t-1})\beta Q_{t-1},$$

where S is the unconditional correlation matrix of the disturbance terms and $Q_t = \left|q_{1,2,t}\right|$.

Appendix D

Table D1

OMXS30	Skewness	Kurtosis
Year 2005	-0,510	4,232
Year 2006	-0,188	6,492
Year 2007	-0,429	3,578
Year 2008	0,645	5,589
Year 2009	0,015	3,305
Year 2010	0,368	5,935
Year 2011	-0,104	4,447
Year 2012	-0,240	4,219
Year 2013	-0,252	4,047
Year 2014	0,094	3,922
Year 2015	-0,106	3,367
Year 2016	-0,971	9,101
Total period 2004-2016	**0,089**	**7,874**

Table D1 shows the skewness and kurtosis of the base portfolio, the OMXS30.

Table D2

MSCI EEM	Skewness	Kurtosis
Year 2005	-0,400	3,717
Year 2006	0,104	3,976
Year 2007	-0,409	4,505
Year 2008	1,287	9,599
Year 2009	0,495	4,318
Year 2010	0,290	4,147
Year 2011	-0,311	5,373
Year 2012	0,011	3,827
Year 2013	0,123	3,868
Year 2014	-0,144	3,256
Year 2015	-0,170	3,694
Year 2016	-0,161	4,433
Total period 2004-2016	**1,209**	**23,532**

Table D2 shows the skewness and kurtosis of the diversification asset, the MSCI EEM.

Table D3

GMV Portfolio - DCC Approach	Skewness	Kurtosis
Year 2005	-0,346	3,775
Year 2006	-0,255	5,919
Year 2007	-0,487	3,910
Year 2008	0,640	5,914
Year 2009	0,016	3,450
Year 2010	0,405	6,038
Year 2011	-0,154	4,718
Year 2012	0,060	3,601
Year 2013	0,053	3,890
Year 2014	0,001	3,792
Year 2015	-0,208	3,907
Year 2016	-0,653	6,943
Total period 2004-2016	**0,150**	**8,805**

Table D3 shows the skewness and kurtosis of the minimum-variance portfolio created with the DCC approach

Table D4

GMV Portfolio - DCC Approach with weight constraints	Skewness	Kurtosis
Year 2005	-0,346	3,775
Year 2006	-0,255	5,919
Year 2007	-0,487	3,910
Year 2008	0,640	5,914
Year 2009	0,016	3,450
Year 2010	0,405	6,038
Year 2011	-0,154	4,718
Year 2012	0,050	3,617
Year 2013	0,047	3,886
Year 2014	0,001	3,792
Year 2015	-0,208	3,907
Year 2016	-0,653	6,943
Total period 2004-2016	**0,149**	**8,816**

Table D4 shows the skewness and kurtosis of portfolio from Table D3, but this time with weight constraints included in the optimization problem.

Table D5

GMV Portfolio - CVaR Approach	Skewness	Kurtosis
Year 2005	-0,347	3,782
Year 2006	-0,251	5,711
Year 2007	-0,506	4,162
Year 2008	0,643	5,977
Year 2009	0,015	3,442
Year 2010	0,364	5,396
Year 2011	-0,151	4,706
Year 2012	0,070	3,584
Year 2013	0,080	3,900
Year 2014	-0,024	3,731
Year 2015	-0,206	3,896
Year 2016	-0,912	8,706
Total period 2004-2016	**0,121**	**8,786**

Table D5 shows the skewness and kurtosis of the minimum-variance portfolio created with the CVaR approach.

Table D6

GMV Portfolio - CVaR Approach with weight constraints	Skewness	Kurtosis
Year 2005	-0,347	3,782
Year 2006	-0,251	5,711
Year 2007	-0,506	4,162
Year 2008	0,643	5,977
Year 2009	*0,015*	*3,442*
Year 2010	0,382	5,680
Year 2011	-0,151	4,706
Year 2012	0,050	3,617
Year 2013	0,047	3,886
Year 2014	-0,024	3,731
Year 2015	-0,206	3,896
Year 2016	-0,912	8,706
Total period 2004-2016	**0,118**	**8,933**

Table D6 shows the skewness and kurtosis of portfolio from Table D5, but this time with weight constraints included in the optimization problem.

Table D7

Sharpe-maximizing Portfolio - DCC Approach	Skewness	Kurtosis
Year 2005	-0,326	3,654
Year 2006	-0,236	5,581
Year 2007	-0,510	4,308
Year 2008	0,722	6,668
Year 2009	0,055	3,694
Year 2010	0,384	5,709
Year 2011	-0,207	5,004
Year 2012	0,106	3,558
Year 2013	0,079	3,900
Year 2014	-0,050	3,661
Year 2015	-0,244	4,005
Year 2016	-0,467	5,742
Total period 2004-2016	**0,250**	**10,468**

*All values are calculated as daily averages

Table D7 shows the skewness and kurtosis of the portfolio that maximizes the risk-adjusted return using the DCC approach.

Table D8

Sharpe-maximizing Portfolio - DCC Approach with weight constraints	Skewness	Kurtosis
Year 2005	-0,326	3,655
Year 2006	-0,233	5,562
Year 2007	-0,510	4,325
Year 2008	0,716	6,631
Year 2009	0,044	3,651
Year 2010	0,384	5,704
Year 2011	-0,193	4,931
Year 2012	0,050	3,617
Year 2013	0,047	3,886
Year 2014	-0,047	3,671
Year 2015	-0,242	4,004
Year 2016	-0,467	5,744
Total period 2004-2016	**0,240**	**10,439**

*All values are calculated as daily averages

Table D8 shows the skewness and kurtosis of portfolio from Table D7, but this time with weight constraints included in the optimization problem.

Appendix E

Figure E1

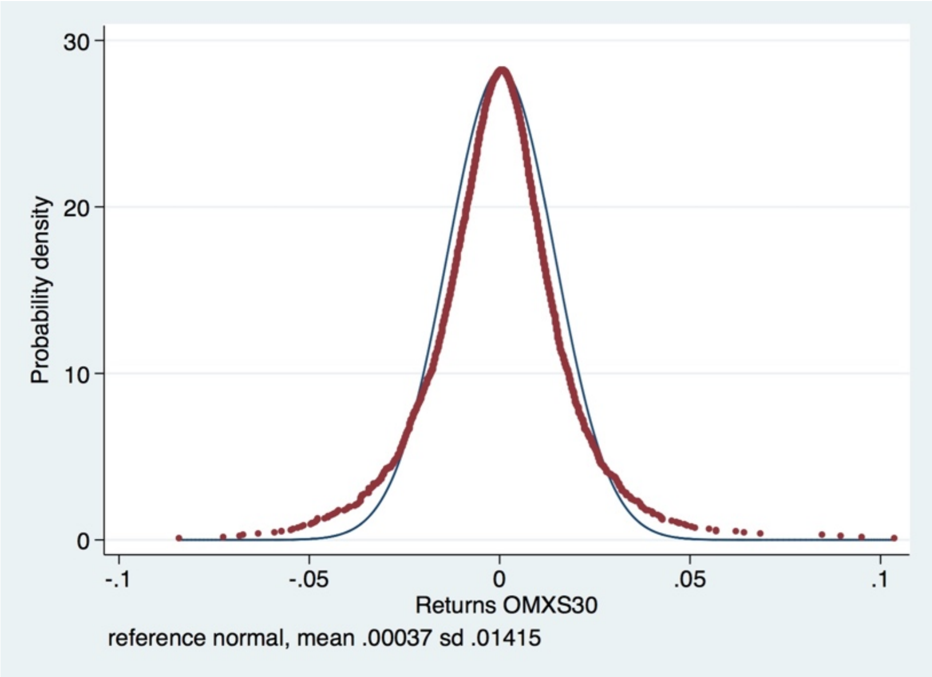

Figure E1 illustrates the return distribution for OMXS30.

Figure E2

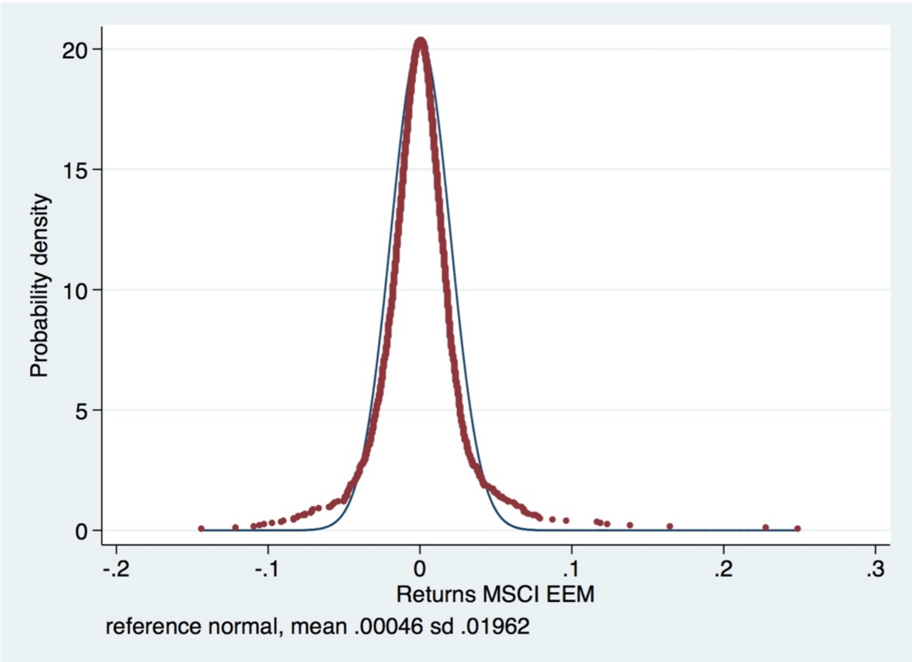

Figure E2 illustrates the return distribution for MSCI EEM.