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Industry versus Country Portfolio Diversification: from the Perspective of the US Investor

Master Thesis

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ABSTRACT

This thesis examines the role of diversifying across different industries in determining equity index returns in contrast to the effect of diversifying across different countries. This research aims at investigating the increasing importance of industry diversification. Furthermore, it examines the optimal portfolio for a US investor when diversifying globally within different industries. For constructing the optimal portfolio for the US investor, the Sharpe ratio is applied. The portfolio theory developed by Markowitz (1952) is presented and the concepts of the optimal portfolio and Sharpe ratio are identified. The views of the main contributors to the topic of portfolio diversification are investigated. To offer contrasting views, a distinction is made between industry and geographic diversification strategies, and prior empirical findings are provided.

The results support the principles of diversification and the portfolio theory developed by Markowitz (1952). Industry effects seem to be more significant compared to country effects in determining equity index returns. Therefore, evidence is found for the increasing importance of industry diversification, and hence the importance of diversifying within multiple industries cannot be ignored. Based on the finding of that an American investor should invest across industries rather than across countries, we give a recommendation for investing across particular industries, for which the lowest average correlations with other industries are obtained. For evaluating the stability of the composition of the optimal portfolio, we apply the out-of-sample method. We find results that are in accordance with most findings that report worse out-of-sample performance in terms of a lower Sharpe ratio. These results are further supported by various prior findings.

Keywords: risk, return, correlation, industry diversification, country diversification, optimal portfolio, Sharpe ratio

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LIST OF ABBREVIATIONS

ADR	American Depositary Receipt
AU	Australia
CDIS	Consumer Discretionary
CH	Switzerland
CML	Capital Market Line
CN	China
CSTA	Consumer Staples
DE	Germany
ENE	Energy
ES	Spain
FIN	Financials
FR	France
GICS	S&P Global Industry Classification Standard
HCARE	Healthcare
HK	Hong Kong
IND	Industrials
IT	Italy
ITECH	Information Technology
JP	Japan
MAT	Materials
MPT	Modern Portfolio Theory
OLS	Ordinary Least Squares
REALE	Real Estate
SE	Sweden
UK	United Kingdom
UTIL	Utilities

INTRODUCTION

Markowitz (1952) and Bernoulli (1954) as contributors to principles of diversification suggest dividing investments exposed to some danger into several parts rather than risking them together. However, total protection from risk is not provided through diversification (Rubinstein, 2002) as macroeconomic risk always exists (Neale and Pike, 2009). The primary motivation in holding a diversified portfolio of stocks is to reduce risk (Solnik, 1974).

Low correlations between index returns in different countries are documented by Grubel (1968), Levy and Sarnat (1970) and Solnik (1974). Their studies show that the benefits of international diversification are greater than the various costs associated with it, which include cultural and regulatory differences, higher direct trading costs alongside political and currency risks (Griffin and Karolyi, 1998). Some of the benefits of international diversification stem from diversifying across industries. Equity markets with different industry composition will not be perfectly correlated due to that different industries are not perfectly correlated (Heston and Rouwenhorst, 1994).

Concerning the trends in different strategies of diversification, country effects have been dominating industry effects in explaining variations in stock returns globally (Baca, Garbe and Weiss, 2000). Even though previous studies demonstrate the greater importance of country factors in determining security returns, both industry and country factors have been significant (Aked, Brightman and Cavaglia, 2000). Roll (1992) assumes industrial composition to be important for explaining cross-sectional differences in volatility as well as the correlation structure of country index returns.

Findings indicate that country-based approaches to global investment management are losing their effectiveness (Baca, Garbe and Weiss, 2000). However, the increasing importance of industry factors is not clearly documented (Aked, Brightman and Cavaglia, 2000). There is some evidence for an upward shift in the industry diversification since 1999 (Ehling and Ramos, 2005), and it is suggested that ignoring to diversify across industries results in losing the advantages from diversification (Phylaktis and Xia, 2006). From now on, industry diversification is suggested to be of increasing interest for global equity portfolio managers (Phylaktis and Xia, 2006). Therefore, the effect of diversifying across industries on a stock portfolio is especially of importance for investigation, which is looked at from the point of view of a US investor. This leads us to examine the effect of industry diversification and find out the relationship between the effect on equity index returns and diversifying across industries contrasted to country diversification. To reflect the discussion on the two different strategies, they are contrasted with each other with prior empirical findings.

This thesis involves determining an optimal industry portfolio for the US investor. It is investigated how he would have to consider the strategy of diversifying across different industries when constructing the optimal stock portfolio aiming to minimize risks while not sacrificing the expected return. The particular industries providing the investor with the maximum Sharpe ratio are suggested. We exclude the United States as a geographical area and thus, this research considers only stocks listed on all European, Asian and Latin American exchanges. Also, all American Depositary Receipts (ADRs) on US exchanges are included. They consist of stocks of most foreign companies that trade in the US markets. All equities are in US dollars or denominated in US dollars. We consider stocks with a market capitalization greater than 2 billion euros, including mid- and large-cap equities. Small-cap equities are excluded. Furthermore, we include only countries (11) with the number of companies higher than 30. The countries included in our analysis are obtained by the Standard & Poor's Capital IQ database according to the above criteria. Sectors (10) follow the S&P Global Industry Classification Standard (GICS). Heston and Rouwenhorst (1994) suggest a panel data model that can explain the country and industry effects on stock returns, which we also apply in our thesis. The theories of an optimal portfolio and the Sharpe ratio are applied for determining the optimal risky portfolio for which expected returns, standard deviations and correlations between the different industries are used as inputs.

This thesis aims at investigating the increasing importance of industry diversification. The main purpose is to examine the role of diversifying across industries in determining equity index returns in contrast to the effect of diversifying across countries. In addition, this research investigates the optimal portfolio for the US investor when diversifying globally within industries. For achieving the purpose of this research, the principles of diversification are identified and the views of the main contributors to this topic are investigated. To offer contrasting views, a distinction is made between industry and geographic diversification strategies, and prior empirical findings are provided. It is hypothesized that industry portfolio diversification dominates country portfolio diversification.

The results support the principles of diversification and the portfolio theory introduced by Markowitz (1952). We find industry effects to be more significant compared to country effects in determining equity index returns. Therefore, evidence is found for the increasing importance of industry diversification, and hence the importance of diversifying within multiple industries cannot be ignored. According to our finding of that an American investor should invest across industries rather than across countries, we give a recommendation for investing across particular industries, for which the lowest average correlations with other industries are obtained. Additionally, we find evidence for the optimal portfolio leading to better portfolio performance in contrast to an equally weighted portfolio. We apply the out-of-sample method for assessing the stability of the composition of the suggested optimal portfolio and come to the conclusion that our results are in accordance with most findings that report worse out-of-sample performance in terms of a lower Sharpe ratio. Various prior findings further support the obtained results.

This study begins with a theoretical framework of the subject under investigation. Chapter one presents the portfolio theory by Markowitz (1952) and the optimal portfolio including the Sharpe ratio. It also defines the concept of diversification and separates two diversification strategies, which are compared. Some prior empirical findings related to the subject are also discussed. Chapter two outlines the data, in which data collection, descriptive statistics and correlations between countries and industries are presented. Methodology consisting of the panel data model used in the thesis is also described. Chapter three presents the empirical findings and analysis. The initial and final results from the tests are included. Finally, the final results are discussed altogether, after which a conclusion is provided with the authors' suggestions for further research.

1. THEORETICAL BACKGROUND AND LITERATURE REVIEW

In the following section, relevant theories for the research are presented. Firstly, the portfolio theory by Markowitz (1952) together with an optimal portfolio and Sharpe ratio is identified. Secondly, the concepts of industry and geographic diversification are discussed, after which the discussion focuses on the comparison of the two strategies. Lastly, previous findings related to the topic are reviewed.

1.1. Portfolio theory

Over 50% of private investors persist in holding a single asset in their portfolios. One may assume that they are unaware of the advantages of spreading risks and the other that they are irrational or not risk-averse (Neale and Pike, 2009). Unlike them, risk-averse investors are conscious of that not all investments perform well simultaneously (Neale and Pike, 2009), and they request a small risk, together with a high expected return (Emanuelsson and Marling, 2012). Furthermore, they understand that a few investments may perform exceptionally well while some may never do. No one is able to predict the accurate performance of investments during any one period, therefore, spreading one's funds over a wide set of investments is rational (Neale and Pike, 2009).

It is suggested by Bernoulli (1954) that goods exposed to some risk should be divided into several parts rather than risking them all together, which is called diversification. Markowitz (1952) assumes that diversification does not generally eliminate risk while it reduces it. However, it can eliminate the specific risk related to an asset, leaving only the macroeconomic risk as the determinant of required asset returns (Neale and Pike, 2009). This is in contrast to the belief of Williams who states that all risk can be diversified away (Rubinstein, 2002).

Markowitz (1952) behind the modern portfolio theory (MPT) shows how an optimal portfolio can be compiled so that its risk is less than the weighted average of risks of individual assets included in the portfolio, without sacrificing the expected return. Consequently, the risk is diversified between the assets in the portfolio (Markowitz, 1952). Since this optimal portfolio is located on the efficient frontier, other portfolios are ignored by an investor (Kren and Sirucek, 2015). Markowitz (1952) therefore introduced the idea of an efficient portfolio, generating the highest expected return from a set of assets at any given risk level. In other words, the efficient portfolio could be described as one involving the lowest level of risk for any required return (Clare and Wagstaff, 2011). Even ordinary investors use the efficient portfolio concept for structuring their portfolios and measuring their performance (Rubinstein, 2002).

Markowitz (1952) suggests the investor maximize the portfolio return while minimizing its risk. As returns on some assets are highly correlated, they tend to move together (Clare and Wagstaff, 2011). However, when the returns are less well correlated, Markowitz (1952) shows that the risk involved in holding these assets together in a portfolio is lower than the sum of individual risks of each asset in the portfolio. The contribution a certain asset makes to the risk of the investor's entire portfolio, which is mainly a question of its covariance with all other assets in his portfolio, is emphasized by Markowitz. Consequently, assets can only be appropriately evaluated as a group rather than in isolation (Rubinstein, 2002).

The theory suggests that the investor should consider three essential characteristics of potential investment for implementing the portfolio theory. They consist of the expected return, the risk of the investments, measured by standard deviation of returns, and the co-movement between them. The risk-spreading portfolio diversifier has to understand the interaction among his investments and as a result, the impact on portfolio risk (Lawson and Pike, 1979). According to Markowitz (1952), there are two common rules among investors. They include that the investors should consider the expected return a desirable thing and the return variance an undesirable thing.

1.1.1. Optimal portfolio and efficient frontier

The tangency portfolio is considered the market portfolio, which is an investor's optimal portfolio that consists of all risky assets in proportions reflecting the total equity values of the companies they represent (Lawson and Pike, 1979). In Figure 1, this market portfolio is indicated as M. The curve AB illustrates the efficient frontier, which is defined as the highest possible portfolio return at any given level of risk.

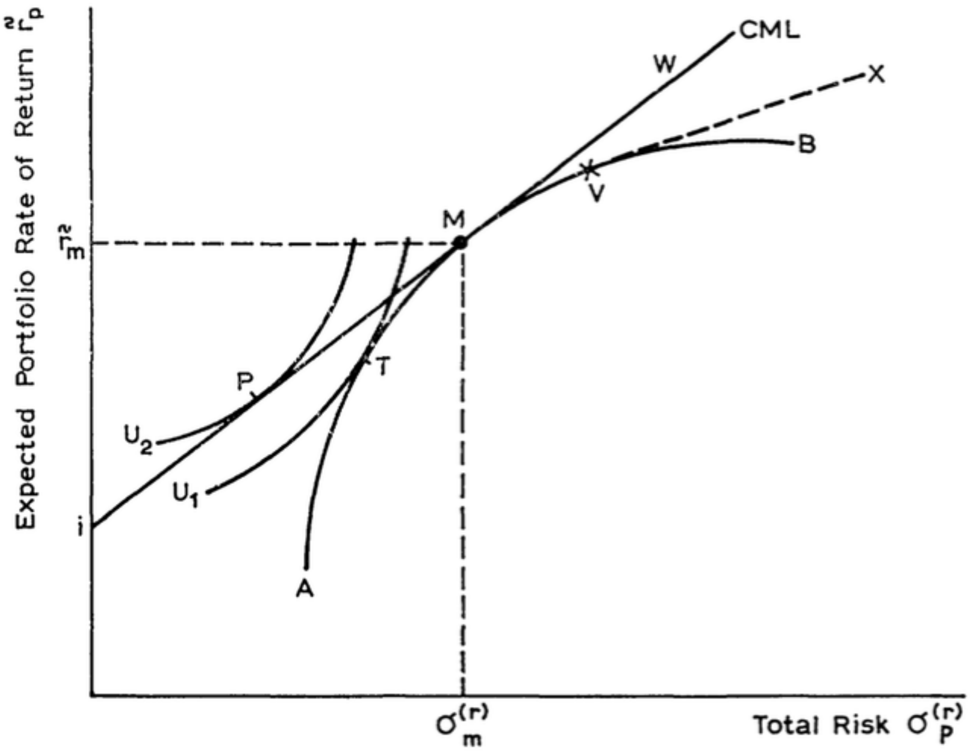

Figure 1. Capital market line (CML) and efficient frontier (AB)
Source: (Lawson and Pike, 1979)

Portfolios that exist to the right of the efficient frontier are not perfectly diversified. The investor will end up choosing the portfolio on the efficient frontier maximizing his utility in the absence of assets other than risky assets. At the tangency point between the efficient frontier and the highest accessible indifference curve, the portfolio yields maximum utility (Lawson and Pike, 1979). The investor aims at being on the highest possible indifference curve for obtaining the maximum level of utility that is possible (Dobbins and Witt, 1979). This is illustrated by the point T and it represents the optimal portfolio (Lawson and Pike, 1979).

As stated by MPT, the portfolio maximizing the Sharpe ratio lies on the mean-variance efficient frontier. It is described as the tangency portfolio since this portfolio corresponds to the point in which the Capital Market Line (CML) is a tangent to the efficient frontier. The tangent derived from the risk-free interest rate, *i*, to the efficient frontier is called the CML. In order for the investor to implement the tangency portfolio, he has to estimate expected returns, variances and covariances for the assets included in his portfolio (Kourtis, 2016).

1.1.2. Sharpe ratio

According to the theory, an investor should consider three main aspects of investments, which are the expected return, the risk of the investments and the co-movement between them. The risk is measured by standard deviation (Lawson and Pike, 1979). The investor needs to understand the interaction between his investments and include assets that have the highest expected return, lowest standard deviation and smallest correlation with other assets in the portfolio for him to construct the optimal portfolio. The optimal portfolio, which is called the tangency portfolio is the one that maximizes Sharpe ratio. It is the point on the efficient frontier with the highest Sharpe ratio.

As one of the most common measures of portfolio performance, the Sharpe ratio is used for evaluating the attractiveness of different investment strategies to a large extent (Goetzmann, Ingersoll, Spiegel and Welch, 2002). The higher the Sharpe ratio for a portfolio, the higher the return per unit of risk (Clare and Wagstaff, 2011). The formula for the Sharpe ratio is the following:

$$SR = \frac{E(R) - Rf}{\sigma} \tag{1}$$

where

SR is the Sharpe ratio,
$E(R)$ is the expected return on a portfolio,
Rf is the risk-free rate,
σ is the standard deviation of asset returns.

For investigating the optimal portfolio for a US investor, we use the Sharpe ratio, which measures the expected excess return per unit of risk. More specifically, we apply the Sharpe ratio when finding out how much of different industry stocks have to be included in the optimal portfolio of the US investor to maximize the ratio. The yield on a Treasury bill is usually used as the risk-free asset (Clare and Wagstaff, 2011). In our thesis, we apply the US 10-year government bond yield to estimate the risk-free rate for an American investor.

Apart from its popularity, the Sharpe ratio is prone to manipulation by strategies that can alter the shape of the probability distribution of returns (Goetzmann, Ingersoll, Spiegel and Welch, 2002). Evidence exists that Sharpe ratios tend to be misleading when the shape of the return distribution is far from normal, which is documented by Bernardo and Ledoit (2000).

1.2. Diversification of investment portfolio

1.2.1. Industry diversification

As one of the diversification strategies, industry diversification is described as choosing investments from different fields for avoiding the decrease in the portfolio value due to a weak performance of one industry, thus, minimizing the overall portfolio risk. As correlations of stock returns in different industries tend not to move in the same direction, the benefits of diversification increase (Saario, 2007). Solnik (1974) provides an example of a portfolio of ten electronics stocks being likely to benefit less from diversification than one made up of stocks from ten different industries.

The effects of business cycles are essential to be considered, meaning that companies are chosen from both the industry to which the fluctuations easily affect and from the industry to which they do not easily affect. When sales are relatively low in one industry, the adverse consequences can be compensated by involvement in another industry in which sales are relatively high (Neale and Pike, 2009). As the fluctuations of stock prices in the industries sensitive to business cycles are larger, it is evident that the stocks are riskier for those sensitive industries. The steel, forestry, information technology and finance industries are some of the sensitive industries. The food, energy, healthcare and retail industries, in turn, are examples of the industries not sensitive to business cycles. The timing of investments is emphasized when investing in the industries sensitive to business cycles as to avoid large price changes in the short term (Saario, 2007).

1.2.2. Geographic diversification

Geographic diversification refers to including investments from different geographical areas in a portfolio for reducing portfolio risk (Marston, 2011). The risk of a stock portfolio that is diversified between US stocks and international stocks is lower than the risk of a portfolio combined only of the US or international stocks (Statman and Scheid, 2008). A study conducted in 1970 for examining the gains from geographic diversification shows that the return for the United States was relatively high while the risk was relatively low. Despite the good performance of US common stocks, American investors were still suggested to benefit from geographic diversification (Levy and Sarnat, 1970). As the correlations of returns among investments were neither perfect nor sufficient, the possibility for portfolio diversification existed (Markowitz, 1952). Including even relatively low return foreign stocks were suggested for reducing the portfolio risk (Levy and Sarnat, 1970).

One study concludes that Americans benefit from diversifying in foreign countries. Investing in countries whose economies are not highly correlated with those of the investing country leads to benefits (Levy and Sarnat, 1970), such as an increase in the expected return, a decrease in variation of returns and lower return correlations of foreign assets with domestic ones (Phylaktis and Xia, 2006). Various studies show that the correlation of returns between emerging and mature markets is low and portfolio diversification into emerging markets results in lower risk and increased returns (Phylaktis and Xia, 2006). Furthermore, several authors demonstrate that movements in stock prices in different countries are almost unrelated (Solnik, 1974).

1.3. Industry versus geographic diversification in prior empirical findings

Concerning the trends in different strategies of diversification, prior literature has documented mixed empirical results. However, previous studies have concluded that, in general, geographic diversification seems to dominate industry diversification in determining equity returns (Phylaktis and Xia, 2006). Grinold et al. found the country effects to be more important, although both industry and country effects were significant. The findings by Ramos (2004) from a sample of ten industry and ten country indexes during the period 1989-2003 indicate that both strategies offer similar performance. This is because the null hypothesis of Lagrange multiplier being zero cannot be rejected both for industry and country diversification. The model specified in the paper applies the Lagrange multiplier as an indicator of industry or country diversification as the only investment strategy, and a linear regression is used to obtain the estimator of the Lagrange multiplier. Additionally, Solnik (1974) provides that the risk of a portfolio diversified across countries is lower than the risk of one diversified across industries. However, there is some evidence that diversifying across industries cannot be entirely ignored (Phylaktis and Xia, 2006).

A study by Phylaktis and Xia (2006) examines the effects of industry and country diversification on international equity returns with a model including 34 countries and 50 industries during the period 1992-2001. The analysis is carried out by applying the dummy variable regression framework of Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998). They document a significant upward shift in the industry diversification since 1999, but show the country effects to still dominate the industry effects during the whole sample period. The transfer in the industry effects is significant especially in North America and Europe. There are differences between industries since in some industries such as technology, consumer services, semiconductors and household products the industry effects are documented to be more significant compared to country effects.

Some studies show that the industry diversification has resulted in a greater risk reduction compared to country diversification (Aked, Brightman and Cavaglia, 2000). According to Aked, Brightman and Cavaglia (2000), this phenomenon is assumed to persist and become more significant along with the strengthening geographical integration of markets. A study conducted by Baca, Garbe and Weiss (2000) also concludes that the country effects no longer dominate the industry effects. Moreover, if it is true that industries are becoming more geographically dispersed, the gains from diversifying across industries would become higher (Ramos, 2004). If industry factors are considered more important, diversification across industries has more weight in leading to risk reductions. In contrast to that, if country factors are more important, diversifying stocks across different countries plays a greater role in the risk reductions of the portfolio (Phylaktis and Xia, 2006). In addition, Phylaktis and Xia (2006) find evidence for the earlier results of the dominance of the country effects over the industry effects since the earlier papers have a sample covering solely the 1980s and the early 1990s.

Overall, there is contradictory evidence related to the effect of industry diversification on risk. It is claimed by Roll (1992) that industry diversification plays a significant role, while Heston and Rouwenhorst (1994) state that its influence is small. Heston and Rouwenhorst (1994) find that industries account for less than one percent of stock return volatility. Their findings indicate industry diversification within a country to be a less effective tool for risk reduction compared to diversification across countries within an industry due to the larger country effects. They investigate the industry and country structure of only European stock returns with a sample of 829 stocks in seven industries and 12 European countries. When looking at the methodology used in different research papers, the majority of literature depends on the methodology of Heston and Rouwenhorst (1994). Extending the Heston and Rouwenhorst model for studying index returns from 25 countries, Griffin and Karolyi (1998) neither find the industry effects greater compared to the country effects when constructing portfolios. Griffin and Karolyi (1998) apply a model that consists of developed non-European markets in addition to a few emerging markets. Nevertheless, they find evidence for that industrial composition could play a minor role in explaining stock return variation.

2. DATA AND METHODOLOGY

In this section, we give an overview of the data collection, descriptive statistics, and correlations between different countries and industries. The criteria under which the data for the thesis is gathered is described. Also, the descriptive statistics of the selected countries and sectors are presented. The correlations between the index returns of the different nations and industries are analyzed since they play a major role in portfolio diversification. Furthermore, this section covers the panel data method.

2.1. Data collection

All the data is gathered from the Standard & Poor's Capital IQ database. We use total monthly equity index returns from 783 listed companies across 11 countries. The final sample includes 783 firms with a complete return history during the sample period. Only mid- and large-cap equities are included in our data, meaning that a company's market capitalization has to be at least 2 billion euros. Therefore, small-cap equities are excluded. By including only mid- and large-cap equities in our data the database gives us a reasonable amount of companies for carrying out the research. We are using the sample period of 2000-2017, which results in 215 observations of monthly total returns at a point in time. All the equity returns are expressed in US dollars since our purpose is to suggest a portfolio diversification strategy specifically to a US investor. To have a reasonable amount of countries in our analysis, we only include the countries with the number of companies higher than 30 in each country as given from the database. Before excluding the countries with the number of companies smaller than this threshold the S&P database gives us 49 countries. Doing this restriction allows us to narrow down the number of countries to 11 from 49 since now the database gives us 11 countries. United States is excluded from the country list because of the purpose of our research to examine whether it is more beneficial for the US investor to invest across foreign countries or different industries. Therefore, we consider stocks that are listed only on all European, Asian and Latin American exchanges. Also, all ADRs on US exchanges are included. The countries included in our sample are Australia, China, France, Germany, Hong Kong, Italy, Japan, Spain, Sweden, Switzerland and United Kingdom.

In order to observe industry effects on the returns, each of the 783 companies is classified into a specific industry following the S&P Global Industry Classification Standard (GICS). In CIGS, 11 sectors consist of 24 industry groups, which in turn include 68 industries in total. An overview of the sectors, industry groups and industries is presented in Appendix 1. In this thesis, we use those 11 sectors as our leading industries for the model. The industries included in the sample are consumer discretionary, consumer staples, energy, financials, healthcare, industrials, information technology, materials, real estate, telecommunication services and utilities. At a later stage, we exclude the telecommunication services industry from the sample, because we need to drop one industry or country variable due to a near-singular matrix error in EViews. Since the telecommunication services industry has very few companies included in that industry classification, we decide to drop this particular industry.

The country and industry classification of each company is shown in Appendix 2. We observe that the majority of the companies belong to the industrials (170) and the least amount of the companies belong to the energy (22) and telecommunication services (20) industries. The industrials industry is a broad sector including all the capital goods, commercial and professional services, and transportation. Thus, it is not surprising that most companies in our sample are classified into it. The majority of the companies in our dataset are located in Japan (205) and the minority in Spain (32). We conclude that Japan has the most substantial number of mid- and large-cap companies, whereas Spain has the lowest number of these firms in our sample.

2.2. Descriptive statistics

The descriptive statistics for countries and industries are shown in detail in Tables 1 and 2, respectively. These are based on average raw monthly returns for eleven countries and ten industries, where they are measured in US dollars and expressed as a percentage per month.

Table 1. Summary statistics for countries

	AU	CN	FR	DE	HK	IT	JP	ES	SE	CH	UK
Mean	0.484	1.346	0.482	0.581	0.595	0.243	0.214	0.532	0.640	0.704	0.440
Std Error	0.374	0.558	0.391	0.452	0.417	0.459	0.309	0.426	0.452	0.302	0.327
Median	1.182	1.303	0.630	1.002	1.186	0.242	0.452	0.907	0.439	0.969	0.839
Std Deviation	5.478	8.178	5.732	6.633	6.120	6.727	4.537	6.244	6.631	4.423	4.789
Sample Variance	30.00	66.884	32.859	44.003	37.449	45.23	20.58	38.986	43.975	19.560	22.93
Kurtosis	1.730	1.362	0.937	1.901	0.544	1.054	0.232	0.897	1.873	0.859	1.887
Skewness	-0.68	-0.016	-0.395	-0.568	-0.236	-0.41	-0.18	-0.107	-0.198	-0.590	-0.56
Range	37.81	58.906	37.875	46.979	36.431	45.18	25.02	39.518	47.724	25.325	33.74
Minimum	-24.6	-25.32	-21.15	-28.77	-18.60	-23.7	-12.9	-19.69	-26.36	-13.68	-20.1
Maximum	13.219	33.588	16.725	18.210	17.834	21.42	12.12	19.827	21.367	11.647	13.65
Sum	103.9	289.45	103.674	124.928	127.861	52.253	45.915	114.358	137.638	151.434	94.635
Count	215	215	215	215	215	215	215	215	215	215	215

Source: (Calculated by the authors using Excel data analysis tool on the basis of the monthly stock returns data) Notes: Table reports the monthly mean, standard deviation, kurtosis and skewness of the stock returns over the sample period 2000-02-29 to 2017-12-29. Key: AU=Australia; CN=China; FR=France; DE=Germany; HK=Hong Kong; IT=Italy; JP=Japan; ES=Spain; SE=Sweden; CH=Switzerland; UK=United Kingdom.

Table 2. Summary statistics for industries

	CDISC	CSTAP	ENE	FIN	HCARE	IND	ITECH	MAT	REALE	UTIL
Mean	0.522	0.786	1.047	0.418	0.734	0.539	0.313	0.677	0.793	0.219
Std Error	0.358	0.262	0.547	0.416	0.286	0.367	0.372	0.477	0.428	0.298
Median	0.689	1.098	1.279	0.693	0.955	1.111	0.915	0.894	1.051	0.625
Std Deviation	5.252	3.843	8.024	6.098	4.190	5.377	5.458	6.987	6.275	4.364
Sample Variance	27.589	14.765	64.391	37.192	17.556	28.910	29.791	48.824	39.374	19.048
Kurtosis	2.474	0.811	2.260	1.205	1.293	1.884	0.881	1.455	1.081	0.415
Skewness	-0.389	-0.579	0.162	-0.470	-0.226	-0.742	-0.654	-0.502	-0.169	-0.500
Range	41.717	24.392	63.274	42.413	27.361	37.420	34.356	47.129	42.232	23.524
Minimum	-21.252	-13.907	-27.930	-26.09	-12.847	-23.283	-22.144	-28.647	-19.137	-13.52
Maximum	20.465	10.486	35.345	16.324	14.514	14.137	12.212	18.482	23.095	10.006
Sum	112.223	169.028	225.098	89.794	157.823	115.808	67.266	145.599	170.516	47.140
Count	215	215	215	215	215	215	215	215	215	215

Source: (Calculated by the authors using Excel data analysis tool on the basis of the monthly stock returns data) Notes: Table reports the monthly mean, standard deviation, kurtosis and skewness of the stock returns over the sample period 2000-02-29 to 2017-12-29. Key: CDIS=Consumer Discretionary; CSTA=Consumer Staples; ENE=Energy; FIN=Financials; HCARE=Health Care; IND=Industrials; ITECH=Information Technology; MAT=Materials; REALE=Real Estate; UTIL=Utilities.

An overview of average returns and standard deviations for countries and industries are shown in Figures 2 and 3, respectively.

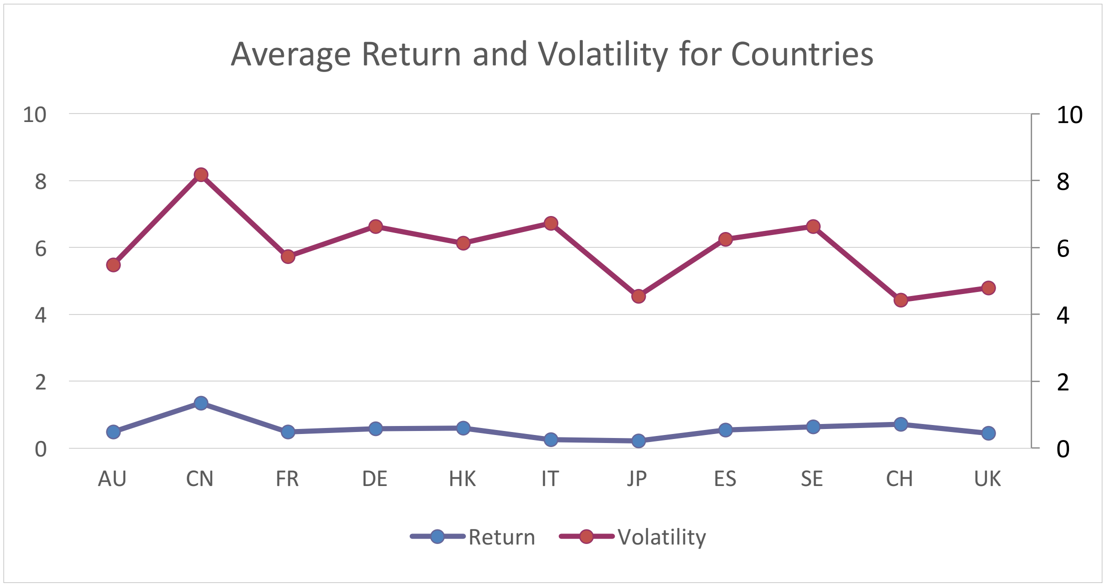

Figure 2. Average return and volatility for countries (%)
Source: (Compiled by the authors on the basis of the monthly stock index returns data)

Firstly, by looking at the average returns and standard deviations for countries in Figure 2, we can see that Chinese (CN) stocks have the largest average return (1.346%) and also the highest standard deviation (8.178%). Investing in China provides an investor with the highest return. At the same time, Chinese equity stocks are incredibly volatile, which means that higher risk is involved with higher yields. The proof of that is also the minimum and maximum values of that country's stock return, which can drop down to -25.3% or go up to 33.6%. In contrast to China, Japan (JP) has the lowest average return with only 0.21% and one of the smallest standard deviations of 4.54%. Since Japan has the most significant number of companies in our sample (205) we can say that all the firms in the country are pretty consistent with their average returns and overall volatility. Also, Italy (IT) has a small average return of 0.243%, which is only slightly higher than that of Japan. In contrast, the stock volatility of Italy is the second highest at 6.7% after China. This indicates that Italy's stocks are risky compared to the reward they can bring to the investor since its overall average return is low as shown in Figure 2.

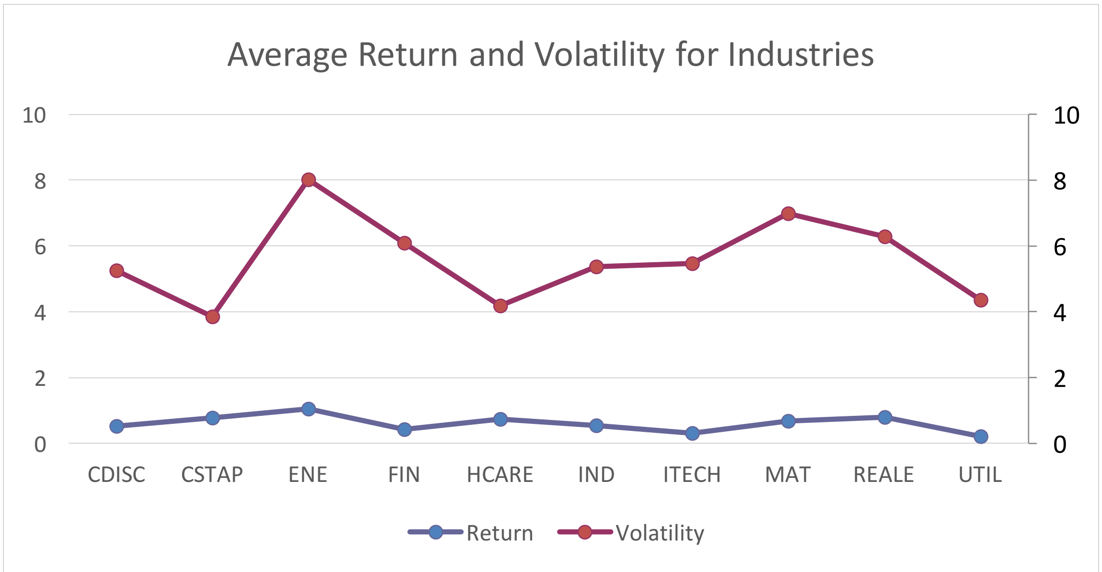

Figure 3. Average return and volatility for industries (%)

Source: (Compiled by the authors on the basis of the monthly stock index returns data)

By looking at the average returns and standard deviations for industries in Figure 3, we can see that the energy industry (ENE) has the highest average yield (1.047%) in the period 2000-2017. It also has the highest standard deviation (8.02%). Investing in the energy industry can be risky, but it is also compensated with a higher reward that can make it worth the risk. The utilities industry (UTIL) has the lowest average return (0.22%) and one of the smallest standard deviations (4.36%). Therefore, investing in the utilities industry won't be that risky, however, it probably won't bring significant returns to the investor. Consumer staples (CSTAP) is one of the more stable sectors, with the third highest average return (0.786%) and the lowest standard deviation (3.84%). Close to these results is also the healthcare industry (HCARE), which has the fourth highest average return on the equity stock (0.79%) and the second lowest standard deviation (4.19%).

By comparing the average returns and standard deviations for countries and industries with each other, we observe that as a group country stocks are more volatile than industry stocks. The average standard deviation for countries is 5.95%, whereas for industries it is 5.59%. In contrast, the industry equity index returns have a higher average performance, which is 0.6%, compared to 0.57% for countries.

2.3. Correlations

A return correlation between different countries and industries plays an essential role in portfolio diversification. International diversification has been preferred in earlier research papers, such as French and Poterba (1991) because of the low level of correlation between countries. Since markets do not move together for different nations, it is assumed to be safer for an investor to invest in various countries rather than in different industries. Furthermore, industries are expected to be more correlated with each other. Nowadays, the integration of the markets between different nations due to the globalization, however, leads to that the markets tend to move together. The correlations for countries and industries are presented in Tables 3 and 4, respectively.

Table 3. Correlations for countries

Country	**AU**	**CN**	**FR**	**DE**	**HK**	**IT**	**JP**	**ES**	**SE**	**CH**	**UK**
AU		0.604	0.729	0.730	0.682	0.625	0.536	0.606	0.715	0.731	0.767
CN	0.604		0.493	0.502	0.670	0.410	0.418	0.398	0.503	0.499	0.546
FR	0.729	0.493		0.921	0.662	0.864	0.569	0.812	0.838	0.815	0.848
DE	0.730	0.502	0.921		0.660	0.851	0.545	0.803	0.839	0.751	0.802
HK	0.682	0.670	0.662	0.660		0.588	0.529	0.564	0.642	0.616	0.645
IT	0.625	0.410	0.864	0.851	0.588		0.509	0.835	0.737	0.707	0.755
JP	0.536	0.418	0.569	0.545	0.529	0.509		0.499	0.513	0.536	0.595
ES	0.606	0.398	0.812	0.803	0.564	0.835	0.499		0.714	0.644	0.690
SE	0.715	0.503	0.838	0.839	0.642	0.737	0.513	0.714		0.726	0.781
CH	0.731	0.499	0.815	0.751	0.616	0.707	0.536	0.644	0.726		0.803
UK	0.767	0.546	0.848	0.802	0.645	0.755	0.595	0.690	0.781	0.803	
Average	0.673	0.504	0.755	0.740	0.626	0.688	0.525	0.656	0.701	0.683	0.723

Avg correlation **0.6613**

Source: (Correlations calculated by the authors using Excel data analysis tool on the basis of the monthly stock returns data) Notes: Table reports correlations higher than 0.8 as highlighted. Key: AU=Australia; CN=China; FR=France; DE=Germany; HK=Hong Kong; IT=Italy; JP=Japan; ES=Spain; SE=Sweden; CH=Switzerland; UK=United Kingdom.

By comparing the country and industry correlations in Tables 3 and 4, we observe that correlation values are similar across countries and industries. However, when we take the average correlation of both, we observe that the average correlation between countries is a bit lower (0.6613) than the average correlation between industries (0.6637). We find this to be a usual finding in the literature as well. For countries, we notice that, on average, the most correlated ones with other countries are France (0.755) and Germany (0.74). China, in turn, is the least correlated (0.504) with other countries. We have seven European countries in our sample, and it makes sense for France and Germany to be the most correlated ones with others since over half of our sample countries are located in Europe.

Table 4. Correlations for industries

Industry	CDISC	CSTAP	ENE	FIN	HCARE	IND	ITECH	MAT	REALE	UTIL
CDISC		0.622	0.564	0.790	0.605	0.893	0.822	0.792	0.716	0.640
CSTAP	0.622		0.487	0.599	0.722	0.659	0.492	0.559	0.618	0.742
ENE	0.564	0.487		0.608	0.406	0.671	0.486	0.753	0.612	0.556
FIN	0.790	0.599	0.608		0.585	0.836	0.734	0.788	0.807	0.644
HCARE	0.605	0.722	0.406	0.585		0.625	0.567	0.540	0.580	0.642
IND	0.893	0.659	0.671	0.836	0.625		0.876	0.860	0.777	0.691
ITECH	0.822	0.492	0.486	0.734	0.567	0.876		0.737	0.644	0.557
MAT	0.792	0.559	0.753	0.788	0.540	0.860	0.737		0.766	0.626
REALE	0.716	0.618	0.612	0.807	0.580	0.777	0.644	0.766		0.569
UTIL	0.640	0.742	0.556	0.644	0.642	0.691	0.557	0.626	0.569	
Average	0.716	0.611	0.571	0.710	0.586	0.765	0.657	0.713	0.677	0.630

Avg correlation **0.6637**

Source: (Correlations calculated by the authors using Excel data analysis tool on the basis of the monthly stock returns data) Notes: Table reports correlations higher than 0.8 as highlighted. Key: CDIS=Consumer Discretionary; CSTA=Consumer Staples; ENE=Energy; FIN=Financials; HCARE=Health Care; IND=Industrials; ITECH=Information Technology; MAT=Materials; REALE=Real Estate; UTIL=Utilities.

By comparing the industry correlations, we conclude that the most correlated industries are industrials (0.765) and consumer discretionary (0.716). The least correlated industry with other industries is energy (0.571). The industrials sector is a broad field, containing capital goods, commercial and professional services, and transportation. Thus, it comes as no surprise that this sector is the most correlated one with the other industries.

Finally, it is better for the investor to invest in countries or industries that are not strongly correlated with each other. This helps the investor reduce risk since holding assets in different countries or industries protects the investor if some of them perform poorly. As Markowitz (1952) shows that when returns are less correlated, the risk involved in holding these assets together in a portfolio is lower than the sum of individual risks of each asset in the portfolio. Therefore, it is essential for the investor to diversify his portfolio and invest in different countries and industries that are not as correlated with each other in order to lower the overall risk of the portfolio.

2.4. Panel data

The main purpose of this thesis is to investigate industry and country effects on equity index returns and construct an optimal portfolio for an American investor. Our primary goal is to find out whether it is more beneficial for the US investor to invest in different countries or industries. As discussed earlier in the literature review, country portfolio diversification has mainly dominated industry portfolio diversification. Recently, there has been a shift, and newer research papers document the industry dominance. Since our sample period is 2000-2017 and it involves 11 countries and 10 industries, we want to find out whether it is better for the US investor today to invest internationally or across sectors. Therefore, a panel data model is employed. After finding out whether an industry or country effect dominates the stock index returns, we determine the optimal portfolio for the US investor. Sharpe ratio is also used in constructing the optimal portfolio for the American investor. We use the Excel application Solver as a tool, which helps us maximize the expected return, minimize the standard deviation and take the correlations between different countries or industries into account.

Our primary examples of the model are Heston and Rouwenhorst (1994) and Flavin (2004). Heston and Rouwenhorst (1994) suggest a panel data model that can explain the country and industry effects on stock returns (Flavin, 2004). Panel data has both dimensions of time series and cross-section, which makes it easy to understand how the industry and country effects affect the stock returns (Brooks, 2014). The panel data has many advantages, such as providing a more accurate inference of model parameters due to containing more degrees of freedom and sample variability than cross-sectional data. It also simplifies computation and statistical inference by involving at least two dimensions; cross-section and time series (Hsiao, 2007). Finally, we receive more observations, higher efficiency and less collinearity, which is why panel data estimation is worth using. Since we have the same number of time series observations (215) for each cross-sectional unit, we deal with a balanced panel.

Similar to previous authors Phylaktis and Xia (2006) and Griffin and Karolyi (1998), we use country and industry indexes to measure returns instead of individual equities. Because all of our equity index returns are in US dollars, we do not take exchange rate risk separately into account. We execute our model in EViews. The following panel data model with fixed dummy variables is used:

$$R_{it} = \alpha + \beta_l + \gamma_m + \varepsilon_{it} \tag{2}$$

where

R_{it} is return for any stock i at time t that belongs to industry l and country m,
α is constant representing the common component for all stocks,
β_l captures the industry effect,
γ_m captures the country effect,
ε_{it} is stock specific error term with zero mean and finite variance.

This kind of model allows separate industry and country effects, but at the same time rules out any interaction between those effects (Phylaktis and Xia, 2006). Since we have data including 11 countries and 10 industries, we have a total of 11 country dummy variables and 10 industry dummy variables in our model. Each of our 783 companies belongs to one of the 11 countries (m= 1 to 11) and one of the 10 industries (l= 1 to 10). Fixed dummy variables express such classification that can have only two values that are 0 and 1. The country dummy is denoted by K_{im}, which means that it will have a value of one if the stock i belongs to country m and zero otherwise. In the same way, the industry dummy is denoted by N_{il}, which means that if the stock i belongs to industry l, it will take a value of one and zero otherwise (Flavin, 2004). Since now we have the specific country and industry dummy variables, we can rewrite the equation (2) for each time period as:

$$R_{it} = \alpha + \beta_1 N_{i1} + \ldots. + \beta_{10} N_{i10} + \gamma_1 K_{i1} + \ldots + \gamma_{11} K_{i11} + \varepsilon_{it} \tag{3}$$

We cannot estimate the equation (3) directly because of perfect multicollinearity issue, since each stock return belongs to both one industry and one country, which makes the dummies sum to unity (Flavin, 2004). Perfect multicollinearity is usually observed when the same explanatory variable is used twice in the same regression (Brooks, 2014). This is the case in our model since every stock return belongs to one industry and one country and is represented by two dummy variables.

There have been different solutions to this problem. One of them would be dropping an arbitrary industry and country and measuring everything relative to these. Another option is to measure everything relative to some benchmark, such as equally weighted index of stocks (Flavin, 2004). This is done by Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998) who estimate cross-sectional regression for each month of the sample. Flavin (2004) notices that even when this method generates unbiased estimates, they are at the same time inefficient. He concludes that this kind of technique tends to over-estimate the standard errors of the variables, which makes the estimates not statistically different from zero. Therefore, Flavin (2004) proposes a pooled regression model, which takes into account that the error term may have a non-constant variance in the pooled dataset. In our thesis, we employ Flavin's suggestion and also estimate a pooled regression to solve the perfect multicollinearity issue and to identify the country and industry effects on the stock returns. This way the interactions between the country and industry effects won't be accounted for. The regression that we estimate is the following:

$$R_{it} = \alpha + \beta_1 N_{i1} + \ldots. + \beta_{10} N_{i10} + \gamma_1 K_{i1} + \ldots + \gamma_{11} K_{i11} + \varepsilon_{it} \qquad (4)$$

R is the return for any stock *i* belonging to one of the 10 different industries and one of the 11 different countries. In the above regression, α is a common component of all stocks, β captures the industry effect and γ captures the country effect. The error term ε_{it}, which is security specific, will have a zero mean and non-constant variance, which can be higher for some companies than for others or in some periods relative to others (Flavin, 2004). Therefore, we estimate a two-way random effects model and use the default Wallace-Hussain estimator of component variances as a method for calculating estimates of the component variances. Wallace and Hussain consider the use of an error components regression model in the analysis of time series of cross-sections. The assumption considered by Wallace and Hussain is that all the components of μ_i, λ_t and v_{it} are random. One of the advantages of this assumption is that it brings a remarkable reduction in the number of unknown parameters to be estimated from data. The Wallace-Hussain estimator applies only OLS residuals (Arora and Swamy, 1972). The two-way error component is defined as:

$$\varepsilon_{it} = \mu_i + \lambda_t + v_{it} \tag{5}$$

where

ε_{it} is the two-way error component,
μ_i is the individual effect,
λ_t is the time effect,
v_{it} is the remaining error term.

As a result, the error-term is either a totally random component, a company-specific (individual) effect or a time-specific effect. This kind of model specification helps us find out the industry and country effects on the stock index returns.

3. EMPIRICAL FINDINGS AND ANALYSIS

In this part, we examine the results of the panel data regression to see whether a country or industry effect has a more prominent impact on equity index returns. After finding out the dominant group, we solve for common econometric problems that can affect the results. We consider heteroscedasticity, multicollinearity and non-normality that should be tested for in a panel data model. After conducting some statistical tests, we construct an optimal portfolio with a risk-free asset for an American investor. The suggested optimal portfolio will consist of either industry or country stocks based on which one of these effects has a more significant influence on the equity index returns. An out-of-sample optimal portfolio is also constructed for evaluating the stability of the composition of the recommended optimal portfolio.

3.1. Initial model results

As described earlier, the sample consists of 11 countries and 10 industries. United States is excluded from the country list since we want to find out an optimal portfolio for a US investor in the last step. We use a panel data model with fixed dummy variables. Results for the initial model are presented in Table 5 below, and a detailed model is shown in Appendix 3. The telecommunications sector is not presented since we drop it out due to the near-singular matrix error.

By looking at the results in Table 5, we observe that the dominating effect belongs to an industry. The average impact of the sector is 0.798% compared to 0.763% for a country. The results are relatively similar for both groups, but the industry effect is still dominating by 0.035% in our sample. Another thing to notice is that all of the coefficients are positive, which means that all the industries and countries affect the equity index returns positively.

Table 5. A summary of initial results

	Industry			Country	
Variable	**Coefficient**	**Probability**	**Variable**	**Coefficient**	**Probability**
CDISC	0.715%	7.64%	**AU**	0.677%	9.35%
CSTAP	0.980%	1.53%	**CN**	1.540%	0.01%
ENE	1.240%	0.21%	**FR**	0.676%	9.42%
FIN	0.611%	13.01%	**DE**	0.774%	5.51%
HCARE	0.928%	2.16%	**HK**	0.788%	5.09%
IND	0.732%	6.98%	**IT**	0.436%	27.96%
ITECH	0.506%	20.98%	**JP**	0.407%	31.33%
MAT	0.871%	3.11%	**ES**	0.725%	7.24%
REALE	0.987%	1.46%	**SE**	0.834%	3.90%
UTIL	0.413%	30.66%	**CH**	0.898%	2.62%
			UK	0.634%	11.66%
Avg effect	**0.798%**		**Avg effect**	**0.763%**	

Source: (Compiled by the authors on the basis of data provided in Appendix 3) Notes: Table reports the coefficients and probabilities for 10 industry variables and 11 country variables.

If we look at the probabilities for each industry, we can see that more industries are statistically significant compared to countries at the 5% level. Those are the consumer staples (1.53%), energy (0.21%), healthcare (2.16%), materials (3.11%) and real estate industries (1.46%). In the country list, the highly statistically significant nations are China (0.01%), Sweden (3.90%) and Switzerland (2.62%).

By looking at the parameter estimates for industries, we notice that the energy industry has the highest coefficient (1.24%), which means that investing in the energy industry can have the most significant positive effect on the investor’s portfolio. Also, the real estate (0.99%), consumer staples (0.98%) and healthcare industries (0.93%) have higher values and they all are statistically significant at the 5% level. The utilities industry has the lowest parameter estimate (0.41%). It is also the most statistically insignificant (30.66%). Investing in the utilities industry therefore won't have as big of an impact on the portfolio of the US investor.

By comparing the parameter estimates for countries, we observe that China has the highest coefficient value (1.54%). It is also the most statistically significant at the 5% level (0.01%). China dominates the other countries, meaning that investing in China will have a remarkable positive impact on the investor's equity returns. Switzerland (0.9%) and Sweden (0.83%) have the second and third highest coefficients, respectively, compared to the other countries. Japan (0.41%) has the lowest parameter estimate, which means that based on our sample, investing in that nation won't have a drastic impact on the investor's portfolio.

3.1.1. Multicollinearity

Multicollinearity occurs when explanatory variables are highly correlated with each other. Usually, there is always some level of correlation between regressors, but a more severe problem occurs when the correlation is more than 0.8. This means that adding or removing a variable from a regression equation can cause the values of the coefficients of other explanatory variables to change. A simplified method to detect multicollinearity is to look at the matrix of correlations between the regressors (Brooks, 2014).

Firstly, we are going to see if there is any severe multicollinearity between the countries in Table 3 on page 23. France and Germany are the most correlated countries with other countries, whereas Australia, Hong Kong, Japan and China are the least correlated ones. This is explained by the fact that seven of the 11 nations first included in the sample are European. This is also why France is the most correlated country since it correlates with all of the other six European countries strongly (Germany, Italy, Spain, Sweden, Switzerland and UK). France's correlation with all of these nations is higher than 0.8.

Secondly, we determine if there is any serious correlation between the different industries in Table 4 on page 24. Industries are overall more correlated than countries, which means that they move together more than nations do. The most correlated sector is the industrials sector, which is a broad industry containing capital goods, commercial and professional services, and transportation. Its correlation coefficient is larger than 0.8 with the four other fields (consumer discretionary, financials, information technology and materials). Since this category includes multiple industries in itself (14), it is not surprising that it is the most correlated with the other sectors. In contrast, the least correlated is the energy sector, where its highest correlation with any other sector is 0.671 with industrials. Other less correlated fields are the consumer staples, healthcare and utilities.

There are different solutions for dealing with the multicollinearity problem. We can either ignore it, drop one of the collinear variables or transform the highly correlated variable into a ratio and include that in the analysis (Brooks, 2014). In our model, we decide to ignore the multicollinearity problem for the most collinear variables such as France and the industrials sector. The reason is that the model we have so far is adequate, meaning that all the coefficients have expected signs and many of them are highly significant at the 5% level. Overall, our primary goal is to see how the countries and industries affect equity index returns as a group rather than individually. Therefore, we are aware of the multicollinearity problem, but decide to ignore it as a solution, because it is not as big of an issue in our model.

3.1.2. Heteroscedasticity

The next econometric problem we want to discuss is heteroscedasticity. This problem occurs when the residuals do not have constant variance, meaning that the assumption of homoscedasticity is violated (Brooks, 2014). There are two ways to test for heteroscedasticity in the model; informal and formal way. The formal way would be applying an appropriate test, for example, White or Breusch-Pagan LM test to detect non-constant variance in error terms. The informal way is to inspect different graphs (Asteriou and Hall, 2007). Since we are dealing with financial data, in which the heteroscedasticity problem is typical, we can already assume that this could be an issue in our model. Therefore, we employ an appropriate solution to relieve the adverse effect of heteroscedasticity. One of the suggested solutions is to transform the variables into logs. Another and a more straightforward way is to use heteroscedasticity-robust standard error estimates that are called robust SE. In our model, we employ the latter solution and include White diagonal in panel data. This application reduces the heteroscedasticity problem by making the standard errors bigger, but without changing the initial coefficient values (Brooks, 2014).

3.1.3. Non-normality

The test of Jarque-Bera tests for normality of regression residuals. According to the assumption five, $u_t \sim N(0, \sigma^2)$, the error terms are normally distributed. The property of a normally distributed random variable is used. The distribution is characterized by the first two moments that are the mean and the variance. Skewness and kurtosis of the distribution are defined as its standardized third and fourth moments. A normal distribution has a coefficient of kurtosis of three and it is not skewed. A coefficient of excess kurtosis is defined as equal to the coefficient of kurtosis minus three. Consequently, the normal distribution has a coefficient of excess kurtosis of zero. The Jarque-Bera test is applied for testing whether the coefficients of skewness and excess kurtosis are jointly zero (Brooks, 2014).

The test statistic JB is defined as a function of the measures of kurtosis K and skewness S that are calculated from the sample. The theoretical values of K and S are 3 and 0, respectively, under the assumption of normality (Büning and Thadewald, 2007). The following equation defines the test statistic of Jarque-Bera:

$$W = T\left[\frac{b_1^2}{6} + \frac{(b_2-3)^2}{24}\right] \tag{6}$$

where T is the sample size. b_1 and b_2 are estimated using the error terms from the OLS regression, û. Under the null hypothesis of symmetric and mesokurtic distribution of the series, the test statistic asymptotically follows a $\chi^2(2)$. The null hypothesis of normality is rejected if the error terms from the model are either significantly skewed or leptokurtic/platykurtic or both (Brooks, 2014).

Results of the Jarque-Bera test for normality are presented in Appendix 4. We observe that the p-value is highly significant (0.00). Therefore, the null hypothesis of normality is rejected, and the residuals are not normally distributed. We cannot fully trust the p-values when the residuals are not normally distributed. There are different solutions to this problem. One can decide to increase the sample size, transform variables (take logs), use dummy variables or do nothing, for instance. In our model, all of our explanatory variables are dummies, thus we have already prevented the results from being worse regarding normality. Another option would be taking logs from variables, but since we also have negative equity index returns as our data, we cannot use this solution. Therefore, we decide that the previously used dummy variables in our model are enough to relieve the adverse effect of non-normality.

3.2. Final model results and analysis

After trying to solve for relevant econometric problems in our model such as multicollinearity, heteroscedasticity and non-normality, we obtain the final results. Our primary goal remains the same, which is to determine whether country or industry effects dominate the equity index returns. Results for the final model are presented in Table 6 below.

Table 6. A summary of final results

	Industry			**Country**	
Variable	**Coefficient**	**Probability**	**Variable**	**Coefficient**	**Probability**
CDISC	0.715%	4.6%	**AU**	0.677%	8.16%
CSTAP	0.980%	0.9%	**CN**	1.540%	0.66%
ENE	1.240%	2.4%	**FR**	0.676%	7.10%
FIN	0.611%	13.1%	**DE**	0.774%	6.42%
HCARE	0.928%	1.9%	**HK**	0.788%	6.43%
IND	0.732%	3.2%	**IT**	0.436%	32.75%
ITECH	0.506%	19.7%	**JP**	0.407%	30.23%
MAT	0.871%	4.8%	**ES**	0.725%	9.71%
REALE	0.987%	2.2%	**SE**	0.834%	5.55%
UTIL	0.413%	27.2%	**CH**	0.898%	1.26%
			UK	0.634%	6.88%
Avg effect	**0.798%**		**Avg effect**	**0.763%**	

Source: (Compiled by the authors on the basis of data gathered from the final model) Notes: Table reports the coefficients and probabilities for 10 industry variables and 11 country variables.

By comparing the final results in Table 6 with the initial results in Table 5, we observe that the coefficients for industries and countries have not changed, whereas the probability values for them have changed. One of the most important research questions in this thesis was to investigate whether investing across industries or countries has a more significant effect on equity index returns. The final results in Table 6 indicate that the average positive effect of sectors is larger than of nations. Investing in industries provides an investor with higher average returns compared to investing geographically. Regarding our sample, the average effect of industry stock index returns is 0.798%, whereas for the country the effect is 0.763%. The difference is rather small (0.035%), however, based on our sample period 2000-2017 investors will benefit more from investing in different industries in contrast to investing across different countries.

In the literature, there has been considerable debate over the portfolio diversification benefits between investing across countries and industries. Based on the trends in different strategies of diversification, country effects have been dominating industry effects in explaining variations in stock returns globally (Baca, Garbe and Weiss, 2000). Even though previous studies have demonstrated the importance of country factors, industry and country portfolio diversification have both been significant (Aked, Brightman and Cavaglia, 2000). In our thesis, we find out that investing in various industries has a more significant impact on equity index returns than investing across various countries. This finding is consistent with the previous literature, in which Ehling and Ramos (2005) documented that there is some evidence for a major upward shift in the industry diversification since 1999, which indicates that there is a more significant risk reduction compared to geographical diversification. In more recent research papers, industry portfolio diversification is vital. Phyklatis and Xia (2006) have documented the importance of industry diversification, which has been gaining more interest from global equity portfolio managers. Previous findings in the literature have also documented that geographical portfolio diversification strategies have been losing their effectiveness to global investment management (Baca, Garbe and Weiss, 2000). Furthermore, Saario (2007) concludes that the benefits of industry diversification could be due to the low level of correlations in stock returns in which different industries tend not to move in the same direction.

Based on our findings, we conclude that the industry effects are more prominent than the country effects. As mentioned earlier, the difference is not significant, but it still exists. In the literature review, it is presented that business cycles are essential to be considered when investing across industries. An investor should diversify his portfolio within the companies in the field to which fluctuations easily affect and fields to which they do not easily affect (Neale and Pike, 2009). The fluctuations of stock prices in the industries sensitive to business cycles are more substantial than of prices in non-sensitive industries and thus, stocks are riskier for those sensitive fields. Saario (2007) gives examples of sensitive industries that include the steel, forestry, information technology and finance industries. In contrast, the food, energy, healthcare and retail industries are classified as not sensitive to business cycles. By looking at our model parameter estimates in Table 6, we observe that the energy industry has the largest coefficient. The real estate, consumer staples and healthcare industries also have higher estimates compared to other fields.

Based on the literature review, we notice that the fields dominating in our model such as the energy, consumer staples and healthcare are the ones that are not that sensitive to business cycles. This means that investing in those industries won't carry as much of a risk to the investor, but they still bring a considerable reward because of their higher positive impact on equity returns. Those industries would be suitable for the investor to invest in for receiving a significant yield without much risk. On the contrary, the utilities industry has the smallest effect on the equity returns in our model. Additionally, the information technology and financial sectors have the smallest impact on the returns after utilities. Based on Saario's (2007) classification of sensitive industries, the financials and information technology sectors both belong to it. The business cycles can have a significant impact on these industries, which makes investing in them risky. To sum up, according to our model, the investor should diversify his portfolio across the energy, real estate, consumer staples and healthcare industries. The utilities, information technology and financial sectors should be avoided since they are more sensitive to the business cycles and won't have as much of a positive impact on the equity returns as claimed by our model.

3.3. Optimal portfolio results and analysis

According to the final results shown in Table 6, we concluded that industry effects are more significant than country effects in determining equity returns. As we find that an American investor should invest across industries rather than across countries, we construct an optimal portfolio for the American investor and give a recommendation for investing across certain industries. The industries, however, are also diversified across countries since each industry may include stocks from not only one country. Firstly, we construct an equally weighted portfolio in order to determine the optimal portfolio for a US investor. This strategy includes investing a portion of 1/N of total wealth in each risky asset, which does not involve any optimization. The equally weighted portfolio is presented in Appendix 5. Because it is challenging to implement negative weights or short positions in practice, the majority of investors impose the constraint that portfolio weights should not be negative when constructing mean-variance efficient portfolios (Jagannathan and Ma, 2003). Consequently, short sales are not encouraged, which is why we do not allow for negative weights in our thesis. Therefore, the weights of the industries sum to one. Results for the optimal portfolio are presented in Table 7 below.

Table 7. Optimal risky portfolio for the US investor during the period 2000-2017

Optimal risky portfolio	
	weights
CDISC	0%
CSTAP	**70.24%**
ENE	**13.02%**
FIN	0%
HCARE	**16.74%**
IND	0%
ITECH	0%
MAT	0%
REALE	0%
UTIL	0%
Sum	100%
Expected return	9.74%
Standard deviation	13.36%
Sharpe ratio	**0.52**

Source: (Portfolio weights, expected return, standard deviation and Sharpe ratio calculated by the authors on the basis of the monthly stock index returns data)

According to our results in Table 7, the consumer staples industry has the highest weight (70.24%), followed by the healthcare (16.74%) and energy (13.02%) industries. Based on the weights, the consumer staples sector should be invested in the most, followed by the healthcare and energy industries. Together these three industries combined in a portfolio form the optimal portfolio for the US investor, of which the summary is given in Figure 4 below. As Lawson and Pike (1979) state that an investor should take an expected return, the risk of the investment and co-movements between them into consideration when investing, we consider those three aspects in our optimal portfolio case. The stocks with the highest expected return and lowest standard deviation are preferred. The expected return obtained for this tangency portfolio is 9.74% and the risk, which is measured by standard deviation, is 13.36%. In contrast to the equally weighted portfolio, it would provide the investor with an expected return of 7.26% that is lower and a standard deviation of 16.20% that is significantly higher than for the optimal portfolio. For these three industries, we obtain the lowest average correlation with other industries. Since they are not correlated with any other industries more than 0.8, it indicates no serious multicorrelation. More specifically, the correlation between the healthcare and energy industries is the lowest in the group at 0.406. It is vital for the securities in the portfolio not to be highly correlated with other industries for the investor to avoid the risk. Our results indicate that the consumer staples, healthcare and energy industries are not as sensitive industries to business cycles as the other industries.

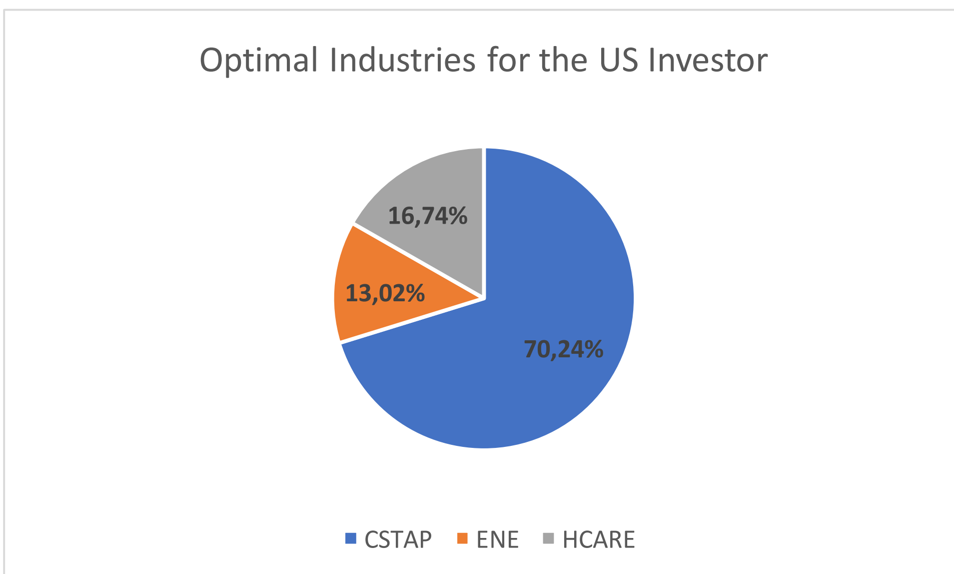

Figure 4. Industry combination of the optimal risky portfolio for the US investor during the period 2000-2017

Source: (Compiled by the authors on the basis of data presented in Table 7)

It is essential for the investor to understand the interaction between the three characteristics and combine the securities providing him with the highest expected return, lowest standard deviation and smallest correlation with other assets in the portfolio. In our model, the consumer staples, healthcare and energy sectors combined together with their respective weights in Figure 4 provide the investor with the highest expected return, lowest standard deviation and smallest correlation with the other industries in his portfolio. In other words, the risky assets in those industries are in proportions that reflect the total equity values of the companies they represent. Therefore, this is the optimal portfolio that maximizes the Sharpe ratio for the investor. The Sharpe ratio for this optimal portfolio is 0.52. For the equally weighted portfolio, the Sharpe ratio is 0.28, which is significantly lower. As we know from the theory presented earlier, the higher the Sharpe ratio for a portfolio, the higher the return per unit of risk and consequently, the more attractive the investment strategy. By looking at the descriptive statistics only, we could assume which industries should be included in the portfolio for maximizing the Sharpe ratio. Based on the average returns of the industries we would expect the energy industry to be included in the optimal portfolio due to its average yield during 2000-2017 being the highest (1.047%). The average returns for the consumer staples and healthcare industries are also among the highest returns.

Our results are in accordance with the theory developed by Markowitz (1952) that an optimal portfolio can be constructed in a way that its risk is less than the weighted average of risks of individual securities included in the portfolio, without sacrificing the expected return. Consequently, the risk is now diversified between the consumer staples, healthcare and energy industries included in the portfolio. Moreover, as these industries are less well correlated according to our model, the risk involved in holding these industries together in the portfolio is lower than the sum of individual risks of each industry in the portfolio, which is documented by Markowitz (1952). We can also confirm that different industries are not perfectly correlated as documented by Heston and Rouwenhorst (1994) due to the below +1 and above -1 correlations we obtain for the industries in our model. The investor should invest in this portfolio located on the efficient frontier and ignore other portfolios as suggested by Kren and Sirucek (2015). This allows the objectives of the investor identified by Markowitz (1952) to be fulfilled since the investor prefers more return to less of it and less risk to more of it. To sum up, the results for the optimal portfolio are in accordance with the final results discussed in the previous part, in which we observed the highest coefficients for the energy, healthcare and consumer staples industries.

3.3.1. Out-of-sample optimal portfolio results and analysis

To evaluate the stability of the composition of the optimal portfolio we apply the out-of-sample method during the period 2000-2017. We divide the sample period into two sub-periods of 2000-2008 and 2009-2017. We obtain optimal portfolio weights for the first sub-period and then apply these weights to compute the out-of-sample expected return, standard deviation and Sharpe ratio. Results for the in-sample optimal portfolio are presented in Table 8 and results for the out-of-sample optimal portfolio are shown in Table 9.

Table 8. In-sample optimal portfolio for the US investor during the period 2000-2008

Optimal risky portfolio	
	weights
CDISC	0%
CSTAP	**56.39%**
ENE	**43.61%**
FIN	0%
HCARE	0%
IND	0%
ITECH	0%
MAT	0%
REALE	0%
UTIL	0%
Sum	100%
Expected return	14.66%
Standard deviation	18.43%
Sharpe ratio	**0.65**

Source: (Portfolio weights, expected return, standard deviation and Sharpe ratio calculated by the authors on the basis of the monthly stock index returns data)

As the in-sample results above show, an investor can expect to receive an expected return of 14.66% and a standard deviation of 18.43%. The Sharpe ratio for this portfolio is 0.65. By comparing the in-sample results with the out-of-sample results, we observe that the in-sample expected return and standard deviation is higher in addition to a significantly higher Sharpe ratio. This is in accordance with most findings that report worse out-of-sample performance in terms of a lower Sharpe ratio.

Table 9. Out-of-sample optimal portfolio for the US investor during the period 2009-2017

Optimal risky portfolio	
	weights
CDISC	0%
CSTAP	**56.39%**
ENE	**43.61%**
FIN	0%
HCARE	0%
IND	0%
ITECH	0%
MAT	0%
REALE	0%
UTIL	0%
Sum	100%
Expected return	6.98%
Standard deviation	15.47%
Sharpe ratio	**0.27**

Source: (Portfolio weights, expected return, standard deviation and Sharpe ratio calculated by the authors on the basis of the monthly stock index returns data)

When comparing the optimal portfolios for the whole period 2000-2017 and out-of-sample sub-period 2009-2017 we find that the optimal portfolio weights differ for the two different time periods. The optimal portfolio for 2009-2017 consists of the consumer staples (56.39%) and energy (43.61%) industries. This provides the investor with the expected return of 6.98% and standard deviation of 15.47%. By comparing the Sharpe ratios, we observe that the Sharpe ratio for the optimal portfolio in the out-of-sample case is 0.27, which is significantly lower compared to the Sharpe ratio for the whole period 2000-2017 in Table 7 on page 37 (0.52).

In the out-of-sample case, the consumer staples and energy sectors combined together with their respective weights in Figure 5 provide the investor with the highest expected return, lowest standard deviation and smallest correlation with the other industries in his portfolio. Similarly, in both samples 2000-2017 and 2009-2017, the consumer staples industry has the highest weight. Also, the energy industry is represented in both cases. However, it has a higher weight in the second sample compared to the first sample. Given that out-of-sample results tend to be noisy (Kritzman, 2010), nevertheless, we notice similarities between the suggested strategies during the two different time periods.

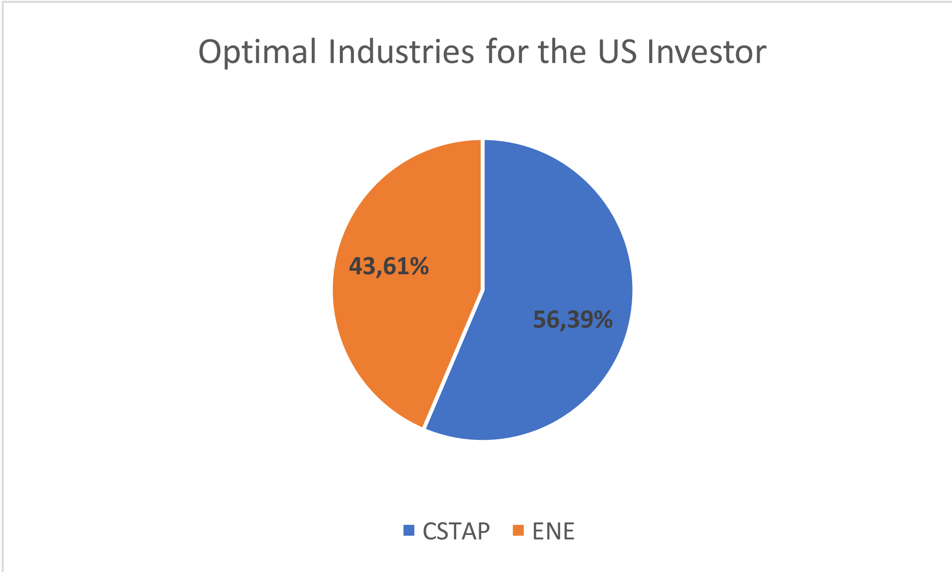

Figure 5. Industry combination of the optimal risky portfolio for the US investor during the out-of-sample period 2009-2017

Source: (Compiled by the authors on the basis of data presented in Table 9)

Concerning the expected return and standard deviation, for the period 2009-2017 the investor can expect to earn a return that is lower than investing in the healthcare industry in addition to the consumer staples and energy industries. The investor is also faced with a higher risk due to the higher standard deviation when investing only in the consumer staples and energy industries. This is in accordance with the theory since by including the third industry, healthcare, in the portfolio the investor is able to reduce the risk of his portfolio. Overall, we observe that during both time periods 2000-2017 and 2009-2017 the optimal portfolio for the investor includes two same industries, the difference being the healthcare industry, which is included only in the portfolio for the period 2000-2017. Relying on the smaller historical sample for estimating the expected return for the US investor is expected to lead to a strategy that would not be chosen by the US investor.

CONCLUSIONS

This thesis investigates the dominance of industry and country diversification in determining equity index returns from the point of view of a US investor. The study had a purpose of investigating the increasing importance of industry diversification and examining whether it is more beneficial for the US investor to invest across different countries or industries. Furthermore, this research aimed at examining an optimal portfolio for the US investor when diversifying globally across different industries. For this purpose, a panel data model was constructed, which is based on a sample period of 2000-2017 and it includes 11 countries and 10 industries. Since Heston and Rouwenhorst (1994) suggested the panel data model that can explain the country and industry effects on stock returns, it was also applied in this study. In addition, Sharpe ratio is used for carrying out the determination of the optimal portfolio for an American investor.

Industry diversification is suggested to have an increasing importance in determining stock returns. The industry effects are more prominent compared to the country effects, however, there is no significant difference between the two strategies. This indicates that Roll's (1992) claim that industry diversification plays a significant role does not perfectly hold. Similar results are obtained from both initial and final models. The only difference observed is that the probability values for the industries and countries have changed. Diversifying a portfolio across industries is more beneficial in contrast to holding a portfolio diversified across countries. The American investor hence earns a higher return by pursuing the industry diversification strategy. This is supported by the founding by Phylaktis and Xia (2006) that diversifying across industries cannot be totally ignored. Additionally, a study conducted by Baca, Garbe and Weiss (2000), in which they stated that the country effects no longer dominate the industry effects can be concluded to be on point. Furthermore, the statement of as correlations of stock returns in different industries tend not to move in the same direction, the benefits of diversification increase (Saario, 2007) is supported since the correlations of stock returns between the different industries vary.

As we find that the American investor should invest across industries rather than across countries, the optimal portfolio that maximizes the Sharpe ratio for the US investor consists of stocks diversified across the consumer staples, healthcare and energy industries. These industries combined together with their respective weights provide the investor with the highest expected return, lowest standard deviation and smallest correlation with the other industries in his portfolio. The fact that these recommended industries are not highly correlated with each other plays a role, therefore, having such a combination in the portfolio is suggested. The correlation between the healthcare and energy industries is the lowest in the group. We did not find evidence of serious multicorrelation since these three industries are not correlated with any other industries more than 0.8. Since we observe these industries to be less well correlated, the risk involved in holding these industries together in the portfolio is lower than the sum of individual risks of each industry in the portfolio as claimed by Markowitz (1952). In the out-of-sample case, we find a significantly lower Sharpe ratio and expected return. This is in accordance with most findings that report worse out-of-sample performance in terms of a lower Sharpe ratio. Furthermore, the study concluded that the consumer staples, healthcare and energy industries are not as sensitive industries to business cycles as the other industries. This is in accordance with Saario's (2007) categorization of not sensitive sectors to the business cycles as we found the coefficients of the energy, healthcare and consumer staples sectors among the highest. It can be concluded that the optimal portfolio is a more attractive investment strategy due to its higher Sharpe ratio compared to the equally weighted portfolio. This is supported by the higher return per unit of risk. Therefore, we find evidence of the optimal portfolio leading to better performance than the equally weighted portfolio.

The results support accepting the hypothesis of that industry portfolio diversification dominates country portfolio diversification. The average industry effect is higher compared to the average country effect. The benefits of the industry diversification strategy for the US investor can be achieved by diversifying across the consumer staples, healthcare and energy sectors. The risk is diversified between those three sectors. The observed results are in accordance with the theories of remarkable contributors to the subject discussed in the paper such as Markowitz (1952). Concerning some drawbacks related to our model, including more countries and industries provides us with a larger sample, which makes the results more reliable. Nevertheless, we are able to obtain results that support the increasing interest in industry diversification.

As some previous studies show that there is a major upward shift in the industry diversification since 1999 (Ehling and Ramos, 2005), a fascinating area for future research would be to investigate further whether a significant increase in the industry diversification exists when researching the periods before and after 1999. Also, it could be investigated if the strengthening geographical integration of markets significantly contributes to this phenomenon as suggested by

Aked, Brightman and Cavaglia (2000). Conducting a case study for comparing the effects of the industry and country diversification strategies on risk would be interesting as well in order to document whether or not a more significant difference between the two strategies can be found. To conclude with, the benefits associated with diversification and especially the industry diversification strategy should be known by a vast audience since they exist to some degree.

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APPENDICES

Appendix 1. An Overview of the Sectors, Industry Groups and Industries

Sectors (11)	Industry groups (24)	Industries (68)
Energy (ENE)	Energy	Energy Equipment & Services
		Oil, Gas & Consumable Fuels
Materials (MAT)	Materials	Chemicals
		Construction Materials
		Containers & Packaging
		Metals & Mining
		Paper & Forest Products
Industrials (IND)	Capital Goods	Aerospace & Defense
		Building Products
		Construction & Engineering
		Electrical Equipment
		Industrial Conglomerates
		Machinery
		Trading Companies & Distributors
	Commercial & Professional Services	Commercial Services & Supplies
		Professional Services
	Transportation	Air Freight & Logistics
		Airlines
		Marine
		Road & Rail
		Transportation Infrastructure
Consumer Discretionary (CDISC)	Automobiles & Components	Auto Components
		Automobiles
	Consumer Durables & Apparel	Household Durables
		Leisure Products
		Textiles, Apparel & Luxury Goods
	Consumer Services	Hotels, Restaurants & Leisure
		Diversified Consumer Services
	Media	Media
	Retailing	Distributors
		Internet & Direct Marketing Retail
		Multiline Retail
		Specialty Retail
Consumer Staples (CSTAP)	Food & Staples Retailing	Food & Staples Retailing
	Food, Beverage & Tobacco	Beverages
		Food Products

		Tobacco
	Household & Personal Products	Household Products
		Personal Products
Health Care (HCARE)	Health Care Equipment & Services	Health Care Equipment & Supplies
		Health Care Providers & Services
		Health Care Technology
	Pharmaceuticals, Biotechnology & Life Sciences	Biotechnology
		Pharmaceuticals
		Life Sciences Tools & Services
Financials (FIN)	Banks	Banks
		Thrifts & Mortgage Finance
	Diversified Financials	Diversified Financial Services
		Consumer Finance
		Capital Markets
		Mortgage Real Estate Investment Trusts (REITs)
	Insurance	Insurance
Information Technology (ITECH)	Software & Services	Internet Software & Services
		IT Services
		Software
	Technology Hardware & Equipment	Communications Equipment
		Technology Hardware, Storage & Peripherals
		Electronic Equipment, Instruments & Components
	Semiconductors & Semiconductor Equipment	Semiconductors & Semiconductor Equipment
Telecommunication Services (TCS)	Telecommunication Services	Diversified Telecommunication Services
		Wireless Telecommunication Services
Utilities (UTIL)	Utilities	Electric Utilities
		Gas Utilities
		Multi-Utilities
		Water Utilities
		Independent Power and Renewable Electricity Producers
Real Estate (REALE)	Real Estate	Equity Real Estate Investment Trusts (REITs)
		Real Estate Management & Development

Source: (Sectors, industry groups and industries derived from the website https://www.msci.com/gics (The Global Industry Classification Standard (GICS®)) Notes: This table reports the overview of the sectors and industry groups compiled according to the Global Industry Classification Standard (GICS) developed by MSCI and Standard & Poor's.

Appendix 2. An Overview of Individual Company's Country and Industry Classification

Countries	Number of companies	Industries	Number of companies
Australia	41	Consumer discretionary	142
China	105	Consumer staples	63
France	49	Energy	22
Germany	51	Financials	82
Hong Kong	76	Healthcare	62
Italy	36	Industrials	170
Japan	205	Information Technology	58
Spain	32	Materials	77
Sweden	34	Real Estate	46
Switzerland	35	Telecommunication services	20
United Kingdom	119	Utilities	41
Total	**783**	**Total**	**783**

Source: (Country and industry classification derived from the Standard & Poor's Capital IQ database) Notes: This table reports the number of companies included in each country and industry in the sample.

Appendix 3. Results of the Initial Model

Dependent Variable: RETURNS
Method: Panel EGLS (Two-way random effects)
Date: 04/25/18 Time: 12:44
Sample: 2000M02 2017M12
Periods included: 215
Cross-sections included: 22
Total panel (balanced) observations: 4730
Wallace and Hussain estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.193515	0.426566	-0.453659	0.6501
CDISC	0.715483	0.403698	1.772322	0.0764
CSTAP	0.979692	0.403698	2.426794	0.0153
ENE	1.240485	0.403698	3.072803	0.0021
FIN	0.611162	0.403698	1.513909	0.1301
HCARE	0.927575	0.403698	2.297696	0.0216
IND	0.732157	0.403698	1.813626	0.0698
ITECH	0.506381	0.403698	1.254355	0.2098
MAT	0.870719	0.403698	2.156858	0.0311
REALE	0.986611	0.403698	2.443932	0.0146
UTIL	0.412772	0.403698	1.022476	0.3066
AU	0.677178	0.403698	1.677437	0.0935
CN	1.539774	0.403698	3.814173	0.0001
FR	0.675722	0.403698	1.673830	0.0942
DE	0.774574	0.403698	1.918697	0.0551
HK	0.788217	0.403698	1.952490	0.0509
IT	0.436551	0.403698	1.081379	0.2796
JP	0.407071	0.403698	1.008355	0.3133
ES	0.725415	0.403698	1.796924	0.0724
SE	0.833690	0.403698	2.065132	0.0390
CH	0.897857	0.403698	2.224081	0.0262
UK	0.633678	0.403698	1.569684	0.1166

Effects Specification

	S.D.	Rho
Cross-section random	0.146857	0.0006
Period random	4.647741	0.6260
Idiosyncratic random	3.589237	0.3733

Weighted Statistics

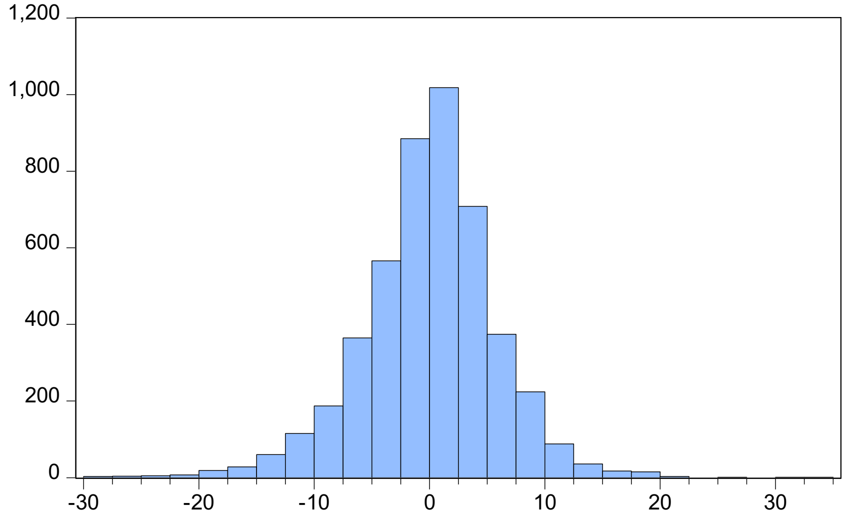
R-squared	0.005306	Mean dependent var	0.089044
Adjusted R-squared	0.000869	S.D. dependent var	3.590798
S.E. of regression	3.589237	Sum squared resid	60651.39
F-statistic	1.195956	Durbin-Watson stat	2.005466
Prob(F-statistic)	0.242910		

Unweighted Statistics

R-squared	0.002703	Mean dependent var	0.550701
Sum squared resid	162351.2	Durbin-Watson stat	1.810731

Notes: This table reports initial model results obtained using EViews.

Appendix 4. Results of the Jarque-Bera Test for Normality



Series: Standardized Residuals	
Sample 2000M02 2017M12	
Observations 4730	
Mean	2.44e-14
Median	0.311608
Maximum	34.29770
Minimum	-29.35050
Std. Dev.	5.859265
Skewness	-0.314240
Kurtosis	5.062998
Jarque-Bera	916.6243
Probability	0.000000

Notes: This table reports results of the Jarque-Bera test for normality obtained using EViews.

Appendix 5. An Equally Weighted Portfolio

Equally weighted portfolio	
	weights
CDISC	10%
CSTAP	10%
ENE	10%
FIN	10%
HCARE	10%
IND	10%
ITECH	10%
MAT	10%
REALE	10%
UTIL	10%
Sum	100%
Expected return	7.26%
Standard deviation	16.20%
Sharpe ratio	**0.28**

Notes: This table reports the expected return, standard deviation and Sharpe ratio for the equally weighted portfolio calculated by the authors.