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Portfolio Diversification and Optimization at Industry Level, Evidence from Turkey

Sektör Düzeyinde Portföy Çeşitlendirmesi ve Optimizasyonu, Türkiye Uygulaması

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Abstract: This paper applies the mean-variance, mean-VaR, and mean-CVaR portfolio optimization approach to investigate opportunities for domestic diversification from Turkey investors' viewpoints. We explore diversification potential and investment opportunities at the industry level for the time period between 2007 and 2020. The study uses factor analysis to determine domestic diversification opportunities and measure the optimal weight of sectors in the market index. Results from factor analysis show that for investors who desire to create a domestic portfolio considerable diversification opportunities are available. Portfolio optimization analysis indicates that the wholesale, retail trade and transportation industries should be prioritized by the policymakers, as these industries earn the highest returns at a given risk level.

Keywords: Portfolio Optimization, Factor Analysis, Domestic Diversification, Markowitz's Risk-Return Framework, Efficient Portfolio

JEL Classification: G11, G12, C61

Öz: Bu çalışma ortalama-varyans, ortalama-VaR ve ortalama-CVaR portföy optimizasyonu modellerini kullanarak Türkiye'de yatırımcıların yurtiçi çeşitlendirme fırsatlarını araştırmaktadır. Bu makalemizde 2007 ve 2020 yılları arasında Türkiye'de sektör düzeyinde çeşitlendirme potansiyelini ve yatırım fırsatlarını incelemektedir. Bu çalışma, yurtiçi çeşitlendirme fırsatlarını belirlemek için faktör analizini kullanmaktadır ve piyasa endeksindeki sektörlerin en uygun ağırlığını ölçmektedir. Faktör analizi sonuçları, yurt içi portföy oluşturmak isteyen yatırımcılar için önemli çeşitlendirme fırsatlarının mevcut olduğunu göstermektedir. Yazarlar toptan ve perakende ticaret, taşıma ve ulaşım sektörlerin siyasete yön verenler tarafından öncelik verilmesi gerektiğini ortaya koymaktadır. Bu sektörlerin belirli bir risk seviyesinde en yüksek getiriye sahip oldukları gözlemlenmektedir.

Anahtar Kelimeler: Portföy Optimizasyonu, Faktör Analizi, Yurtiçi Çeşitlendirme, Markowitz'in Risk-Getiri Modeli, Etkin Portföy

JEL Sınıflandırması: G11, G12, C61

1. Introduction

Investors' choice for domestic securities continues to be the subject of disputes since a number of studies point out, there is the possibility to reduce the risk and limit the loss by diversifying internationally. Levy and Sarnat (1970) indicate a strong propensity for returns on single stocks within a market to vary together. As the degree of comovement increases, the risk reduction through diversification tends to decrease. Donald (2008) points out that these

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generic features are even more dominant in developing countries than in developed ones. This is true for a variety of reasons including but not limited to: susceptibility to changes in global economic conjecture, political instability, accumulation of economic profit from few business cycles, erratic movements of the national currency. The level of economic performance can be related between the countries, but each country has a separate source of movements that will eventually offset the negative impact. (Cooper, 1965)

Despite the growing literature around the benefits of international diversification, investors continue to favor their domestic markets. Kilka and Weber (2000) report that active equity ownership displays a strong bias toward domestic stocks and explain that this bias can be revealed by the stock return expectations and their probability judgments. There are plenty of legitimate reasons that can explain this phenomenon and one of them is absolute freedom of internal capital flows that illuminate investors' choice. This study, therefore, investigates portfolio diversification and optimization among a group of domestic industries in Turkey. This study displays that investment in domestic industries with a corresponding level of development can limit the loss and create effective lending and borrowing strategies for domestic investors.

Markowitz's (1952) mean-variance portfolio optimization model is the portfolio construction theory that gives a solution to the important issue of how market participants should assign their funds among assets to create an efficient portfolio. The study suggests that after risk and return estimations investors will choose some point on efficient frontier based on their ability to tolerate risk. Markowitz's mean-variance portfolio optimization process uses standard deviation or variance as an appropriate statistical tool to measure the risk of individual assets and portfolios. Despite the vast number of research initiatives, the portfolio optimization problem after Markowitz has not yet clearly been solved. There is no single consensus on the most accurate modern tool that can be used to enhance investment decisions on minimizing the risk and optimizing the returns. Literature provides several risk estimators and value at risk (VaR) was developed in response to the financial disasters of the 1990s. Since then VaR has turned into a valuable tool for risk management. The focal point in VaR estimation is the downside tail risk that shows the worst loss of a portfolio for a time period with a given level of confidence. Extreme volatilities are related to the fat tails of the time series. Mandelbrot (1963) shows that most of the financial time series including returns are fat-tailed. This risk measure estimates a single value that gives information on the overall market risk faced by market participants (Dowd, 1998). However, previous literature discloses some limitations of the risk measure. Artzner, et (1999) and Embrechts, et (1999) argue that the risk estimator is logical and consistent if it meets the conditions such as positive homogeneity monotonicity, subadditivity, and translation equivariance. The risk measure under VaR is merely consistent when the subjacent loss distribution function is standard; otherwise, the risk estimator lacks subadditivity (Arztner et al (1999; 1997)). According to Rockafellar and Uryasev, (2002) VaR risk estimator cannot explain the losses beyond the margin.

Another risk estimator is the Conditional Value-at-Risk (CVaR) provides several distinct advantages compared to VaR, and Minimum Variance. CVaR is the provisional prospective loss that surpasses VaR for a given time horizon, therefore it can be used in situations when the optimization objective is high-dimensional and the loss distribution is not standard. According to Allen and Powell (2011), CVaR estimates the loss that can be observed in the tail distribution. The CVaR is closely connected to VaR but compared to VaR it displays greater risk.

This study investigates and compares industry-based portfolios using three various risk measures namely minimum variance, VaR, and CVaR across 12 Turkey industry sectors based on equity return variations over the time period from 2007 to 2020. We intend to provide greater awareness on an industry sector risk in a Turkey context. In addition, specific goals include portfolios diversification and portfolio optimization based on the relative rankings of risk and return on an industry level. This study also shows that portfolio selection depends on the degree of joint fluctuation of return on selected indices. Once returns for individual industries display a high degree of commonality through variance, there might be a significant advantage from domestic diversification. The degree of joint fluctuation on securities has been tested using a multivariate setting and the factor analysis is considered as an appropriate tool to identify interrelationship of a large sample size. Since the factor analysis can’t show the real gains and risks from diversification and the risk and return variability with the change of the weights we also implement the portfolio optimization analysis. The optimization analysis is implemented by altering combinations of securities to maximize the objective function.

The paper is organized as follows: Section 2 contains previous theories and practices related to the process of portfolio selection; Section 3 discusses data and empirical methodology, including risk measure and factor analysis. Section 4 explains the results and findings from empirical analysis and portfolio optimization. Section 5 provides concluding remarks.

2. Literature Review

The conventional risk-return tradeoff model introduced by Markowitz has long been used to estimate the asset distribution for a given investment. Glen and Jorion (1993) apply the risk-return tradeoff to evaluate the gains from international diversification. Despite its widespread applicability, Markowitz portfolio optimization model has been criticized as being limited, as the securities don't normally belong to the same linear combination of location-scale families (Wong, 2007). Leung, Ng, and Wong (2012) and Bai, Liu, and Wong (2009) further enhance Markowitz's mean-variance portfolio optimization model by applying bootstrap-corrected estimates and deriving explicit formulas for the estimator of the optimal portfolio.

Portfolio optimization has been performed using Intertemporal Capital Asset Pricing Model (ICAPM) framework and dynamic conditional covariance (Xiao, 2013; Bali, 2010, Brandt, 2002; Huh, 2010; Merton, 1973) and applying extensions of Bayesian and Markowitz portfolio analyses (Trichilli 2020; Pastor, 2000; Pogue 1970; Sharpe 1964; Tobin 1965). Another research stream (Konno et al. 1993, Kane 1982; Simonson 1972) included skewness of asset returns and proposed that the risk estimator's third moment augment the mean-variance trade-off in the optimization process.

Return performance pattern has been tested by (Girard 2008; Donald 2008, Levy 1970) in factor and co-integration analysis. Most of these studies suggest that a high level of diversification can occur among developing countries in a segregated geographical zone. Solnik (1995) proves that considerable gains in risk reduction can be attained through portfolio diversification in domestic common stocks as well as in foreign assets. Carrieri, Errunza, and Sarkissian (2004) display that one way to improve portfolio performance for country-specific investment is to use cross-industry portfolio diversifications. French (1991); Tesar (1995) and Antoniou (2010) report that most investors manage nearly all of their assets in domestic portfolios.

Eduardo (2020); Al Janabi (2014); Chen & Yu (2013); Charpentier (2008); Alexander &Baptista, (2002); Campbell, Huisman, &Koedijk, (2001), investigate portfolio optimization using the VaR framework. The studies use different ways of VaR estimation methods such as historical simulation, the Monte Carlo simulation, and the parametric method. In particular, Eduardo (2020) develop a model for the VaR and CVaR estimate based on normal inverse Gaussian distribution and obtain the parameters that describe the function and adjust the empirical data of the equity returns reasonably. Campbell et al. (2001) propose a theory for US stocks and bonds that maximize the anticipated return with the diminishing risk, calculated by VaR. Hannah Nadiah (2019), Boffey, Akyuwen, Wijaya, and Powell (2017), Kramadibrata, Allen Powell, and Singh (2012), and Allen and Powell (2011) focus on the application of contingent CVaR in the optimization process. Hannah Nadiah (2019) applies the variance and CVaR as risk measures in the portfolio selection problems. The optimal portfolios are evaluated across three different target returns that represent the low risk-low returns, medium risk-medium returns and, high risk-high returns portfolios. The results show that the composition of portfolios for mean-variance are generally more diversified compared to mean-CVaR portfolios. Boffey, Akyuwen, Wijaya, and Powell (2017) investigate relative industrial risk in Indonesia and report that in terms of optimal weights variation exist in different industries. The study concludes that the parametric and historical methods used to measure risk under VaR and CVaR have analogous outputs. Kramadibrata, Allen, Powell, and Singh (2012) analyze the global mining industry in several markets with an application of CVaR. Results show that the optimal allocations of individual markets in market portfolios vary over different research periods. Moreover, the findings demonstrate that the optimization process using CVaR is different from those acquired through the conventional mean-variance framework.

3. Data and Empirical Analysis

3.1. Data

The data used for analysis in this paper come from Investing.com, including returns on twelve industries of Turkey such as wholesale and retail trade, transportation, banks, telecommunication, insurance, electricity, chemical petrol plastic, metal machinery products, basic metal, textile, food beverage, and tourism. We use the simple nominal 3-month Treasury bills interest rate series as a relevant proxy for the risk-free rate. We obtained the risk-free rate series from the Central Bank of Turkey data dissemination platform. The research period is 04.01.2007-27.02.2020. The sample for this analysis consists of daily return data on common equity sub-indices. We perform econometric analysis using E-views software.

3.2. Empirical Methodology

3.2.1. Factor Analyses

Factor analyses have been applied to test the diversification effect for a group of twelve industries in Turkey. The factor methods of factor analysis theorize that for each i, the traceable factor p vector X_i composed from:

$$X_i - \mu = LF_i + \epsilon_i \ ,$$

where μ is v vector of means of factors, L is a $v \times m$ coefficient array or factor loading, F_i is a $m \times 1$ vector of common factors which are standardized and unobserved, ϵ_i is a $v \times 1$ unique error factors.

The percentage of observables factors is lower than the percentage of non-observable factors. The individual loading connects the observables to the non-observables. (Dziuban and Shirkey, 1974).

To estimate the factor model we have to put on supplementary restrictions so that

$$\mathcal{E}(S_i) = 0 \text{ and } \mathcal{E}(w_i) = 0, \mathcal{E}(S_i w) = 0 , \mathcal{E}(S_i S_i^{'}) = \phi \text{ and } \mathcal{E}(w_i w_i^{'}) = \Omega ,$$

where $\Omega\psi$ are cater-cornered matrices of individual variances. Based on these assumptions the fundamental relationship for a factor model is as follows:

$$\sigma^2(V) = \mathcal{E}[(V_i - \mu)(V_i - \mu)^{'}] = \mathcal{E}[(TS_i + w_i)(TS_i + w_i)^{'}] = T\phi T^{'} + \Omega.$$

In addition, the factor pattern comprising the correlations between factors and variables can be estimated as follows:

$$\sigma^2(V, S) = \mathcal{E}[(V_i - \mu)S_i^{'}] = \mathcal{E}(TS_i + \epsilon_i)T_i^{'} = T\phi .$$

In addition, with the hypothesis that factors are orthogonal indicating that ϕ=1, the variance can be estimated as follows:

$$\sigma^2(V) = TT^{'} + \Omega.$$

In this study the numbers of factors were chosen based on minimum eigenvalues (Anderson and Rubin (1956) and Harman (1976)).

3.2.2. Portfolio Optimization

To compare and understand the most suitable risk parameter, rather than one measure only, the risk measure in this study is estimated using standard deviation, VaR and CVaR. Due to the fact, that equity returns may experience skewness or kurtosis, this analysis applies the historical method to estimate CVaR, as applied in current research (Hong et al., 2018; Powell et al., 2017, 2018; Allen et al., 2011, 2012). Respectively, historical CVaR 99 percent is the mean of 1 percent returns that go beyond VaR 99 percent. CVaR addresses real losses that exceed VaR and therefore is used to estimate a variance-covariance matrix.

In 1952 Harry Markowitz published a manuscript about contemporary portfolio methodology, where the author interpreted an optimization process for risk-averse investors. The paper illustrates efficient frontier, which shows various combinations of portfolio returns at a specific level of risk. The optimization method is attained by altering combinations of securities with the objective function to minimize the risk and maximize the return. The objective function is as follows:

$$min \sum_{f=1}^{n} \sum_{m=1}^{n} \sigma_{f,m}\, w_f w_m$$

To minimize the objective function the following constraints must hold:

$$\sum_{f=1}^{n} w_f = 1$$

$$\sum_{f=1}^{n} r_f w_f = r_p$$

$$0 \leq w_f, f = 1,2, \ldots, n$$

In this equation w_f and w_m are the securities weights, r_f is the return of securities, and $\sigma_{f,m}$ is the covariance term between returns on securities f and m. Obviously, the weight for any single security is non-negative, while the total weights of securities bounded to 100 percent. The portfolio's weighted average expected rate of return is always equal to the predefined level of r_p.

4. Results

4.1. Statistical Outputs

Table 1 displays segregation in absolute returns across twelve industries. Investors are not interested in the returns in segregation but in comparison to some alternative investments. The second column of the table shows a comparison of a fund's return to the BIST 100 index. The average returns and excess returns for all industries are mostly positive. The transportation sector has the largest returns this followed by trade. Surprisingly enough, tourism has the lowest return. This is an important result indicating on a significant variation of tourism sector returns from one period to the next.

Table 1. Average Daily Returns across Industries, 2007-2020, in percent

Industry	Return	Excess Return
Wholesale and Retail Trade	0.074	0.027
Transportation	0.108	0.061
Banks	0.051	0.004
Telecommunication	0.041	-0.006
Insurance	0.060	0.013
Electricity	0.047	0.0004
Chemical Petrol Plastic	0.063	0.016
Metal Machinery Products	0.065	0.018
Basic Metal	0.083	0.036
Textile	0.078	0.031
Food Beverage	0.055	0.008
Tourism	0.021	-0.026
Mean	0,062	0.015
Min	0.020	-0.026
Max	0.108	0.061

Table 2 displays estimated risk parameters. Risk measures are a central issue to portfolio optimization, therefore this study applies three different risk measures for comparison and understanding. Using Annel and Powel's (2007) methodology we calculate VaR at 99% confidence level and CVaR as the average of the remaining 1% extreme losses. Considerable variation between risks measures exists in relation to the different industries. The textile and metal machinery industries appear to be the best industries, with the lowest standard deviations. Most notably, however, is the fact that the metal machinery, food beverage, and tourism portfolios have a negative VaR (value at risk). This means that even in the 1 percent worst cases, the market participant can anticipate revenue. On the other hand, electricity and tourism appear to be the best performing industries, with the minimum CVaR. Investors relying on CVaR as a proxy for risk most probably consider industries with the lowest CVaR as a safe investments.

Table 2. Average Standard Deviation, VaR and CVaR across Industries, 2007-2020, in percent

Industry	Standard Deviation	VaR	CVaR
Wholesale and Retail Trade	1.730	0.860	0.191
Transportation	2.371	4.075	0.928
Banks	2.577	2.090	0.426
Telecommunication	1.953	0.658	0.228
Insurance	1.790	2.630	0.600
Electricity	1.956	0.431	-0.180
Chemical Petrol Plastic	1.698	0.691	0.293
Metal Machinery Products	1.630	-0.316	0.325
Basic Metal	2.142	3.586	0.940
Textile	1.633	0.920	0.252
Food Beverage	1.750	-1.857	0.178
Tourism	2.045	-0.426	0.019
Mean	1.940	1.112	0.350
Min	1.630	-1.857	-0.180
Max	2.577	4.075	0.940

Table 3 shows correlations across the diagonal. Correlations are significant and mostly positive. Most pairs display correlations higher than 20%. This indicates a co-movement pattern among different sub-indices. In fact, we can observe from correlation figures that the degree to which sub-indices move together has increased over time. This can be explained by the fact that the sub-indices are affected by the same systematic risks. For our analysis on the other hand the more correlated the data is better. Highly correlated data is more appropriate for the application of the factor model.

Table 3. Correlation among the industries, 2007-2020, in percent

	Wholesale/Retail	Transp.	Banks	Telec.	Insur	Electric.	Chem. Petrol	Metal Mach.	Basic Metal	Textile	Food	Tour
Wholesale/Retail	1.0000											
Transp.	0.3256	1.0000										
Banks	0.5611	0.5095	1.0000									
Telec.	0.3487	0.4291	0.4544	1.0000								
Insur.	0.5100	0.4088	0.7027	0.3801	1.0000							
Electric.	0.4118	0.4653	0.5256	0.3877	0.4942	1.0000						
Chem.Petrol	0.4199	0.5235	0.5309	0.4619	0.4945	0.5296	1.0000					
Metal Mach.	0.4721	0.5411	0.5890	0.4532	0.5375	0.5896	0.6265	1.0000				
Basic Metal	0.3595	0.4381	0.4963	0.3886	0.4709	0.4837	0.5493	0.5681	1.0000			
Textile	0.3832	0.5210	0.4923	0.4162	0.4552	0.5587	0.5533	0.5960	0.4902	1.0000		
Food	0.3959	0.4270	0.4711	0.4099	0.4056	0.4009	0.4814	0.4831	0.3599	0.4808	1.0000	
Tour	-0.0085	0.0213	0.0174	0.0217	0.0384	0.0319	0.0505	0.0460	0.0494	0.0133	0.0196	1.0000

4.2. Factor Analysis

We first test the appropriateness of factor analysis to estimate ex-post covariance matrices of Turkish lira-equivalent returns. Kaiser-Meyer-Olkin measure with 94.31 percent value shows the sampling adequacy. The test results are above 5 percent and correlation coefficients are significant. This result justifies the use of factor analysis to forecast the extent to which all returns of industries move together.

Table 4. Kaiser-Meyer-Olkin Measures

Industry	KMO
Wholesale and Retail Trade	0.9468
Transportation	0.9510
Banks	0.9050
Telecommunication	0.9664
Insurance	0.9107
Electricity	0.9582
Chemical Petrol Plastic	0.9512
Metal Machinery Products	0.9482
Basic Metal	0.9571
Textile	0.9472
Food Beverage	0.9577
Tourism	0.6744
Overall	0.9431

Figure 1 shows the components from one to twelve and eigenvalues associated with each component. The first two components have values above one. That is eigenvalue starts from 5.8 for the first component and declines to 1 for the second component. This is followed by other diminishing components. It is obvious that other components are not contributing that much in terms of variation that they explain. Further shrink in the values and significant break between components indicate that we should retain only the first two components.

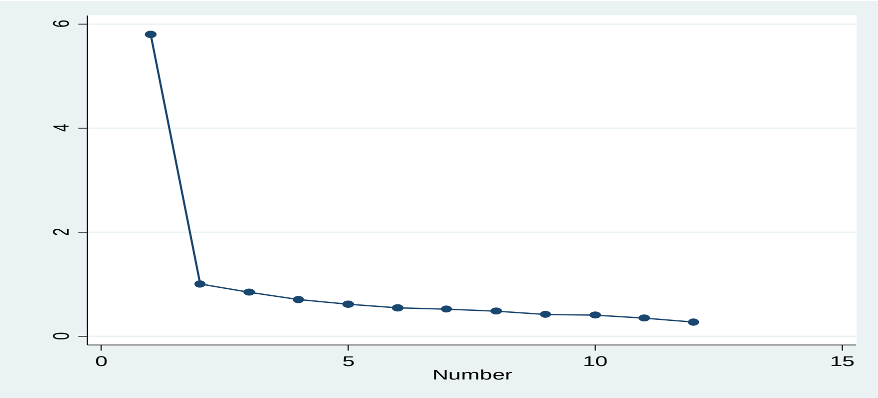


Figure 1. Scree Plot of Eigenvalues

Table 5 displays the proportion of total variation in data explained by the first two components. The first component explains 48 percent and the second explains 8 percent of the variation in the data. The first 2 components reveal up to 56 percent of the variation in the data.

Table 5. Proportion of Data Variation Explained by first and Second Principal Components

Component	Eigenvalue	Proportion	Cumulative
Comp 1	5.80385	0.4837	0.483
Comp 2	1.00668	0.0839	0.5675

Table 6 displays the weights and correlations between each variable and the component. Two components with eigenvalues over 1 are retained. The higher the correlations the more relevant it is in defining the component's dimensionality. The first component is defined with almost all industries, the second component is defined by tourism and wholesale and retail sub-sectors mostly. A negative value indicates on an inverse impact on the component.

Table 6. Component Loadings

Industry	Component 1	Component 2	Unexplained
Wholesale and Retail	0.2672	-0.1309	0.5685
Transportation	0.2908	0.0115	0.5091
Banks	0.3316	-0.0611	0.3581
Telecommunication	0.2629	-0.0075	0.5989
Insurance	0.3066	-0.0284	0.4537
Electricity	0.3060	0.0154	0.4563
Chemical Petrol Plastic	0.3234	0.0533	0.3901
Metal Machinery	0.3394	0.0316	0.3304
Basic Metal	0.2925	0.0728	0.4982
Textile	0.3109	-0.0053	0.4390
Food Beverage	0.2739	-0.0321	0.5636
Tourism	0.0193	0.9837	0.02368

Figure 2 shows how observations load on two components. Figure 2 displays that returns are mostly clustered. In other words, industry returns fall mostly within a certain range of -1 and +1 and display rather asymmetric collocation centered towards zero.

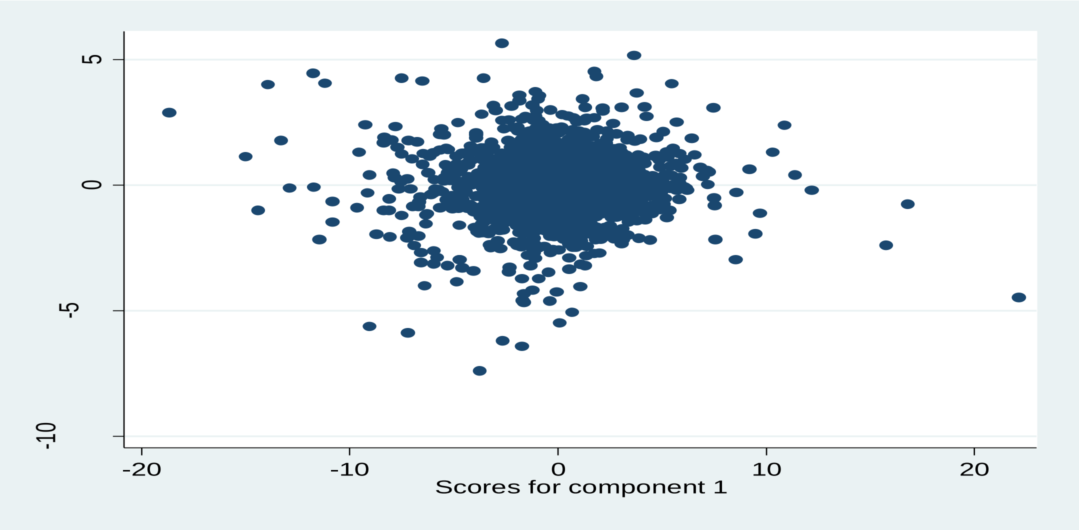


Figure 2. Score plot

Table 7 displays the proportion of total variance (trace) of the individual covariance matrix accounted by the first two components. According to Donald R. Lessard (2008) this share of the total variance is coequal to that acquired by estimating the best odd index and calculating the share of the total variance of single assets that can be revealed by that index. The proportions of the trace revealed by the first component of the returns for Turkey are high. The results are identical to those obtained for Latin American countries, which vary between 40 percent and 70 percent for the time period from 1958 to 1968. However, these results are higher than the proportion explained of U.S assets, which is around 30 percent (Blume 1971).

Table 7. Percentages of Variance Revealed by First Two Varimax Components of the Covariance Matrix of TL-Priced Returns, 2007-2020

Component	Variance	Proportion	Cumulative
Comp 1	5.80385	0.4837	0.4837
Comp 2	1.00668	0.0839	0.5675

We display the robustness check of our findings by using varimax rotation. The varimax rotation extract group of factors with diminishing shares to the total variance. The varimax estimations show that returns of a single industry can be revealed by a single index. The results from varimax don’t vary greatly from unrotated components. That is the first component is identified by almost all industries, while the second component is identified by tourism and wholesale and retail sectors.

Table 8. Robustness Analysis, Component Loadings with two Varimax Factors

Industry	Component 1	Component 2	Unexplained
Wholesale and Retail	0.2695	-0.1259	0.5685
Transportation	0.2905	0.0168	0.5091
Banks	0.3327	-0.0549	0.3581
Telecommunication	0.2629	-0.0026	0.5989
Insurance	0.3070	-0.0227	0.4537
Electricity	0.3057	0.0211	0.4563
Chemical Petrol Plastic	0.3224	0.0593	0.3901
Metal Machinery	0.3388	0.0379	0.3304
Basic Metal	0.2911	0.0783	0.4982
Textile	0.3109	0.0005	0.4390
Food Beverage	0.2744	-0.0270	0.5636
Tourism	0.0011	0.9839	0.02368

Figure 3 shows how twelve original sub-indexes load in component space. The return of industries such as wholesale and retail, transportation, banks, telecommunication, insurance, electricity, chemical petrol plastic, metal machinery, basic metal, textile, food beverage, and tourism loads heavily on component 1. R12 is represented by tourism and loads heavily on component 2. Overall, Component 1 shows that there are significant diversification opportunities as it includes almost all industries.

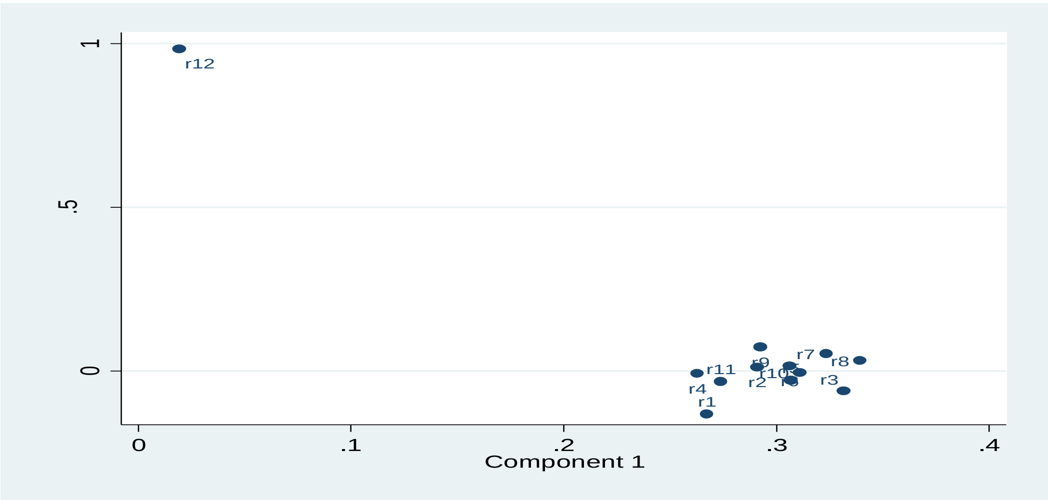
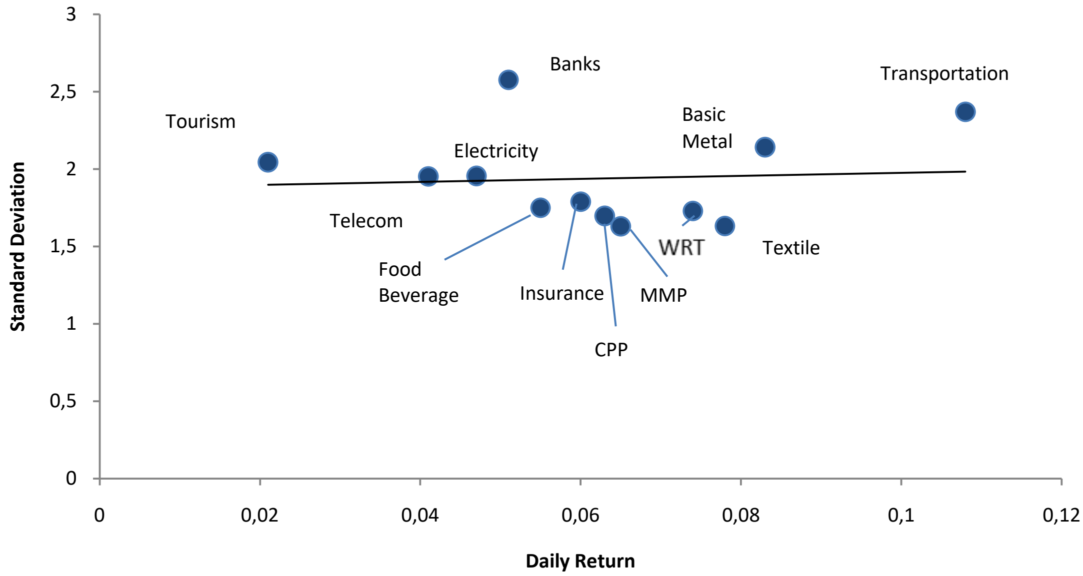
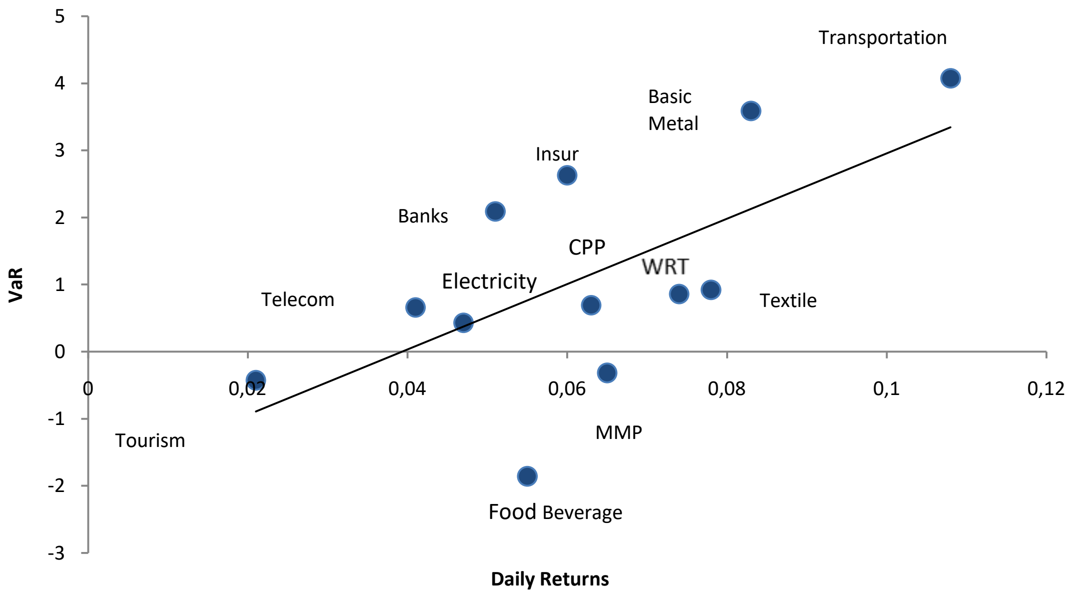


Figure 3. Components Loadings

4.3. Portfolio Optimization

Figure 4 displays the correlation between risk parameters as calculated by the standard deviation, VaR and CVaR, and returns data in twelve sectors in the analysis. On the whole, the results show that the relationship between returns and all three risk measures is not fully consistent. When the proxy for the risk measure is standard deviation the correlation coefficient is 0.071. The estimated coefficients imply moderate results and suggest that returns and risks have an insignificant relationship. While the proxies for the risk measures are VaR and CVaR, the correlation coefficients are 0.634 and 0.723 respectively. This suggests on the strong association between returns and risks. Results on the correlation between returns and risks come out to be very analogous when VaR and CVaR are used to calculate risk, rather than the standard deviation.





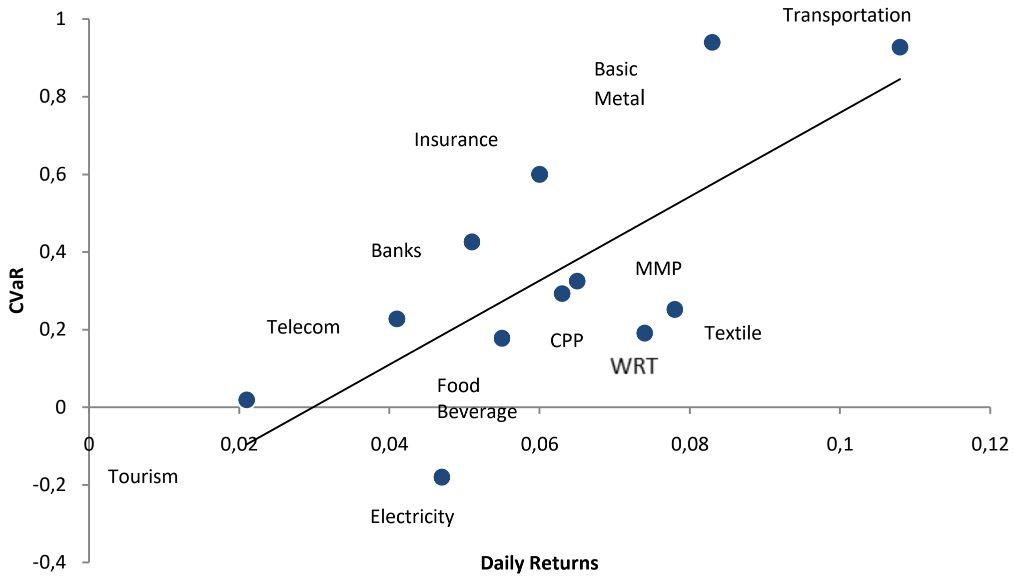


Figure 4. Relationships between Returns and Risks

Table 9 illustrates findings on the optimal weight for each sector. Overall, the results show that the investment opportunities are mostly consistent for three risk measures. At different levels of contribution, wholesale and retail, and transportation sectors are the greatest contributors to the market portfolio in Turkey. CVaR estimates the highest contribution of the wholesale and retail sectors which accounts for 38.59 percent. On the other hand, standard deviation calculations, with a weight of 27.04 percent show the contribution of the transportation industry.

Table 9. Average weight for each industry, 2007-2020, in percent

Industry	Standard Deviation	VaR	CVaR
Wholesale and Retail	28.36	30.25	38.59
Transportation	27.04	13.81	17.17
Banks	3.65	4.77	2.58
Telecommunication	0.00	3.17	0.00
Insurance	2.90	6.18	4.85
Electricity	4.80	4.17	1.61
Chemical Petrol Plastic	2.45	6.56	5.47
Metal Machinery	4.50	7.02	6.21
Basic Metal	10.71	9.77	10.65
Textile	10.89	8.99	9.40
Food Beverage	0.00	5.31	3.45
Tourism	4.69	0.00	0.00
Mean	8.33	8.33	8.33
Min	0.00	0.00	0.00
Max	28.36	30.25	38.59

Our estimations facilitate the investment decision process and explore the best sectors in relation to the tradeoff between returns, excess returns, risks, and weights. Findings suggest that for the period under analysis the winners sectors in Turkey are wholesale, retail trade, and transportation industries. Not surprisingly, geopolitical location and ambitious modernization of railway system and other transport infrastructure investments, construction of the third Bosporus Bridge and new Istanbul ‘mega’ airport lead to the growth of the industries at an even faster pace.

5. Concluding Remarks

The current study is designed to analyze the performance of the domestically diversified portfolios in Turkey and investigates optimal weights of industries in the market portfolio by applying the mean-variance, mean-VaR, and mean-CVaR portfolio optimization. Comparing outcomes under different risk measures, we find that future wealth in one risk measure for one industry can dominate the other, but this dominance is consistent throughout the industries. Finally, this paper provides evidence on the fact that the investment options are mostly consistent for three risk measures. In fact, this condition holds true if the loss is normally distributed. When the subjacent loss distribution is a regular minimum variance model, VaR and CVaR give identical optimal weights. Academic research attempts to provide reasons why investors display a local bias but little evidence is available on actually measuring domestic diversification potential. This study display that for investors who desire to create a domestic portfolio considerable diversification opportunities are available. We measure domestic diversification opportunities using factor analysis. Results from the empirical tests suggest that the factor analysis is an appropriate statistical tool to estimate ex-post covariance matrices of Turkish lira-equivalent returns and to predict the extent to which returns at the sector level in Turkey over the time period from 2007 to 2020 display joint movement. A few sets of outcomes have been obtained as a result of factor analyses. Firstly, the analyses show that each industry has similar patterns of responses of returns while groups of industries have relatively independent patterns. In addition, the first component is identified by almost all industries. These results indicate that a high level of diversification can occur in a separate country case like Turkey. The results of this study support previous findings that domestic profits are possible with meticulous investment analysis and accurate strategies (Solnik (1995), Kilka etl (2000), Antoniou (2010)). The results of the statistical tests are of great importance since they suggest that profits are possible with meticulous investment analysis and accurate strategies. This brings up the question of how the market participants should distribute their funds to reach an efficient portfolio. Since the multivariate analysis can’t show the real gains and risks from diversification the portfolio optimization was also implemented.

To our best knowledge, this is the pioneer study that investigates portfolio optimization analysis in Turkey on an industry basis. Results from mean-variance, mean-VaR, and mean-CVaR portfolio optimization, show that wholesale, retail trade, and transportation industries are the greatest contributors to the market portfolio in Turkey. That is CVaR and VaR estimate the highest contribution of the wholesale and retail sector, which accounts for 38.59 and 30.25 percent respectively. CVaR and VaR indicate that the second contributor to the market contributor is transportation, which accounts for 17.17 and 13.81 percent respectively. On the other hand, standard deviation calculations, with a weight of 28.36 and 27.04 percent show the highest value for wholesale and retail, and transportation industries. Academic literature also show that relevant economic policies can be formulated by policymakers to take advantage of the relative potential and strength of various industries in their domestic markets (Duc Hong V etl. (2018), Hannah N. (2019), YousraT. (2020)).

Another important finding is that the relationship between returns and all three-risk measures display variability. That is the correlation coefficient between the standard deviation and returns is insignificant. On the other hand, high correlation coefficients indicate the significant association between VaR, CVaR, and returns. Although the results from optimization reflect similarities of outcomes, investors can rely on different risk measures to verify the accuracy of estimations.

This analysis will be of special interest to investors, policymakers, and academicians. Our estimations facilitate the investment decision process and explore the prime sectors in relation to the balance achieved with the returns, excess returns, risks, and weights of assets. Findings in this paper give important information for policymakers to incorporate adequate economic measures and policies that bring prosperity to key industries.

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