AN ANALYSIS OF THE LOW-VOLATILITY ANOMALY ON THE BORSA İSTANBUL

A Dissertation

by

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Submitted to the

Graduate School of Sciences and Engineering
In Partial Fulfillment of the Requirements for
the Degree of

Master of Science
in the
Department of Financial Engineering

Özyeğin University
June 2021

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To Gunslingers

ABSTRACT

In financial markets, obtaining high returns against high systematic risk is basically the expected situation. It is regarded as a financial anomaly that high-risk stocks yield lower returns than low-risk stocks. This situation is called as low volatility anomaly or beta anomaly in financial literature. In this study, it was investigated whether there was a low volatility anomaly in BIST 100 between 2010-2019. 80 companies listed on the stock exchange between 2010 and 2019 were included in the study. Within the scope of the study, the presence of beta anomaly was investigated for periods of semiannual, 1, 2, 5 and 10 years. In addition, it was examined whether there was a beta anomaly for the years 2010-2013 and 2014-2019. The results obtained show that there is a beta anomaly within a certain beta value range in each period examined. Especially periodically, the presence of a general beta anomaly was detected in the period 2014-2019. In addition, it has been determined that beta anomalies generally do not occur in cases where the beta value is 1 and above in the short term, and very low and very high beta values reduce the return rate in the long term.

ÖZET

Finansal piyasalarda temel olarak yüksek sistematik riske karşılık yüksek getiri elde etmek beklenen durumdur. Yüksek riske sahip hisse senetlerinin nispeten daha düşük riskli hisse senetlerine göre daha düşük getiri sağlaması finansal piyasalarda bir anormallik olarak kabul edilmektedir. Bu durum finans literatüründe düşük oynaklık anomalisi veya beta anomalisi olarak adlandırılmaktadır. Bu çalışmada, 2010-2019 yılları arasında BIST 100'de düşük volatilite anomalisi olup olmadığı araştırılmıştır. Araştırmaya 2010-2019 yılları arasında borsada işlem gören 80 şirket dahil edilmiştir. Çalışma kapsamında 6 aylık, 1, 2, 5 ve 10 yıllık dönemlerin yanı sıra 2010-2013 ve 2014-2019 yılları arası için de beta anomalisinin varlığı incelenmiştir. Elde edilen sonuçlar, incelenen her dönemde belirli bir beta değer aralığında bir beta anomalisi olduğunu göstermektedir. Özellikle dönemsel olarak 2014-2019 döneminde genel bir beta anomalisinin varlığı tespit edilmiştir. Ayrıca kısa vadede beta değerinin 1 ve üzeri olduğu durumlarda genellikle beta anomalilerinin oluşmadığı, çok düşük ve çok yüksek beta değerlerinin ise uzun vadede getiri oranını düşürdüğü tespit edilmiştir.

ACKNOWLEDGMENTS

I would like to pay my special regards to the universe of opportunities, to equity markets.

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CHAPTER I

INTRODUCTION

The low-volatility effect is an anomaly that has been found to occur in equity markets the world over. Going against the long-believed theory that investing in a higher risk asset should compensate an investor with a higher return, empirical evidence has found the contrary to be true (Ang, Hodrick, Xing and Zhang, 2006). That is, lower risk stocks have been found to outperform higher risk stocks over the long run. This phenomenon is a particularly peculiar one as it goes against the traditional theories that are still taught academically in finance, consisting of Sharpe (1964), Lintner (1965) and Mossin's (1966) Capital Asset Pricing Model (CAPM), the Markowitz (1952) theory of the Efficient Frontier and the more recent Fama-French (1993) multifactor asset pricing models, all of which prescribe higher risk equating to higher returns. As a result, it is evidently an important topic that cannot be pushed aside if investors understanding of financial market predictions and pricing models are to continue to become more efficient.

The positive relationship between market risk and expected return is one of the underlying principles of financial theory that has resulted due to the proposition of the CAPM, presented by Sharpe (1964), Lintner (1965), Mossin (1966) and Treynor (1965). Since its inception, CAPM has been greatly criticized in both theoretical and empirical terms. Nonetheless, CAPM is the most commonly used asset pricing model (Levy, 2012). The linear relationship between a share's expected return and its market beta suggests that investors are compensated for taking non-diversifiable risk. If this relation holds, the riskier the shares are in relation to the market portfolio, the higher the expected return.

However, a discrepancy exists between theoretical predictions and the empirical studies regarding the risk-return relationship. Black, Jensen, & Scholes (1972) and Miller & Scholes, (1972) discovered that the security market line for US shares was flatter than predicted by the CAPM. Haugen and Heins (1972) was the first paper to suggest that the relationship was not merely flat but inverted. The seminal paper by Fama and French (1992) extended the analysis of Haugen and Heins (1972) and found that, after adjusting for size effects, the relation between CAPM beta and return is flat over the period from 1963 to 1990. Recently this anomaly has been found across international markets in papers such as Blitz & van Vliet (2007), Frazzini & Pederson (2014); Baker, Bradley, & Wurgler (2011) and Baker and Haugen (1996, 2010, 2012). This finding holds true in South Africa, as several papers including Van Rensburg and Robertson (2003), Strugnell, Gilbert and Kruger (2011) and McClelland (2013) examined the relationship between market beta and share returns and have also found that an inverse relationship between beta and returns exists on the JSE. McClelland (2013) found that low beta shares significantly outperformed high beta shares, even when size, value and liquidity were taken into account. Baker et 01. (2011) suggested that this anomaly is potentially the greatest financial anomaly in capital markets.

The reason that the effect has earned the name of “low-volatility” as opposed to “lowrisk” is due to the fact that volatility, as measured by the standard deviation of returns, is the most common metric in the financial world used to measure risk. Augmentations of studies in this area have also referred to it as the “low-beta” effect, as beta from the CAPM can be seen as a stock’s exposure to systematic risk (Blitz and Van Vliet, 2007), which has also been found to incorrectly prescribe the risk-return relationship. Given the prior research into the topic, there is not as much of a need to prove the effects existence as there is to discover and explain its causes, as the effect has continuously been documented across both developed and emerging markets by respected academics such as Ang et al. (2008) and Blitz, Pang and van Vliet (2013) covering both areas.

One of the key areas of examination outlined in this paper is whether volatility, the metric commonly used to measure risk, is itself flawed in capturing how investors commonly perceive risk in equity markets. There has been extensive research into different statistical methods of calculating volatility by accounting for its relationship and variation with time, and how this might more accurately account for the variation of stock returns. These models are commonly known as Generalised Autoregressive Conditional Heteroskedasticity or GARCH volatility models. Additionally, other financial measures of risk that have recently become more prominent, including Valueat-Risk (VaR), Expected-Tail-Loss (ETL) and Downside Deviation are considered in terms of their relationship with returns. This paper looks at whether accounting for volatility or risk using these different derivations alters the results of the low-volatility anomaly and whether low-risk stocks continue to outperform on a relative basis.

Not only will the question of how-to best measure risk and its impact on the low-volatility anomaly be examined, but in addition, a more fundamental analysis on what other factors might be impacting returns is looked at. It is entirely possible and in fact likely that the return generating process of equity assets and the fundamental characteristics that determine the risk behind these assets are not yet fully understood by financial academics and practitioners. This implies that only considering the variation in a stock's returns may be an overly simplistic way of looking at risk. Rather, by looking at other characteristics of the stock, such as its valuation, its exposure to macroeconomic variables, its ability to return cash to investors and how predictable the performance of the firm behind the stock is, alongside volatility, may paint a better picture of how best to measure expected return.

One of the nuances of the low-volatility anomaly is not only the outperformance of low-volatility stocks compared to their high-volatility counterparts, but the fact that this outperformance is unexpected based on current expected return models. Centered on this, the performance of each stock or portfolio of stocks needs to be assessed from an alpha (unexpected performance) return perspective as opposed to an absolute return one. The assumption here is that the alpha of low-volatility stocks or portfolios consisting of them is positive according to expected return models such as the CAPM or Fama-French three factor model. While it may not be feasible to expect to construct a model that perfectly predicts stock returns and thus results in a zero alpha, it may be possible to minimize the unexpected overperformance of low-volatility stocks or the unexpected underperformance of high-volatility stocks.

The Turkey equity market, the Borsa İstanbul (BIST), is the market landscape within which this research is considered. While still a developing market, the BIST has appeared to become more efficient over the last one decade as it has evolved into a more complex and liquid financial market for equity investors. This is the main reason why the time frame of only data from 2009 and later is considered in this research, since an analysis of risk and return requires that the market within which this takes places is efficiently pricing assets in the first place. On the other hand, it must be acknowledged that only, approximately, the top seventy company stocks on the market could be considered to be liquid and efficiently priced assets. Seventy stocks were used as a more conservative amount since this study covers a longer time-span. Thus, this study is restricted to using this smaller sample of stocks compared to what could be looked at in a more developed stock universe, such as that of the U.S. Nonetheless, a robust investigation is still able to be conducted and can still shed light on the low-volatility anomaly in an emerging market context.

This research focuses on the fundamental relationship between market risk (beta) and return, which CAPM predicts to be linear. The next section will provide an overview on the existing literature regarding this relationship. In the next section, the conceptual background is discussed. In this context, Capital Asset Pricing Model (CAPM) and Low Beta Share Anomaly issues were discussed. Under the subject of Low Beta Share Anomaly, "Presence of the Low Beta Anomaly" and "International Evidence Explanations of the Low Beta Anomaly" titles are discussed.

CHAPTER II

LITERATURE REVIEW

The natural convention that has applied to financial markets and investments since the beginning of its academic analysis involves the idea that when investing in a riskier asset, the investor should be compensated for having taken on this higher risk with a commensurate higher return (Baker and Haugen, 2012). If this would not be the case, there would be no reason for the investor to invest in the riskier asset over the safer asset, which has become the tenant of finance teachings through any academically studied finance or financial economics course. This notion has more recently been challenged however, with empirical evidence across markets showing an opposite result, this being that a lower volatility or lower risk asset has actually accumulated higher returns than the equivalent higher volatility or higher risk asset over time.

One of the key assumptions to take note of when analyzing the low-volatility anomaly is whether it is occurring in markets that are efficiently pricing assets. "The Efficient Market Hypothesis (EMH) as described by Fama (1991) in its strongest form indicates that security prices fully reflect all available information." "While trading costs and information costs make it unlikely for markets to follow this extreme level of efficiency, a more plausible version of the hypothesis is one where prices reflect information to the point where the marginal costs of acting on information exceed the marginal benefits" (Jensen, 1978).

Congruent to the EMH is that security price changes follow a random walk, reacting to new information as it becomes readily available, while already accounting for all prior information (Malkiel, 2003). If the low-volatility anomaly is apparent on equity markets, this would suggest that either, equity markets are not efficient and do not follow a 6 random walk process as described above, or, that current equilibrium pricing models against which market efficiency is being tested are inaccurate due to the joint hypothesis problem, which points out that market efficiency can only be tested when compared to an accurate equilibrium price prediction model, such as the CAPM (Fama, 1991).

Baker and Haugen (2012) analyze different markets over the period 1990 - 2011. They find that low risk shares had better performance than high risk shares in all the markets. They attribute the persistence of the low volatility effect in global markets to the fund manager's preference for high volatility shares as they have a better and more attractive compensation structure.

Goldberg and Mohmoud (2013) observe three risk-only investment strategies including minimum variance, risk parity and low beta, over four asset classes (Equity, Treasury Bonds, US Investment Grade Corporate Bonds and Commodities). They find that all three risk-only strategies outperformed an equally weighted strategy over the period of 1988-2010. Among others: Haugen and Baker (1991, 1996, 2010); Pettengill, Sundaram, and Mathur (1995) Clarke, de Silva and Thorley (2010); Poullaouec (2010) found further evidence supporting the persistence of the low-risk anomaly in the US market. Blitz, Pang and Van Vliet (2012) studied the Low Beta Anomaly within developing markets. Baker, Bradley and Taliaferro (2013) studied the outperformance of low beta shares through a decomposition using micro and macro effect.

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CHAPTER III

CONCEPTUAL FRAMEWORK

3.1 Capital Asset Pricing Model (CAPM)

“The Capital Asset Pricing Model, attributed to Sharpe (1964), Lintner (1965), Mossin (1966) and Treynor (1965) is an exante static, one period asset pricing model.” “The model is premised on the fundamental relationship between systematic risk and share returns (Fama & French, 1992).” “The CAPM draws on the portfolio theory as developed by Markowitz (1959), where investors are assumed to be risk averse, profit maximizing agents that operate in a frictionless market environment, free from taxes. Therefore, investors are expected to choose portfolios based on the mean and variance of their one period investment return.”

It has been well documented that total risk consists of two components when evaluating the volatility of an individual share; systematic risk and idiosyncratic risk. Systematic risk (beta) is simply the variability that is derived from exposure to non-diversifiable risk factors. These can be macro-economic factors like interest rates or, if the CAPM holds true, they can be fully captured by the sensitivity to market movements. The second risk is unsystematic risk, also known as idiosyncratic, it is the risk specific to individuals' shares. Modern Portfolio Theory (MPT) indicates that the relevant risk of a share is the risk added by the individual share to the investor's portfolio i.e. systematic risk (Simon, Zani, Morias & Costa, 2013). Whereby in an efficient market, idiosyncratic risk can be eliminated through holding a diversified portfolio and therefore is not relevant when pricing individual shares.

The CAPM equation is presented as follows:

$$E(r_i) = r_f + \beta_i [E(r_m) - r_f]$$

and Beta as:

$$\beta_i = \frac{Cov(r_i, r_m)}{Var(r_m)}$$

where E(ri) is the expected return on the share, rf is the risk-free rate, βi is the beta coefficient representative of a share's systematic risk, E(rm) is the expected market return, and [E(rm) - rf] is the market premium - the difference between the expected market return and the risk-free rate. Beta is the covariance of the returns of a particular share with the market, divided by the variance of the market portfolio. The CAPM assumes a linear relationship between the risky asset's expected excess returns and its beta. Beta is the systematic risk which captures the cross section of average returns. Therefore, suggesting that beta captures all systematic risks, making it the only risk necessary to describe return. The relationship implies that assets can only earn a high average return if they have a high beta.

Since its proposition, the CAPM has been the subject of much criticism. Literature has revealed three dominant tests of the CAPM specifically regarding the relationship between expected return and beta (Fama & French, 2004). “The first aspect tests whether cross-sectional and time series regression, are able to accurately reflect the risk-free rate as the intercept term and the excess return of the market over the risk-free rate as the slope. The second aspect of the CAPM that is often tested, is whether the assumption that beta is the only risk factor that can explain the actual return on an investment holds true.” Suggesting that the expected returns on all assets are fairly close to the actual return generated as well as whether any other measure can describe returns once Beta is accounted for. The final aspect of CAPM that is usually examined is whether the beta premium is always positive, whereby the risky asset should always have a return that is higher that the risk-free rate. This research focuses on the last test of CAPM.

Extensive research on CAPM has resulted in the identification of additional variables / factors that provide explanatory power other than the beta for average share returns. Fama and French (1993, 1996) referred to these additional variables as anomalies. Fama and French (2004) provide a summary of the various empirical studies testing the CAPM, mostly with negative results regarding the explanatory power of share's betas in explaining share returns. Basu (1983) finds that the earnings-prices ratio (E/P) helps to explain the cross-section of US shares whereby high E/P shares experienced on average higher risk adjusted returns compared to low E/P shares. Banz (1984) identifies that smaller companies have higher risk adjusted returns, on average, than larger firms. Bhandari (1988) identifies a positive relationship between leverage and the cross-section of average returns. Rosenberg, Reid and Lanstien (1985) find a positive relationship between average return and the ratio of a firm's book-to-market equity. Fama and French (1992) through cross-section regressions conclude that factors such as size and earnings-to-price ratio, debt-to-equity ratio and book-to-market ratio substantially increase the explanatory power of the model. The Low Beta Anomaly is just one of many anomalies identified within the asset pricing literature.

Studies such as Black (1972)' Chen, Roll and Ross (1986) or Campbell, Giglio, Polk and Turley (2012) and Merton (1973) argue that CAPM still has a place in financial practice and can arguably be salvaged. Despite of the fact that these examinations are concentrated by the investigation that the main CAPM does not work, the argument which this can be determined by ranging the model, without the need to abandon the fundamental notion of a positive risk-reward alliance.

Black (1972) developed another version of CAPM called the zero-beta CAPM, where it is not assumed that a risk-free asset exists. Black's findings show that the model fits the data better. Similarly, the model presumes that there is higher return for higher beta. Merton (1973) introduced the ICAPM, whereby investors are not only concerned with the return on a portfolio at the end of the period, but also the opportunities that will be available for them to invest the return. The ICAPM assumes that an investor will be interested in how their wealth varies with certain state variables, including earnings from labor activities, inflation and investment opportunities. Therefore, the optimal investment portfolio is multifactor efficient and other variables are required over and above the market beta in order to explain expected returns (Merton, 1973).

3.2 Low Beta Share Anomaly

The literature regarding the low-risk effect can be divided in terms of the type of risk measurement. The types of risk include; a total risk measure in terms of volatility, market risk (beta) and the unsystematic risk (idiosyncratic risk, which traditional finance suggests to be diversified away in an efficient market). This research focuses on the "Low Beta Anomaly" however, some of the literature regarding the total variance and idiosyncratic risk has been summarized. The anomaly is investigated within the framework of the CAPM, as these limitations of risk only work in a CAPM framework.

3.2.1Presence of the Low Volatility Anomaly-International Evidence

The academic awareness of the low-volatlility (Beta) anomaly goes back to Black (1972) and Black, Jensen, and Scholes (1972). For the period between 1931 and 1965, Black (1993) reports that the study conducted by Black et al. (1972) showed that low-beta shares in the US performed above expectations by the CAPM model, while greater beta shares performed worse than expected. Black (1972) highlights that if market participants' risk apetite increases much more than the other actors in the market, they can apply leverage to their portfolio mix. However, if leverage is appears with an unpleasant cost or with limits, investors could decide to buy greater risk (high volalitity) shares instead. Black declared this concept by stating that the CAPM line should appear flatter under conditions of restricted leverage than it would be otherwise (Black et al. 1972). Haugen and Heins (1975) found the marriage between risk and return to not merely be flatter than predicted by the CAPM, but in their sample period it was found to be negative.

The Low Beta Anomaly attract attention from a huge amount of investors. The majority of the findings contradict CAPM's underlying principle. Fama and French (1992) popularised the idea that value shares and small cap shares generate out-sized returns, which has become known as the size and value effects.

Through their assessment of the US, European and Japanese markets, Blitz and van Vliet (2007) present evidence of more significant positive risk adjusted returns in shares with low volatility. They found this to be true even against the FTSE World Development Index. They provide a detailed analysis of the volatility anomaly and demonstrate the robustness of their findings even after size, value and momentum effects have been taken into account. Another important finding of this research is that shares with high volatility exhibited high betas and similarly, low volatility shares exhibit low betas. Therefore, suggesting that using beta or variance as a measure of volatility should produce a similar impact on the portfolio's return and risk profile. Blitz and Van Vliet

(2007), similar to Black (1972), believes that the low volatility performance is due to restricted borrowing and behavioral biases such as the "preference for lotteries".

Clarke, de Silva and Thorley (2006) introduced one of the first comprehensive studies on what is more commonly being referred to as the “low-volatility” effect in which they analysed minimum variance portfolios in SP500 between 1968 and 2005. They found that, going against Markowitz’s original hypothesis of the Equilibrium Portfolio Theory where the bottom variance portfolio returns should lie below that of the optimal risky portfolio returns, the returns from their constructed low or minimum variance portfolio actually clearly outperformed that of the optimal risky portfolio which can also be considered to be the market portfolio. In other words, one could “reduce portfolio volatility without sacrificing returns” (Clarke, de Silva and Thorley, 2006), something that would clearly be to the benefit of any rational investor.

Critics of the results that found the long believed high-risk high-return axiom to be false have questioned the validity of these studies. One of the most common issues arising is the way that risk and/or volatility is being measured, a problem that has long confronted practitioners in the finance world and is still being investigated in a number of different finance topics. Blitz and Van Vliet (2007) explained that a common metric that has been used to measure exposure to systematic risk is the beta of a stock as derived from the Capital Asset Pricing Model (CAPM). They empirically observed that portfolios consisting of stocks with low-volatility exhibit a low beta, while those consisting of stocks with high volatility exhibit a high beta, making beta a useful tool in the investigation of the differences in returns to low and high-risk stocks. Following this distinction, Blitz and Van Vliet (2007) expand the evidence of the low-volatility effect by analyzing and finding it’s occurrence in not only the U.S. market, but also the European and Japanese markets in isolation, as well as concluding that size, value and momentum factors fail to subsume the volatility effect, meaning that their results indicate that low returns for high volatility stocks is in fact its own separate effect.

Chouefaty and Coignard (2008) proposed that using the maximization of the diversification ratio as a way to achieve superior risk-adjusted return over that of the market cap-weighted benchmark. The diversification ratio is the weighted average of the shares volatility divided by the portfolios volatility. They observed that the minimum variance and the maximum diversification portfolios outperformed the market cap indices with lower volatility.

Ang, Hodrick, Xing and Zhang (2009) analyzed 23 markets of the MSCI Developed Country Index during the period of 1980 to 2003. The authors used Fama and French's (1993) three Factor Model to measure idiosyncratic volatility. They found that within the countries investigated, shares that had previously high idiosyncratic volatility tended to significantly 18 offer lower returns in comparison with low idiosyncratic volatility. They concluded that the anomaly with better performing low idiosyncratic shares was a global phenomenon.

Baker et 01. (2011) research data of all US listed shares for the begginig of the 1968 to the end of 2008. Examinators sort shares into five different class for monthly returns accordingly five-year trailing beta, and note the results on these portfolios. They then repeat the same work and calculate the cumulative partial returns of each group. The authors illustrate that no matter how risk is defined (i.e., beta or volatility) or whether they look at all shares or only large cap shares, low risk portfolios consistently outperform high risk portfolios in the long-term. Their results, similar to other studies, suggest that the low beta and volatility quintiles exceed the high beta / volatility quintiles. The authors' initial results indicate that a dollar invested in the lowest beta portfolio grew to $60.4.

Once inflation was accounted for, the real return value was $10.28. One dollar invested in the highest beta portfolio grew to $3.77, with the inflation adjusted value of 64 cents. Therefore, underperforming the low beta portfolio by 964%. Baker et 01. (2011) uses behavioral finance and institutional benchmarking limitation as the main explanation for the anomaly. Thus, attributing the superior returns of the low risk to investors' preference for positive skewness or lottery payoffs with high volatility shares and the institutional limitations on using leverage (Black, 1972).

In an analysis of the low-volatility effect in emerging markets, Blitz, Pang and Van Vliet (2013) provide evidence that there is in fact a flat or even negative relationship between risk and return in emerging equity markets, much like that found in developed markets in prior research. In addition, they find that this volatility effect may be growing over time in emerging markets, perhaps due to the increased delegated portfolio management in these markets as they evolve. Contrasting the findings of Ang, Hodrick, Xing and Zhang (2008) however, the authors of this more recent paper find that while the low-volatility anomaly exists in emerging markets, it is only weakly related to the same effect in developed markets, which argues against the common factor explanation previously thought to be prevalent. Investigating why there is the same effect in both types of markets despite the fact that it does not co-move between them may provide an inkling for future research into isolating the factors that are driving the effect overall.

Frazzini and Pederson (2014) in their paper find empirical evidence that portfolios with high beta assets have lower alphas and smaller Sharpe ratios than those of low-beta share portfolios; both for shares traded in the US market and in international markets. The authors find that the security market line is flatter than predicted by the CAPM model in the U.S. market and in eighteen of the nineteen international markets tested. The authors argue that this is due to funding constraints and margin requirements faced by investors, who are then unable to invest in the portfolio with the highest expected excess return per unit of risk and then leverage their portfolio to match their risk preferences. The authors believe that this deviation from the CAPM model can be captured by investors using portfolios with Betting Against Beta Factors - BAB. These portfolios can be constructed through selling high-beta assets and using leverage in order to invest in low-beta assets (Frazzini & Pedersen, 2014).

3.2.2 Explanations of the Low Beta Anomaly

Many recent paper have cancentrate on justify the low-volatility anomaly. These justifications can be generally gathered into those based on behavioral demand and those based on limits to arbitrage.

3.2.2.1 Behavioral Impacts

While explanations of the low-volatility effect using Fama and French (1993) factors such as size and book-to-market factors have not yet been exhaustive, other influences that may be causing the anomaly have been introduced by academics such as Baker, M., Bradley and Wurgler (2011). Describing the long-term achievement of low volatility and low beta stock portfolios as being “among the many bidder for the greatest anomaly in finance”, these authors apply the principles of behavioral finance to investigate the drivers of this anomaly and to assess the likelihood of it persisting. Using the behavioral finance principle of irrational investors making poor decisions, the hypothesis is that a preference for lotteries and the well-established human and investor biases of representativeness and over confidence may (incorrectly) lead to a demand for high volatility stocks that is not warranted by the true fundamentals of the stock, leading them to be over priced (Baker, Bradley and Wurgler 2011).

Adding on to the behavioral finance theory, a further explanation is one based on the concept of benchmarks as a limit to arbitrage. While the irrational investor theory makes sense, it doesn't explain why the educated institutional investors that should know better than to chase stocks on factors other than fundamentals would also follow the same suit. One would expect the demand by these investors to counteract the price impact of irrational investor's demand, however, one way in which these investors are limited in doing this is through the constraint of benchmarking, Most of the istitiutional investors that has a chance to balance the demand that is not rational have some predetermined benchmark obligations. Because of this reason, they are less motivated to invest in stocks that have a lower risk (Baker, Bradley and Wurgler, 2011). Because of this reason, they are less motivated to invest in stocks that have a lower risk. The question is why the institutional investors do not short the high volatility low performing stocks; however, the issue is that a majority of these stocks are small cap stocks, which are expensive to trade in large quantities as well as far more illiquid, also making borrowing the stock more difficult for shorting (Baker, Bradley and Wurgler, 2011).

Despite a number of plausible explanations coming to light from the behavioral finance perspective on the low-volatility anomaly, there is yet to be concrete evidence 11 proving that these theories are without a doubt accurate. The perspective of how market participants themselves impact securities however has been delved into further, such as by Baker and Haugen (2012). After confirming through their own research that there is clearly evidence of the anomaly's existence across markets, they analyze the possible explanations related to the nature of manager compensation and agency issues between professionals within an organization and between these professionals and their clients.

The issue that comes into play here is that many investments managers compensation structure involves being paid a base salary, with additional bonus compensation for any outperformance over and above the benchmark of their portfolio. The benchmark return could be seen as the expected return of all stocks in the index and thus, assuming normality, the mean of the normal distribution of returns. Managers will then receive bonus compensation when their portfolio return exceeds this expected return by a certain amount and as a result, these managers naturally attempt to hold the more highly volatile stocks in their portfolio, as given the very definition of volatility as the standard deviation of returns, this gives the manager a higher chance of surpassing the expected return or in other words outperforming and receiving a higher level of compensation (Baker and Haugen, 2012). Exacerbating this problem is the fact that these managers are investing their client's money as opposed to their own, meaning that they face less personal risk if their risky bets do not pay off as planned.

3.2.2.2 Accuracy of Risk Measure Used

An issue that has been raised with the premise that a low-volatility anomaly is also a low-risk anomaly is whether or not volatility (also known as the standard deviation) is a truly accurate measure of what investors define as risk. As Sortino and van der Meer (1991) discuss, both the standard deviation and Beta's ability to accurately portray what risk means to investors have increasingly been questioned. The core of the problem is that these measures incorporate both downside and upside risk, while in reality, most investors are only concerned about the risk of possible losses on their investments and are only too happy when high variability brings about greater than expected gains (Sortino and van der Meer, 1991). If this is the case, one could argue that only the lower-than-expected portion of the variability of returns should be considered when analyzing risk, with the higher-than-expected portion being ignored entirely.

The Sortino ratio (Sortino and van der Meer, 1991) is a risk adjusted performance measure similar to the Sharpe Ratio in that the measure of return is taken as the excess return on the portfolio, however, rather than dividing this return by the standard deviation, risk is measured as the downside deviations from the mean only. This lends itself to analyzing risk adjusted returns on a more intuitive basis than the Sharpe Ratio and could change the results of any low-volatility stock analysis.

Another alternative to volatility that has increasingly received attention as its use has become more popular is Value at Risk (VaR). VaR is defined as the loss in portfolio value over a specific time horizon that can be expected to occur with a certain level of probability (Duffie and Pan, 1997). For example, if a portfolio has a 1% 10-day VaR of -5%, this implies that there is a 1% probability of the portfolio losing 5% or more of its value over that ten-day period, sometimes also stated as there being a 99% chance that, at a maximum, the portfolio will lose less than 5% of its value over that ten-day period. The benefit of using VaR as opposed to volatility as a risk measure is that it focuses on what most investors would consider as “risk”, namely extreme losses that could possibly occur with a certain level of confidence.

With regards to how the use of VaR instead of volatility may impact the evidence of any low-risk anomaly, a paper by Alexander and Baptista (2001) looks at the difference between creating mean-variance versus mean-VaR efficient portfolios. Their study finds that when comparing two mean-variance efficient portfolios, the higher variance portfolio may in fact have a lower VaR. This discovery does have the limitation that an efficient portfolio that globally minimizes VaR may not exist, but that it is possible for risk-averse investors to select portfolios with lower standard deviations that have a higher VaR, implying that a low-volatility anomaly may not actually translate into being a low-risk anomaly if VaR is used as the risk measure of choice. Instead, the higher VaR (or higher risk), lower standard deviation portfolio accrues the higher returns as would traditionally be expected.

An even more in-depth analysis of VaR as a risk measure might introduce Conditional VaR or CVaR. VaR provides the level of loss that can be reasonably assumed will not be exceeded with certain probability, while CVaR goes one step further than VaR in that it provides an estimate of the size of the loss an investor could expect given that this loss has exceeded VaR itself. In a later paper, Alexander and Baptista (2004) compare mean-variance portfolios imposing VaR as a constraint against imposing CVaR as a constraint and find that, under certain conditions, imposing the CVaR constraint may actually result in a portfolio that has both lower CVaR and lower standard deviation. The results change under different conditions however, also finding portfolios that have a lower CVaR but a higher standard deviation. This shows that although not yet fully determined, it is possible that using the correct risk measure may cause the low-risk anomaly to disappear.

More recently, Xiong, Idzorek and Ibbotson (2014) conducted a study specifically aimed at determining whether either volatility or tail risk are compensated in equity returns. In their analysis, they too found that there was no risk premium or compensation to investors for taking on higher levels of volatility in equity portfolios, however, tail risk was found to be economically significant in its compensation of higher return. Tail risk is defined as CVaR and Excess CVaR, where Excess CVaR is the portfolio CVaR which is in excess of that implied by a normal distribution using the same mean and standard deviation. The measure was calculated using actual historical portfolio returns and finding the average of the returns that were less than VaR. Additionally, tail risk premium remained significant when controlling for size, value, portfolio Beta and portfolio momentum, as well as in both U.S. and non-U.S. equity mutual funds. These findings indicate that volatility may not be the correct measure of risk being used in the market, and that tail estimation is the metric with a positive risk premium.

Another angle through which to look at the low-volatility anomaly is not whether volatility is the incorrect risk metric to use, but rather the possibility that the calculation of volatility does not take into account the time-varying nature of financial markets. There is a large body of evidence on volatility clustering in financial markets, whereby large shocks to the market result in volatility changes and a higher probability of further large shocks taking place (Alexander, 2008). Risk metrics should take into account 15 the ability of volatility to change over time rather than remain constant, and how time impacts what level of volatility could be expected to persist given its current movements. It is not impossible that accounting for volatility in this way may alter the prevalence of the low-volatility anomaly in stock markets.

3.2.2.3 Fundamental Impacts

Continuing on a different path, there has also been research into factors explaining the low-volatility effect that is independent from the existence of market anomalies or inefficiencies of market participants that others have used to analyze the effect. In one such study, Dutt and Humphery-Jenner (2012) focuses on operating returns as a key driver of stock returns, specifically analyzing whether low-volatility stock companies have higher operating returns, and thus whether the higher operating returns are driving the outperformance of such stocks as opposed to the low-volatility itself. They focus their research outside of the U.S., specifically in emerging markets, where they find this low-volatility effect to be apparent. They also conclude that low-volatility stocks do tend to exhibit strong operating performance and that strong operating returns would increase expected stock returns.

While operating returns are found to be a robust explainer of low-volatility anomalies, the authors do accept that this is simply an additional factor that may explain the effect and does not wholly explain the phenomenon on its own. Controlling for operating performance significantly influences the relationship between stock returns and 16 volatility which leads to the possibility that it is one of the key drivers of such relationship (Dutt and Humphery-Jenner, 2012).

Given the mounting evidence of a low-volatility effect's existence across markets, and the new findings of Blitz (2016) as well as those mentioned previously that the value effect and other factors such as size, momentum and liquidity fail to account for this low-volatility anomaly, Fama and French (2016) have come out with new research including an augmented version of their three-factor model which includes an additional two factors, resulting in a five-factor model that specifically attempts to address the low-volatility question. The two factors being added to the model are those related to investment, and, along similar lines of the operating "return" or in other words "profit" results found by Dutt and Humphery-Jenner (2012), a factor for profit. In the results of this paper, exposure to stocks based on these two factors, with exposure being defined as the stock having high profitability for the profit factor and conservative investment for the investment factor, appear to account for the high average returns of low beta (and/or volatility) stocks by raising the predictions of their average returns, and conversely a lack of exposure to these factors accounts for the low average return of high beta (and/or volatility) stocks by lowering the predictions of their average returns (Fama and French, 2015).

The results that profitability and operating performance are to be the defining factors that may capture the low-volatility effect as discussed and finally answer the long-asked question about why a low-volatility effect exists in equity markets make logical and economic sense in addition to their statistical significance. When a firm is consistently profitable and has good recurring results, it makes sense that its stock price and thus stock returns are less volatile than one that exhibits volatile or low profit performance and hence has other more volatile factors driving the up-movements in the stock's price. It also makes sense that these same stocks with consistent profitability and good results outperform those with volatile or low profit performance over the long-run, thus linking the "low-volatility" stocks with higher returns. On the other hand, critics of these results still question whether there is in fact enough evidence to say that the low-volatility conundrum has been outright solved.

Blitz and Vidojevic (2017) conduct an investigation in a recent paper, in which they argue that although it seems that the low-volatility anomaly has been explained by the new Fama-French (2015) five-factor model, this conclusion is premature given the lack of empirical evidence for a positive relationship between risk and return. Their results find that "exposure to market beta in the cross-section is not rewarded with a positive premium, regardless of whether we control for the new factors in the five-factor model" as well as observing that there is a stronger mispricing of volatility than of beta, suggesting that the volatility related phenomenon is the dominant one. Despite these findings, the conclusion of this paper explains that it is just one attempt at finding a positive risk-return relation after controlling for factors that others have found might be significant in explaining why such a relation has failed to be found empirically. The fact that their attempt is unsuccessful does not entirely rule out that portfolios constructed in a different manner might find the positive risk-return relationship found by Fama and French in their models (Blitz and Vidojevic, 2017).

In what is probably the most recent and relevant paper to have been published on this topic in September of 2017, Driessen, Kuiper and Beilo examine whether the interest

18 rate exposure of stocks explains the low-volatility anomaly in the U.S. market. They show that the outperformance of low-volatility stocks can in fact be explained by a premium for interest rate exposure, with low-volatility stock portfolios having negative exposure to interest rates and high volatility stock portfolios having positive exposure to interest rates. While there are several explanations as to why this might be the case, the most logical one is that low-volatility stocks also tend to be the ones that come from defensive sectors, such as utilities, consumer staples, healthcare or real estate. These companies are, in general, large, profitable, have generally little growth opportunities and often pay out dividends, all characteristics that make the cash flows of these firms more predictable and result in lower valuation uncertainty, making these stocks a lot more similar to bonds, and thus, just like bonds, having a negative exposure to interest rate movements (Driessen, Kuiper and Beilo, 2017).

Frazzini and Pederson (2014) produced one of the key papers with regards to taking advantage of the low risk and low beta effect that is evident in the context of the above research. As opposed to attempting to explain the reasons or causes of the effect, this paper outlines how to take advantage of its existence in equity markets. The idea is that because investors with constraints (such as the lack of ability to short stocks for mutual fund investors) bid up high beta assets, high beta is associated with low alpha or outperformance. As a result, introducing a new “Betting against beta” (BAB) factor, which consists of long leveraged positions in low-beta assets using the funds from shorting high-beta assets, produces significant positive risk adjusted returns. This finding is however dependent on the availability of funding, and finds that as funding constraints tighten, the return of the BAB factor is lower. It also depends on the assumption that more constrained investors hold riskier assets to find outperformance, which is empirically found to be true in the underlying research (Frazzini and Pedersen, 2014).

CHAPTER IV

AN ANALYSIS ON BIST IN TERMS OF LOW VOLATILITY

4.1 Data

The data set of the study consists of BIST 100 stocks traded on Borsa Istanbul, also known as XU100. The index is the main indicator for measuring the performance of the sharesin terms of market capitilization and trading volume on Turkish Equity Market. The transaction code of the BIST 100 index, which is also accepted as an indicator of the Turkish stock exchange, is: XU100.

BIST 100 index, the most popular and the most liquid indicator of Borsa Istanbul, is an index tracked by market participants. The main reason for this is; The stock market's comments on the rise and fall are made by taking the BIST 100 index into account. In summary; stocks of these 100 companies show the overall performance of the stock market. The stocks traded on Borsa Istanbul are re-announced quarterly a year and the stocks to be included in the BIST 100 index are determined in terms of market cap, average trading volume and floating rate.

Stocks that rank high in both rankings are included in the index by ranking from top to bottom according to the free float (FF), market value and daily average trading volume. Periodic changes are announced at least 10 days before the start of the relevant index period.

Company shares to be included in the BIST 100 index are selected only from star market stocks. In other words, main and sub markets not included in BIST 100. Shares in market main and sub carry more risks than those star market. BIST 100 index; It is re-determined every 3 months as January-March, April-June, July-September, October-December.

The 10-year change in the BIST 100 index value between 2009 and 2019 is shown in Figure 1. Although there are ups and downs over the years, it is seen that there is an increasing trend in general. The biggest increase among the increases occurring over the years is the increasing trend starting from the end of 2016 until mid-2018.s

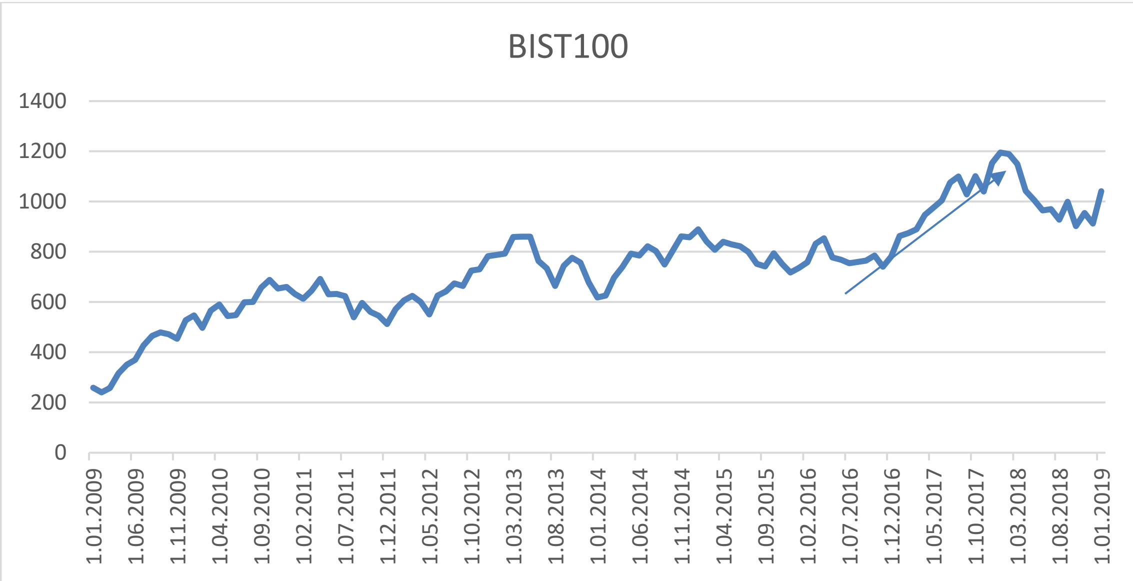

Figure 1:BIST 100 Index Values (2009-2019)

Figure 1 shows BIST 100 index 2009 to 2019. Despite the volatility trend is uprising. The rally between 2016 and 2018 can be seen very easily.

The data set of the study consists of stocks traded on Borsa Istanbul and included in BIST 100. Eighty companies that were continuously traded in the 2010-January / 2019-December period were included in the study. Twenty companies included in the BIST 100 but were not included in the study were not included in the study since they were not included in the BIST 100 continuously in the said period. The codes of the stocks included in the study are shown in Table 1.

Table 1: 80 Stocks Included in the Study

AEFES	AFYON	AGHOL	AKBNK	AKSA	ALARK	ALBRK	ALGYO	ANACM	ARCLK
ASELS	BIMAS	BJKAS	CCOLA	CEMTS	CLEBI	DEVA	DGKLB	DOAS	DOHOL
ECILC	EGEEN	ENKAI	EREGL	FENER	FROTO	GARAN	GEREL	GLYHO	GOLTS
GSDHO	GSRAY	GUBRF	HALKB	HEKTS	ICBCT	IEYHO	IHLAS	IHLGM	IPEKE
ISCTR	ISFIN	KARSN	KCHOL	KERVT	KONYA	KORDS	KOZAA	KRDMD	METRO
MGROS	NETAS	NTHOL	OTKAR	PARSN	PETKM	PRKME	SAHOL	SASA	SISE
SKBNK	SODA	TAVHL	TCELL	THYAO	TKFEN	TOASO	TRKCM	TSKB	TTKOM
TTRAK	TUKAS	TUPRS	TURSG	ULKER	VAKBN	VESTL	YATAS	YKBNK	ZOREN

The data set was obtained from Bloomberg terminal. Monthly closing data were used in the study. 20 shares which are included in BIST 100 have to be removed from this work due to continuity. The reason why they are removed is they are discontinuous in the time period. In order to have a consistent result, 20 shares are excluded from this work.

4.2 Methodology

Risk can be defined as the uncertainty of the return of an investmen opportunity. Market participants take risks in order to make an aplha. Variablity can be considered as a measure of risk. In this case, the risk can be calculated by statistical methods. In financial markets, the standard deviation or variance of the expected return is called as risk. Addition to that, Standard deviation is the square root of the variance. Namely, in this work they can both mean same thing.

Capital Assets Pricing Model (CAPM) is a model that shows the linear relationship between the expected return of any security and its degree of risk (Ceylan and Korkmaz, 2000: 291). Capital Assets Pricing Model, first introduced in 1964 by William F. Sharpe (Sharpe, 1964: 425-442), was later introduced in 1965 by John Lintner (Lintner, 1965: 587-615) and by Jan Mossin (Mossin, 1966). 1966: 768-783), and it is also known as the Sharpe-Lintner-Mossin model in the literature (Kocaman, 1995: 57). Capital Assets Pricing Model is a widely used model in practice in calculating the cost of equity (Maruca, 1996: 9-10). The profitability expected when investing in a security with a certain risk for the investor constitutes the equity cost for the company (Yilgör, 1998: 86 as cited in Damodaran).

In the Capital Assets Pricing Model, the cost of equity or the expected return on investment is calculated by using risk-free interest rate, market risk premium and systematic risk criterion beta coefficient. The mathematical expression of the Capital Assets Pricing Model is as follows (Copeland and the others, 1996: 266).

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f))$$

where

$E(R_i)$ = expected return of the stock

R_f = risk-free rate

β_i = beta coefficient (systematic risk)

R_m = expected return of the market

The beta coefficient is the measure of a stock's systematic risk. In other words, the beta coefficient of a stock's cause is a measure of the stock's market risk. At the same time, the Beta coefficient indicates the volatility of the stock against the index. In order to better understand what the beta coefficient is, what the concept of systematic risk means should be examined very well. Systematic risk refers to a market-wide risk and companies being affected by these market conditions independently of each other in a certain direction. As an example of such risks, we can give inflation and interest rates and political risks, which are a factor affecting changes in these rates. Because the market catching a positive or negative atmosphere is very closely related to such factors. In addition, diversification of an investor's portfolio does not change the risk taken in terms of systematic risks. Because the impact of systematic risks is not linked to a specific area, on the contrary, it affects all fields of activity.

It is a coefficient that shows the mobility of the stock. The beta of a stock is calculated by dividing the percentage change in the stock price by the percentage change in the market index. The coefficient indicates the tendency of a stock to move with the market or its variability according to the market (Yılgör, 1998: 88). In other words, the beta coefficient shows how sensitive the expected return from a security is to changes in the market portfolio (Bozkurt, 1988).

A stock's beta coefficient can be determined by dividing the covariance between the rate of return of the stock and the rate of return of the market index by the variance of the market return ratio. By the following formula, this relation can be seen (Cuthbertson,1996):

$$\beta_i = \frac{Cov_{i,m}}{Var_m} \qquad \text{(I)}$$

Table 2: Interpretations of Beta Value

Value of β	Interpretation
β<0	Stock moves completely different from index.
β=0	There is no relationship between stock and Index.
β<1	The stock movement is slower than the index (less risk, low volatility).
β=1	The performance of the share is the similar to the index
β>1	The share performance is faster than index (higher risk, higher volatility).

The interpretation of the beta value according to the value it takes is seen in Table 2. As the beta coefficient is lower than 1, then fund managers examine that the movement in the share will be limited . As if the general volatility in the market is 5%, the company with a beta coefficient less than 1 shows less volatlity. Moreover, a beta coefficient less than 1 can be examined as the stock's being insensitive to market conditions.

As the beta coefficient is less than 0, the share moves completely different from the index. In this case, this stock rises as the index decreases, and decreases as the index increases. If the beta coefficient is zero, there is no relationship between stock and index. If the beta coefficient is greater than 1, the stock movements will be in a wider slice than the market movement. If there is a 2% increase in the market, the price of that stock increases by 2% according to the beta coefficient. The same is true when the direction of the market is negative.

From 2010 to 2019, the average return and the calculated beta coefficients of the BIST 100 stocks, as well as all these monthly tables, are the most basic input of study model testing the “Low Volatility Anomaly” (Beta Anomaly) to be used in our calculations. Here, the mean return is the outcome gather by cuting the sum of the input sets presented in the specified range by the input length. As the outcome is greater than zero; the mean return is positive, there is alpha and if the mearn retun negative, there is no alpha.

Risk free rate is the return of an investment with zero risk. Basically, the time value of capital to investors is compensated by this return. Inflation decides that potential assets are not going to purchase as much as they do today, and the risk-free rate pays interest to investors when their money is tied up. Treasury rates are the indicator of the risk free assets, in our case CDS should also be included.

Alternatively, there are suggestions that since stocks are volatile investment strategies, the most long-term Treasury should be used. What you prefer to use as a risk-free rate in the calculations is not as critical as remaining consistent. A fair risk-free rate should, however, be selected. The risk-free interest value for this study was obtained from the Central Bank website between 2009-2019.

Another important value of the study is the Sharp value. The Sharpe Ratio is obtained by dividing the difference between the portfolio's average return and the risk-free rate of return by the absolute portfolio risk. The total risk of the portfolio is measured with standard deviation. Sharpe Ratio to calculate portfolio output established by Treynor is the same as the Sharpe ratio. However, Treynor used the beta coefficient, the systematic risk indicator, instead of the standard deviation, which is the total risk indicator, to calculate portfolio risk. This is because securities investment funds can eliminate nonsystematic risk due to diversification and the possibility to be selected according to appropriate risk groups. Therefore, only the systematic risk represented by beta remains.

$$SharpeRatio = \frac{\left(R_a - R_f\right)}{\beta_a} \tag{II}$$

In the formula, Ra shows the mean return of the portfolio, Rf shows the mean return of the risk-free interest rate, and βa represents the portfolio's systematic risk (beta). The equation systematically measures the excess return per unit of risk. An increase in the Treynor index means an increase in portfolio success.

Borsa İstanbul BIST 100 stocks are ranked in order according to the Beta coefficient for each month of the data set consisting of average return and Beta coefficient 2010-2019. In this study, it is tried to determine low Volatility Anomaly (Beta Anomaly) for 1, 2, 5 and 10 years from 2009 to 2019 by using beta and return values for monthly periods in BIST 100.

The shares traded in XU 100 between 2009 and 2019, the sequence created in practice is as follows;

S_y : 10-year share as series annually

$$\left\{S_y\right\}_{y=1}^{10} = \left\{Y1, Y2, Y3, Y4, Y5, Y6, Y7, Y8, Y9, Y10\right\}$$

Y_m : The stock month of 12 months each year

$$\left\{Y_m\right\}_{m=1}^{12} = \left\{M1, M2, M3, M4, M5, M6, M7, M8, M9, M10, M11, M12\right\}$$

$$\left\{M_p\right\}_{p=1}^{10} = \left\{P1, P2, P3, P4, P5, P6, P7, P8, P9, P10\right\}$$

P_s = Each portfolio consists of 10 shares

$$\left\{P_s\right\}_{s=1}^{10} = \left\{S1, S2, S3, S4, S5, S6, S7, S8, S9, S10\right\}$$

The following calculations are made for these generated portfolio sequences;

S_β : Single stock beta

P_β : Portfolio beta;

n : Portfolio shares counted

$$P_\beta = \frac{\sum_{i=0}^{n} S_{\beta,i}^{2}}{\sum_{i=0}^{n} S_{\beta,i}} \qquad \text{(III)}$$

S_{pw} = Stock weight

$$P_\beta = \frac{S_{\beta,i}}{\sum_{i=1}^{n} S_{\beta,i}} \qquad \text{(IV)}$$

S_r = Average return yield

P_r = Average portfolio return

$$P_r = \sum_{i}^{n} (S_{pw,i} \cdot S_{r,i}) \qquad \text{(V)}$$

S_{RFR} : Risk free rate

4.3 Findings

For the ten stock portfolios generated by monthly data between 2010 and 2019, the average return and beta values are calculated at 1,2, 5 and 10 years. Within the scope of the study, the period in which the beta anomaly is examined is ten graphs when it is selected as a year, five graphs when it is selected for two years, two graphs when it is selected as five years and one graph is obtained when the period is selected as ten years.

Within the scope of the study, firstly, one-year periods were discussed in order to detect the presence of beta anomalies in the short term. The first year covered by the study is 2010. The graph of the return and beta value for this year is shown in Figure 2. Under normal conditions, the expected situation is to increase the return with the increase in risk. As seen in the figure, as the average return increases up to β = 1.14, the beta coefficient decreases, after this value, as the beta increases, the average return of the portfolio also increases. In this case, it can be mentioned that there is a partial beta anomaly (up to β = 1.14) for 2010.

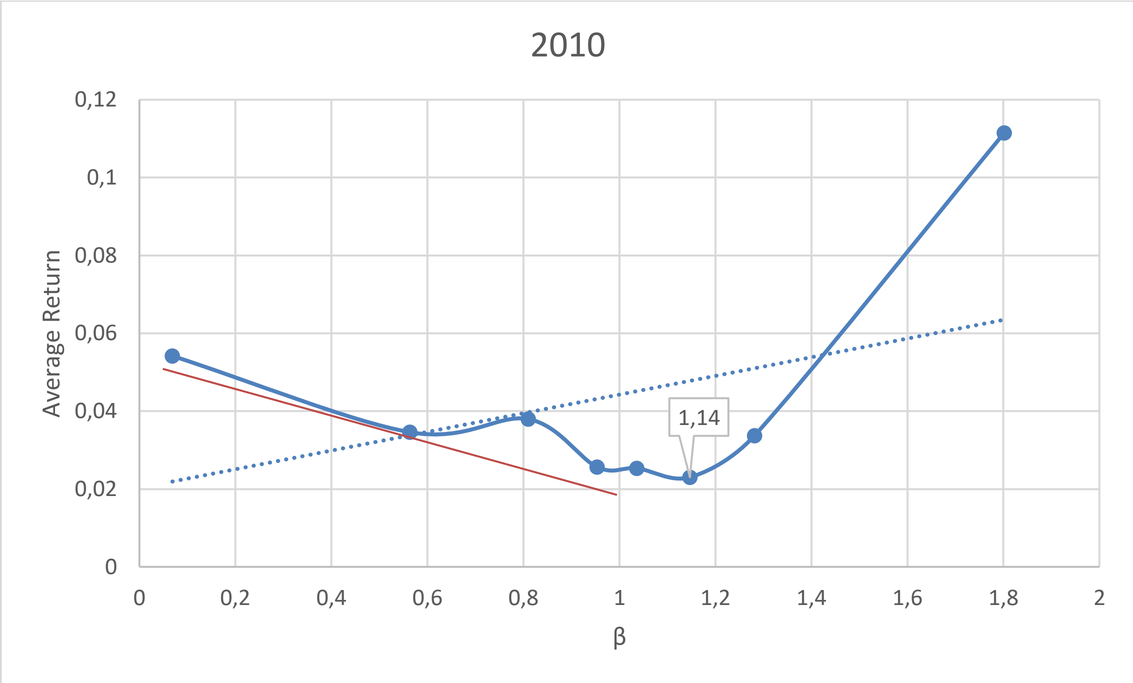

Figure 2: 2010 Beta - Return Monthly Change

The graph of return and beta value for 2011 is shown in Figure 3. The results show that between β = 0.81 and β = 1.02, while the beta value increases, the rate of return decreases. In this case, it can be stated that there is a beta anomaly in terms of these beta values.

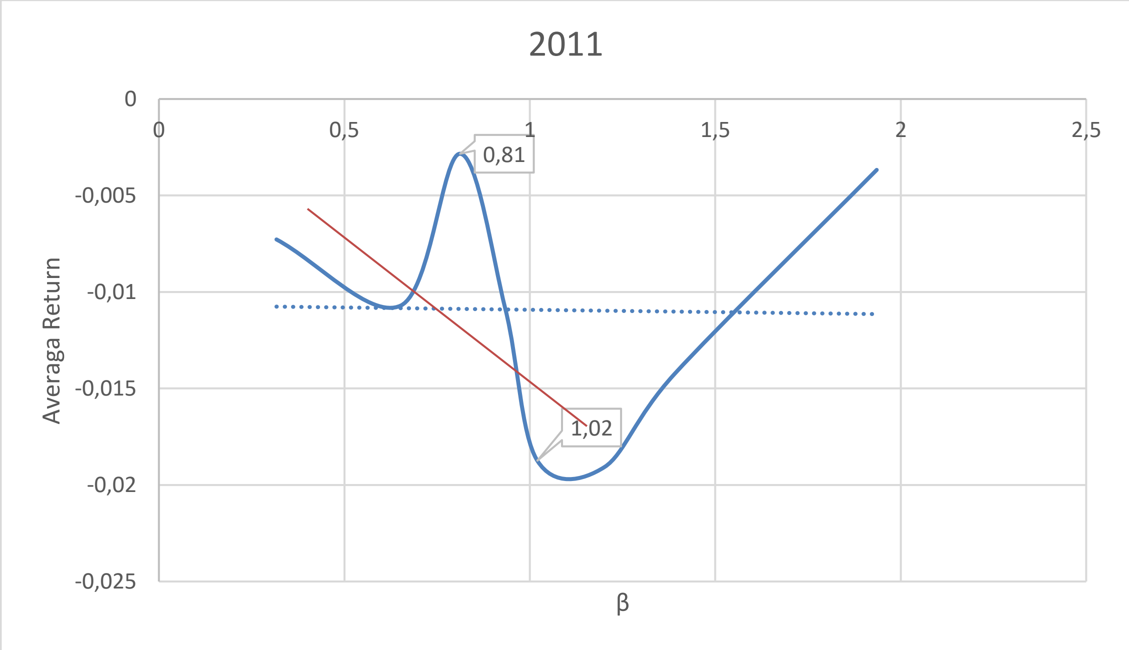

Figure 3: 2011 Beta - Return Monthly Change

The graph of return and beta value for 2012 is shown in Figure 4. According to the values obtained, after the value of β = 0.31, while the beta value increases, the rate of return also increases. In this case, although a beta anomaly up to = 0.31 is mentioned partially, it cannot be mentioned that there is a beta anomaly after β = 0.31.

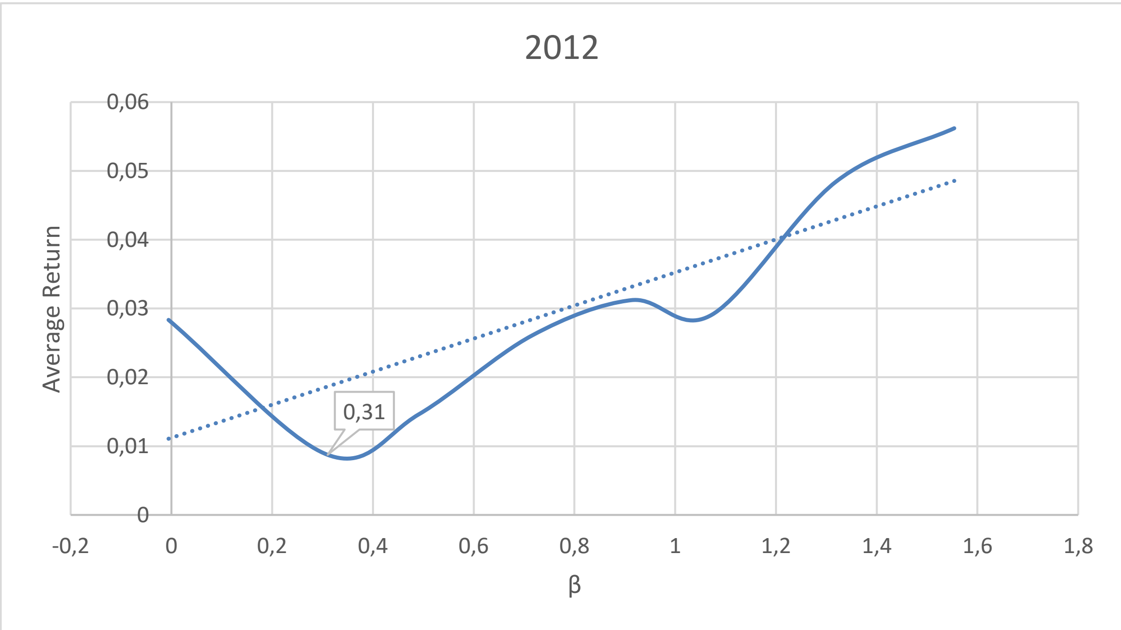

Figure 4: 2012 Beta - Return Monthly Change

The graph of return and beta value for 2013 is shown in Figure 5. As can be seen from the figure, there is a general decrease in the rate of return up to β = 0.99. From this value to β = 1.21, while the risk increases, there is also an increase in return. On the other hand, while the risk decreases between β = 1.21 and β = 1.42, there is an increase in the rate of return. This situation can be considered as an indicator of beta anomaly.

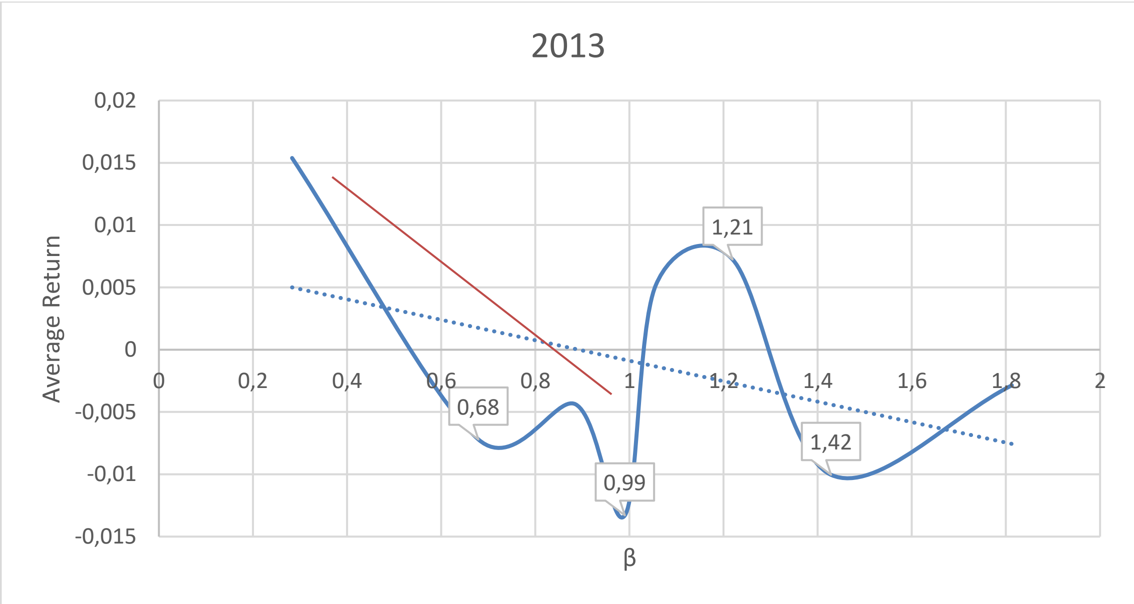

Figure 5: 2013 Beta - Return Monthly Change

The graph of return and beta value for 2014 can be seen in Figure 6. Up to β = 0.14, beta value increases in line with the rate of return. But between β = 0.14 and β = 1.05, as the beta value increases, the rate of return decreases. In this case, there is a beta anomaly between β = 0.14 and β = 1.05. Beta anomaly disappears after β = 1.05.

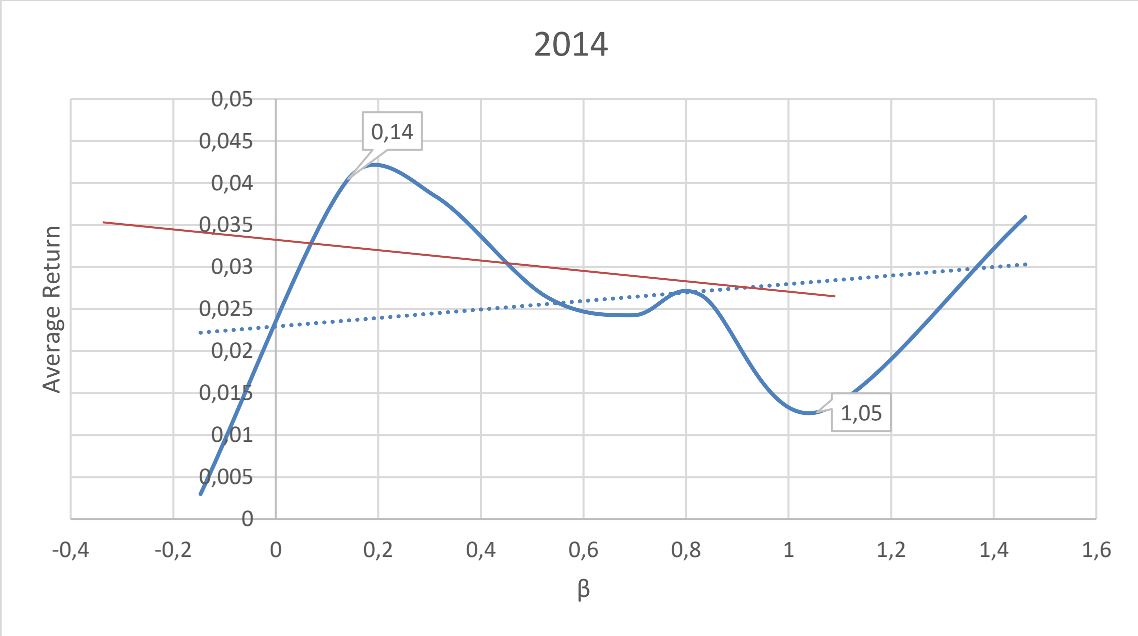

Figure 6: 2014 Beta - Return Monthly Change

The graph of return and beta value for 2015 is shown in Figure 7. The rate of return decreases as the beta value increases up to β = 0.79. Also, the same situation is observed between the values of β = 0.79 and β = 0.97. In this case, there is a beta anomaly among these values. Beta anomaly disappears after β = 1.43.

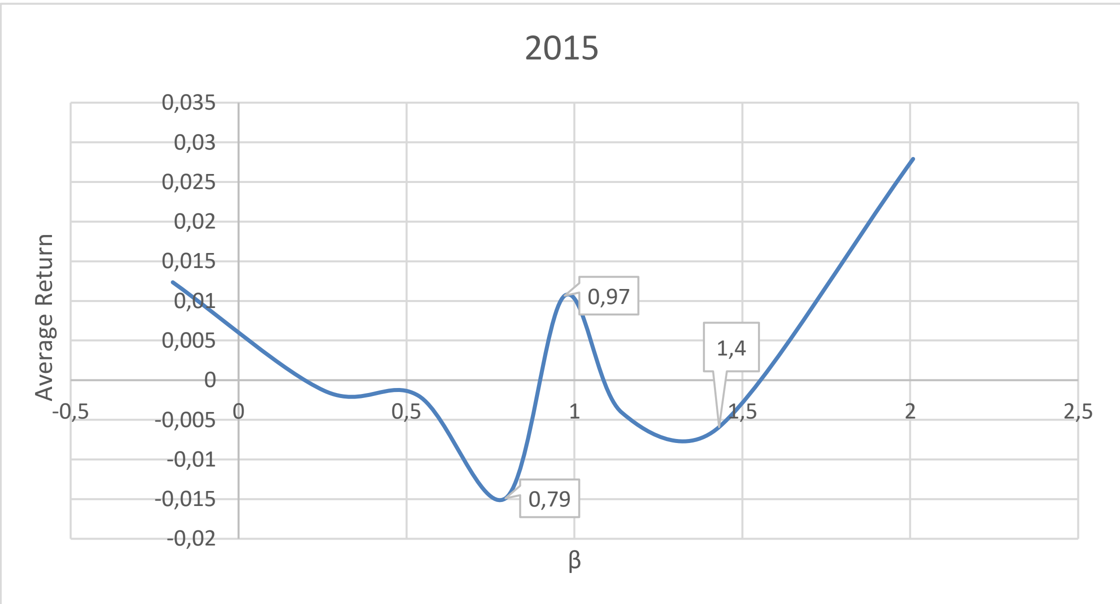

Figure 7: 2015 Beta - Return Monthly Change

The graph of the return and beta value for 2016 is shown in Figure 8. The rate of return decreases as the beta value increases up to β = 0.43. Also, the same situation is observed between the values of β = 0.67 and değerleri = 1.26. In this case, there is a beta anomaly among these values. Beta anomaly disappears after β = 1.26.

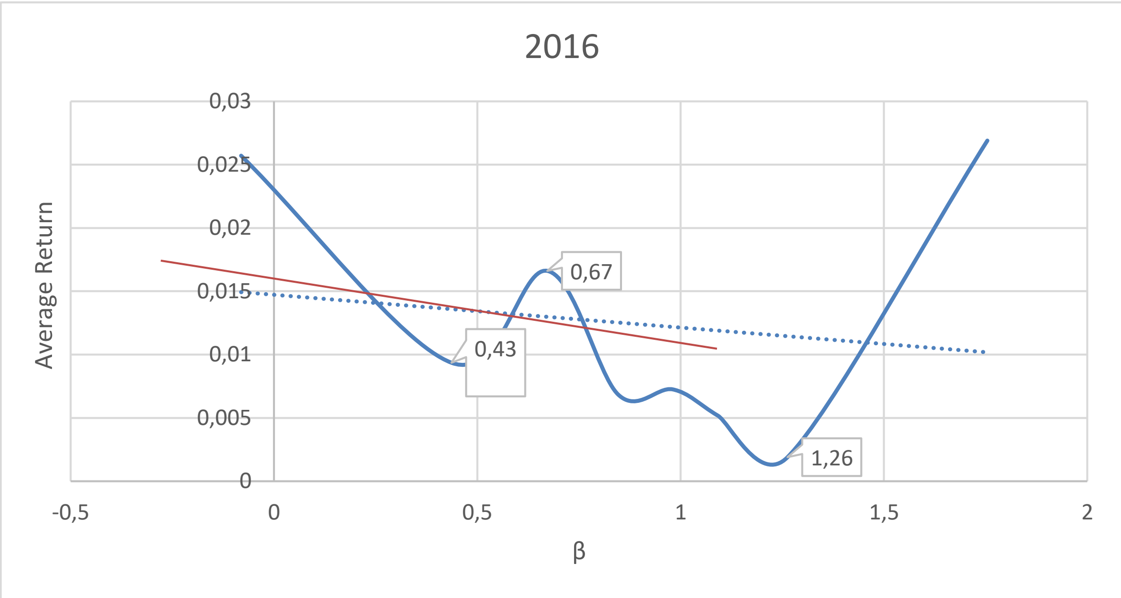

Figure 8: 2016 Beta - Return Monthly Change

The graph of return and beta value for 2017 is shown in Figure 9. The rate of return decreases as the beta value increases until = 0.60. In addition, the same situation is observed between the values of β = 1.06 and β = 1.45. In this case, there is a beta anomaly among these values. Beta anomaly disappears after β = 1.45.

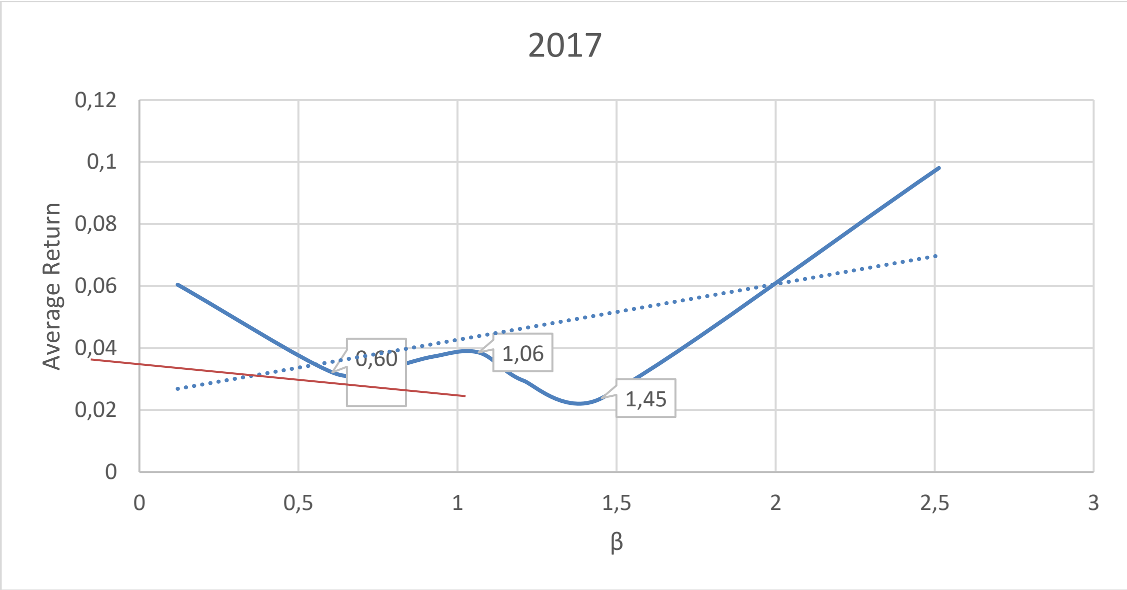

Figure 9: 2017 Beta - Return Monthly Change

The graph of return and beta value for 2018 is shown in Figure 10. Up to β = 0.25, the rate of return decreases as the beta value increases. Also, the same situation is observed between β = 0.85 and β = 1.28. In this case, there is a beta anomaly among these values. Beta anomaly disappears after β = 1.28.

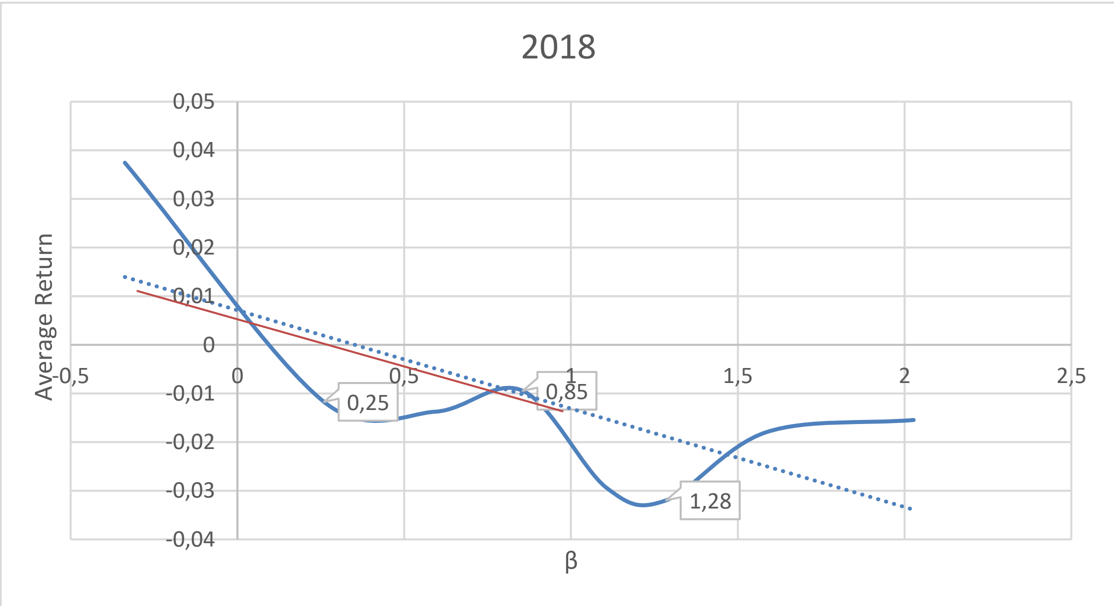

Figure 10: 2018 Beta - Return Monthly Change

The graph of return and beta value for 2019 is shown in Figure 11. Up to β = 0.51, the rate of return decreases as the beta value increases. Although there is a partial fluctuation after this value, generally, as the beta value increases, the rate of return increases. In this case, there is a beta anomaly up to = 0.51. Beta anomaly disappears after β = 0.51.

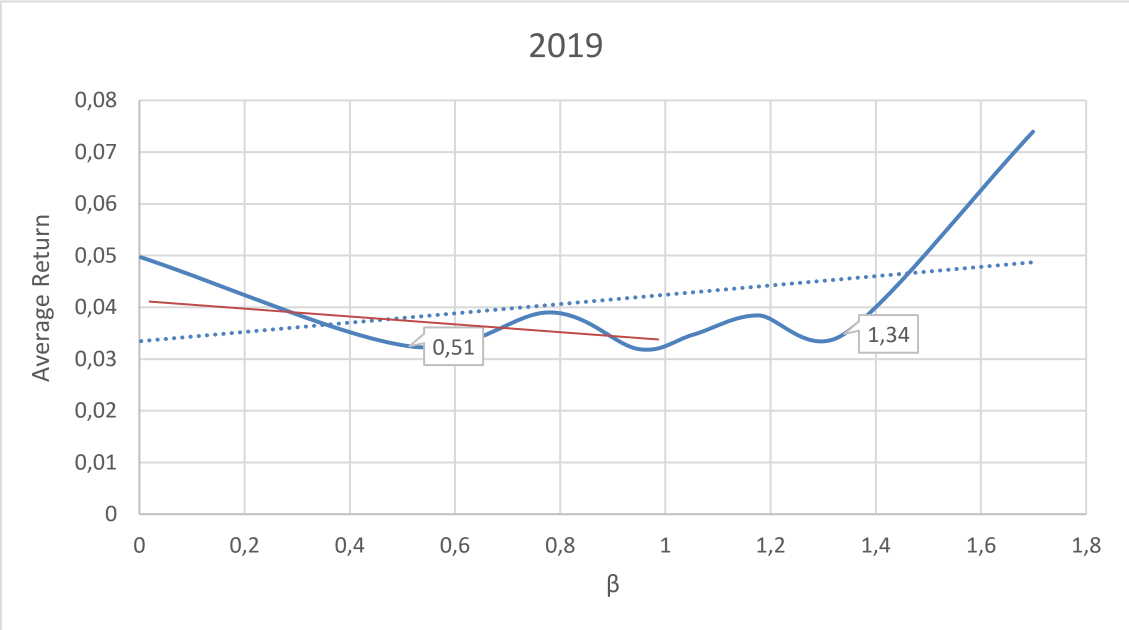

Figure 11: 2019 Beta - Return Monthly Change

The graph of return and beta value for the years 2010-2011 can be seen in Figure 12. Up to β = 1.27, the rate of return generally decreases as the beta value increases. In this case, there is a beta anomaly up to this degree. After β = 1.27, as the beta value increases, the rate of return increases. As a result, beta anomaly disappears.

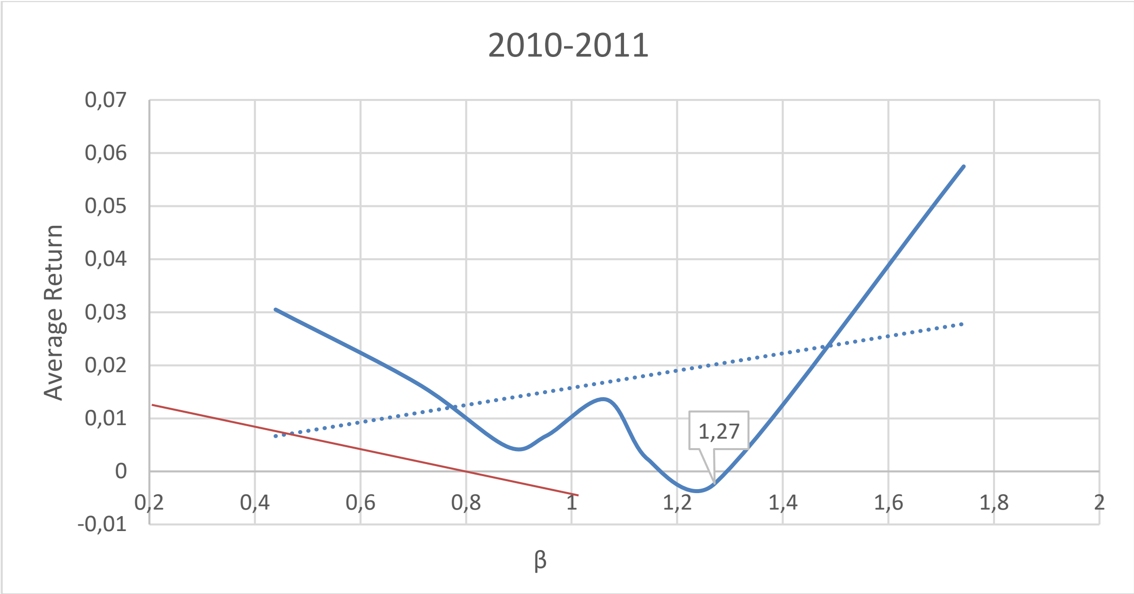

Figure 12: 2010-2011 Beta - Return Monthly Change

The graph of return and beta value for the years 2012-2013 can be seen in Figure 13. The rate of return decreases as the beta value increases up to β = 0.58. Also, the same situation is observed between the value of β = 0.84 and β = 0.95. In this case, there is a beta anomaly among these values. Beta anomaly disappears after β = 0.95. Partially, after again = 1.20, beta anomaly occurred again.

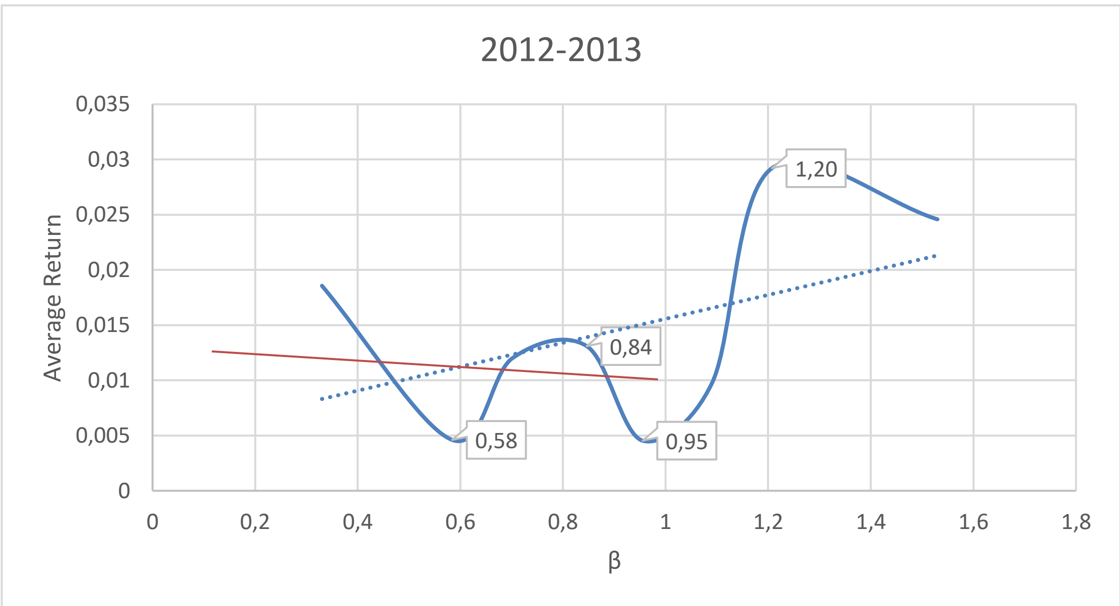

Figure 13: 2012-2013 Beta - Return Monthly Change

The graph of return and beta value for the years 2014-2015 is shown in Figure 14. The rate of return decreases as the beta value increases up to β = 0.58. Also, the same situation is observed between the values of β = 0.34 and β = 0.48, β = 0.62 and β = 0.74 and β = 0.83 and β = 1.05. In this case, there is a beta anomaly among these values. Beta anomaly disappears after β = 1.05.

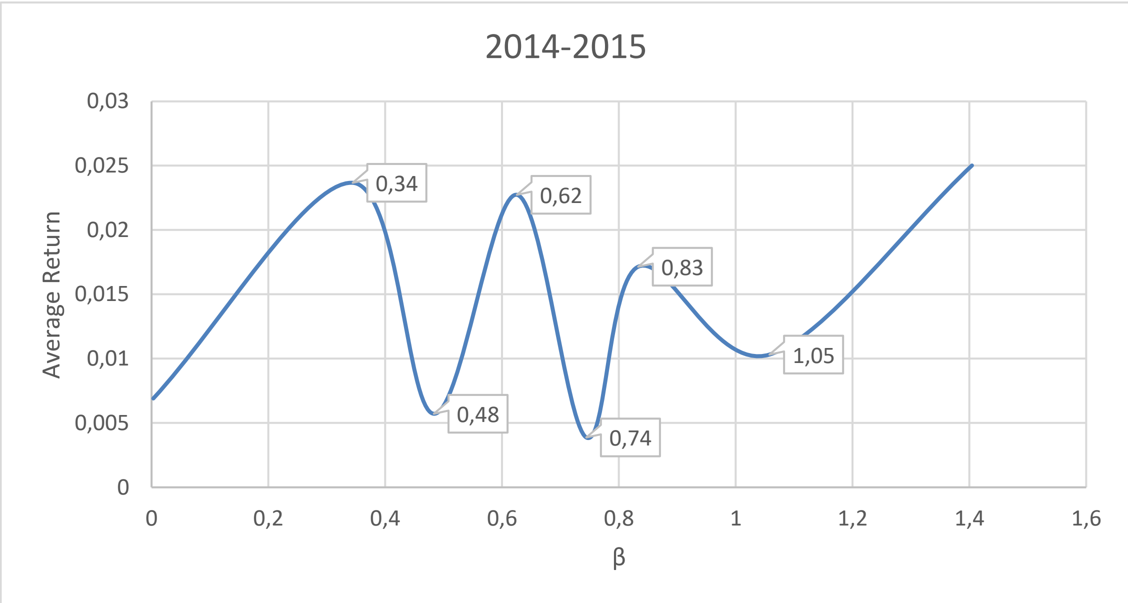

Figure 14: 2014-2015 Beta - Return Monthly Change

The graph of return and beta value for the years 2016-2017 is shown in Figure 15. The rate of return decreases as the beta value increases up to β = 0.97. In this case, there is a beta anomaly up to = 0.97. Beta anomaly disappears after β = 0.97.

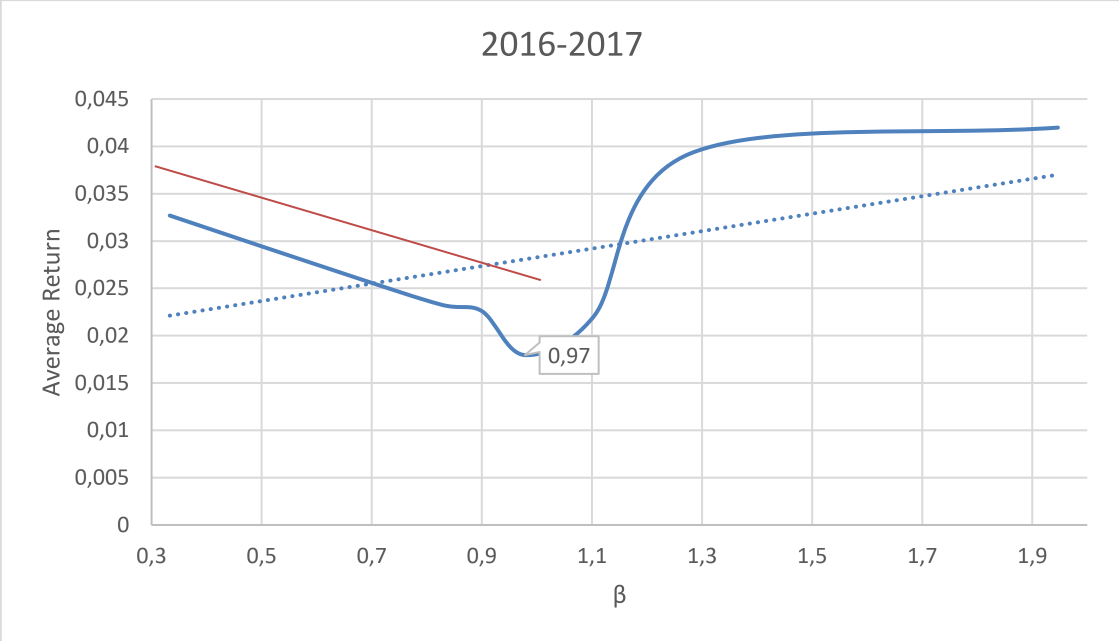

Figure 15: 2016-2017 Beta - Return Monthly Change

The graph of the return and beta value for the years 2018-2019 is shown in Figure 16. Until β = 1.06, the rate of return decreases as the beta value increases. In this case, there is a beta anomaly up to β = 0.97. Beta anomaly disappears after β = 1.06.

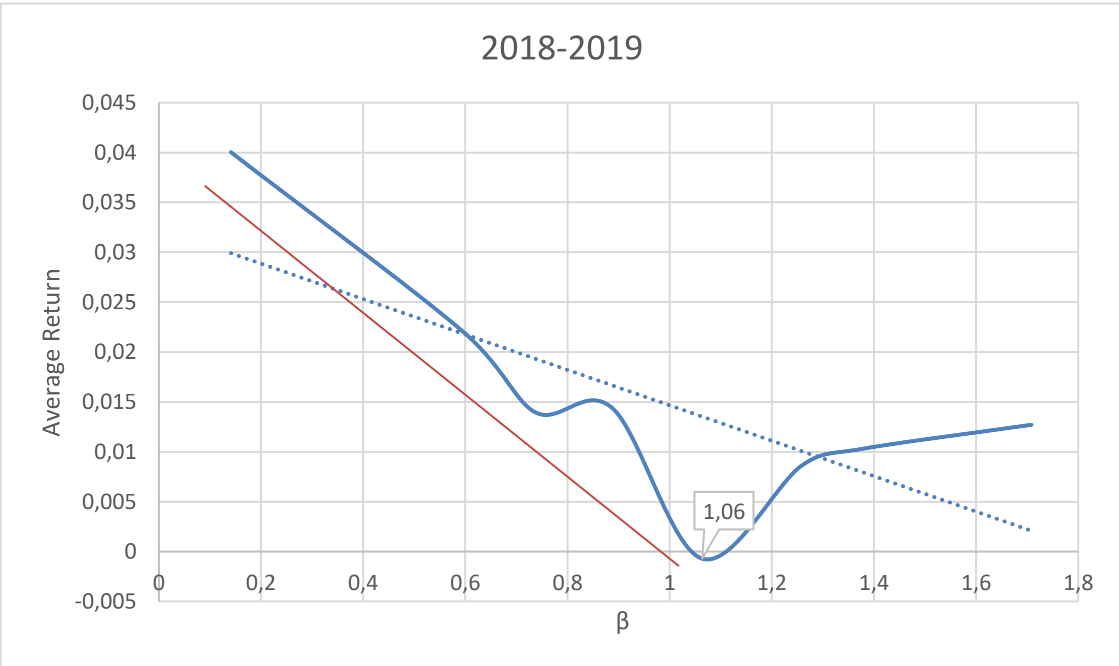

Figure 16: 2018-2019 Beta - Return Monthly Change

The graph of return and beta value for the years 2010-2014 is shown in Figure 17. The rate of return decreases as the beta value increases up to β = 0.63. The same situation is also observed between the values of β = 0.75 and β = 0.84 and β = 1.06 and β = 1.15. In this case, there is a beta anomaly among these values. Beta anomaly disappears after β = 1.15.

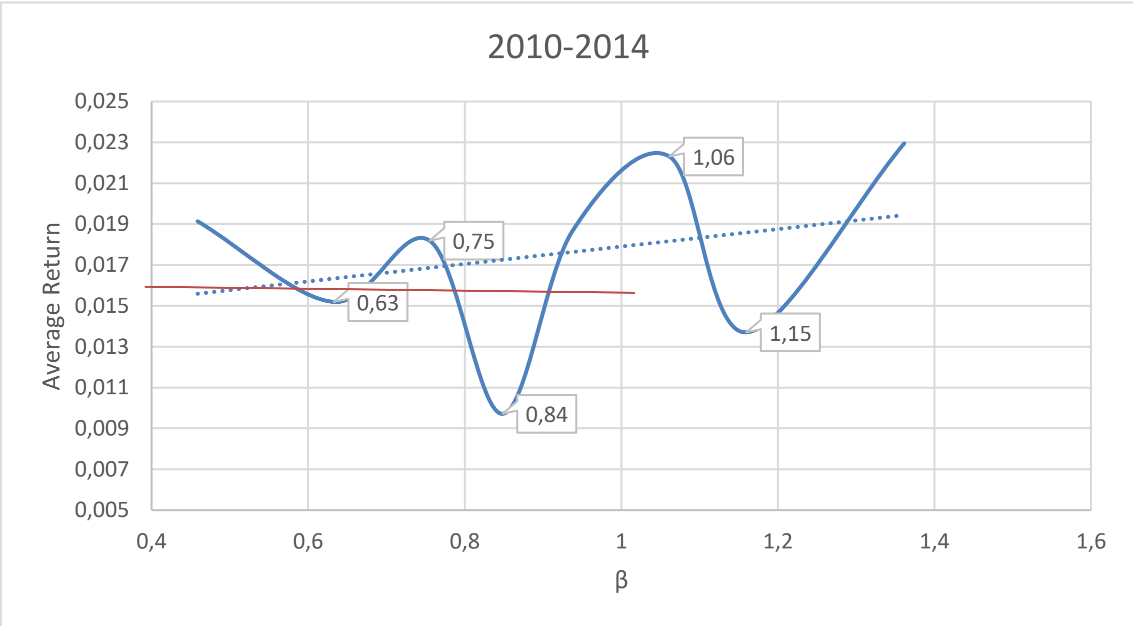

Figure 17: 2010-2014 Beta - Return Monthly Change

The graph of return and beta value for the years 2015-2019 is shown in Figure 18. The rate of return decreases as the beta value increases up to β = 0.63. Also, the same situation is observed between the values of β = 1.12 and 1, = 1.24. In this case, there is a beta anomaly among these values. Beta anomaly disappears after β = 1.24.

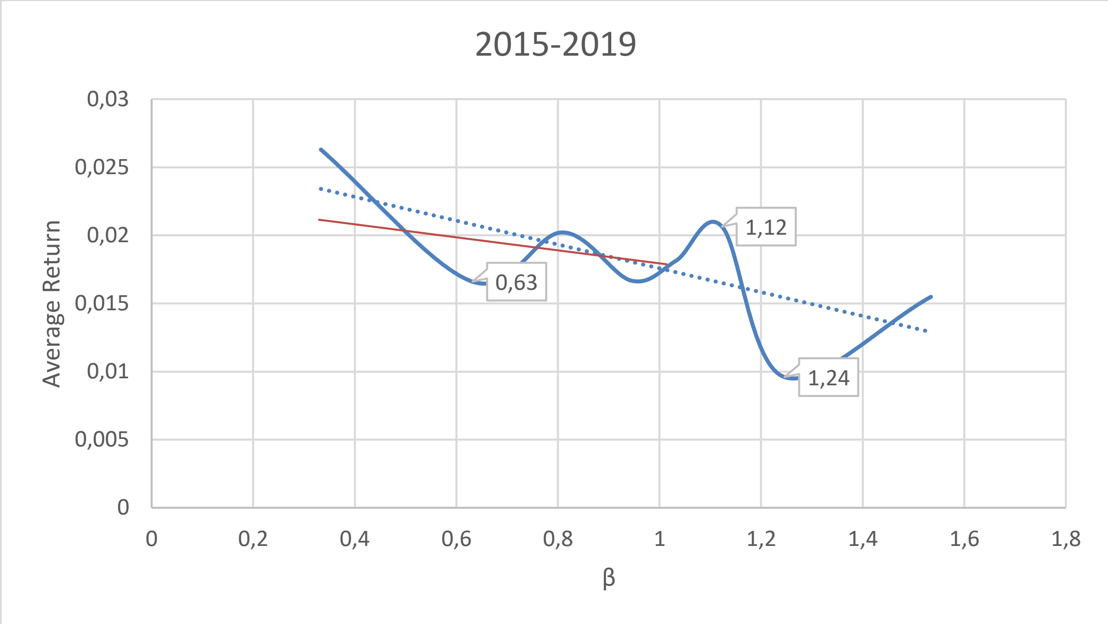

Figure 18: 2015-2019 Beta - Return Monthly Change

The graph of return and beta value for the years 2010-2019 is shown in Figure 19. The rate of return decreases as the beta value increases up to β = 0.84. Also, the same situation is observed after β = 0.89 and β = 1.02 - β = 1.14. In this case, there is a beta anomaly among these values.

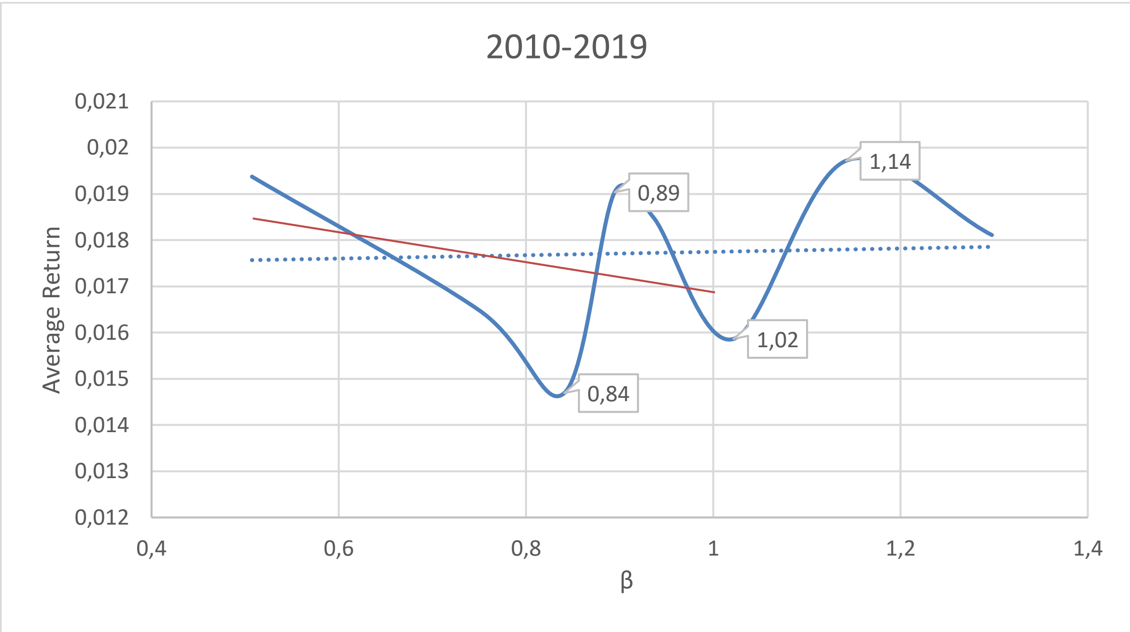

Figure 19: 2010-2019 Beta - Return Monthly Change

In Turkey, a structural break occurred in economic policies after 2013. For this reason, the period until 2013 was compared with the period after 2013. As an indicator of the period before 2013, the period between 2010-2013 was taken into account.

The graph of return and beta value for the years 2010-2013 is shown in Figure 20. The rate of return decreases as the beta value increases up to β = 1,03. After this value, an increasing rate of return is observed in response to the increasing value of β. While the return decreases up to a reasonable risk (β = 1,03), the return against the increased risk increases after this value. In this case, it can be mentioned that there is a beta anomaly up to β = 1,03, but this anomaly has disappeared after this value.

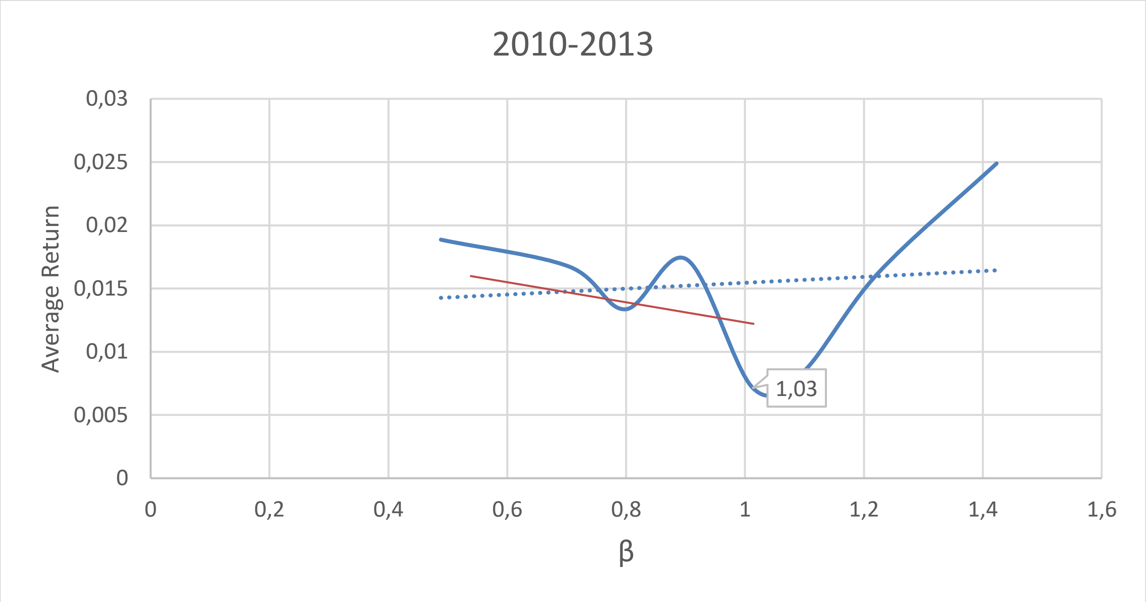

Figure 20: 2010-2013 Beta - Return Monthly Change

The graph of return and beta value for the years 2014-2019 is shown in Figure 21. It is observed that there is no sharp change between risk and return between these years. Although there is a partial beta anomaly between 0.75 and 0.98, there is a stability in the return-risk relationship after 0.98.

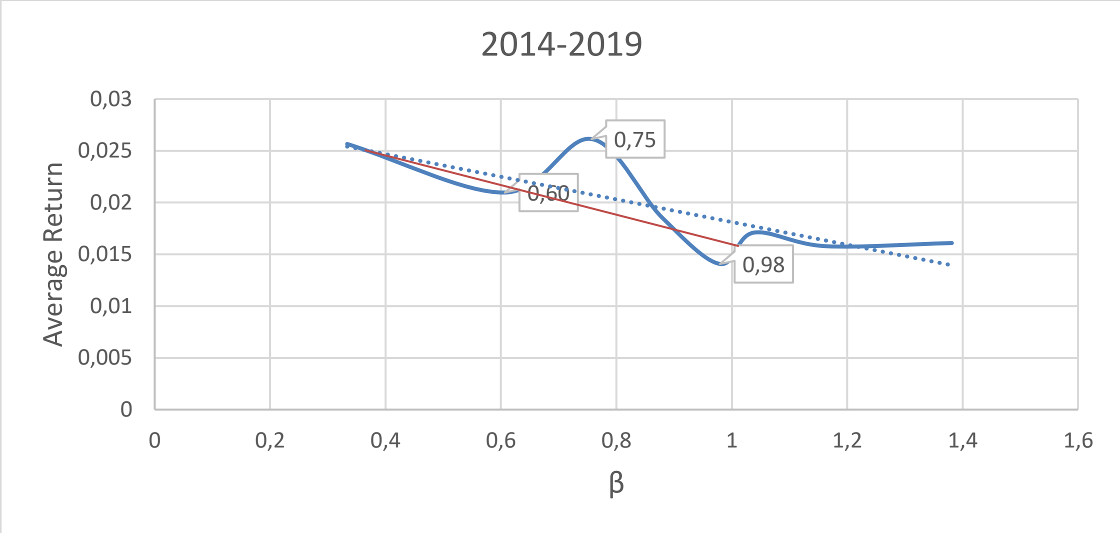

Figure 21: 2014-2019 Beta - Return Monthly Change

In order to determine whether beta anomalies existed in shorter periods between 2010 and 2019, 6-month periods were considered. The graph of return and beta value for the years 2010-1st semiannual is shown in Figure 22. In this period, it is generally seen that as the beta value increases, the return also increases. In this case, it is not possible to talk about a beta anomaly.

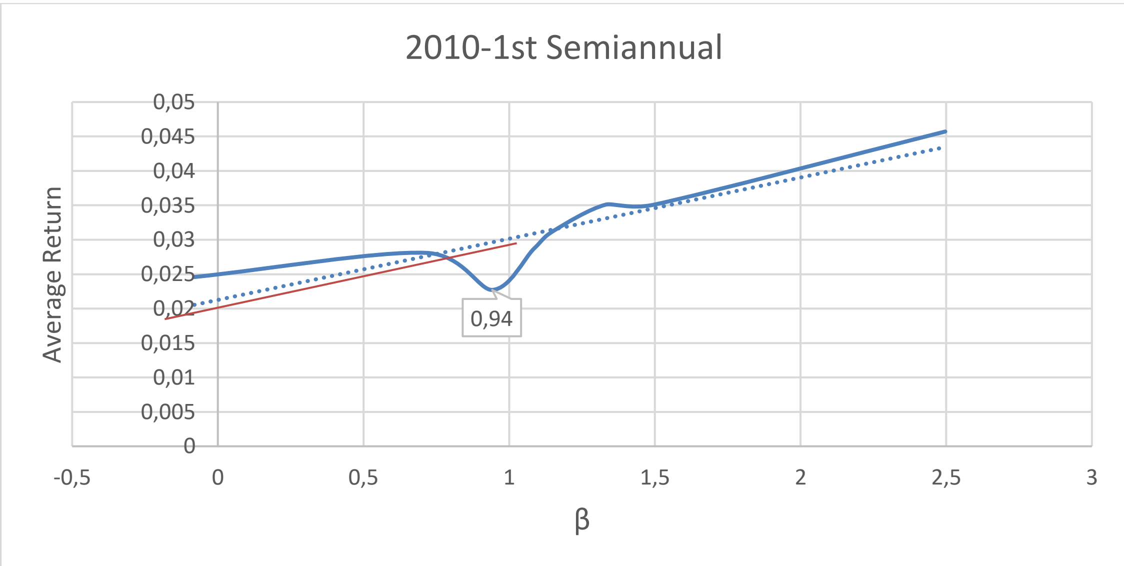

Figure 22: 2010-1st Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2010-2nd semiannual is shown in Figure 23. The rate of return decreases as the beta value increases up to β = 0.37. The same situation is also observed between the values of β = 0.55 and β = 0.70 and β = 0,88 and β = 1.17. In this case, there is a beta anomaly among these values. Beta anomaly disappears after β = 1.17.

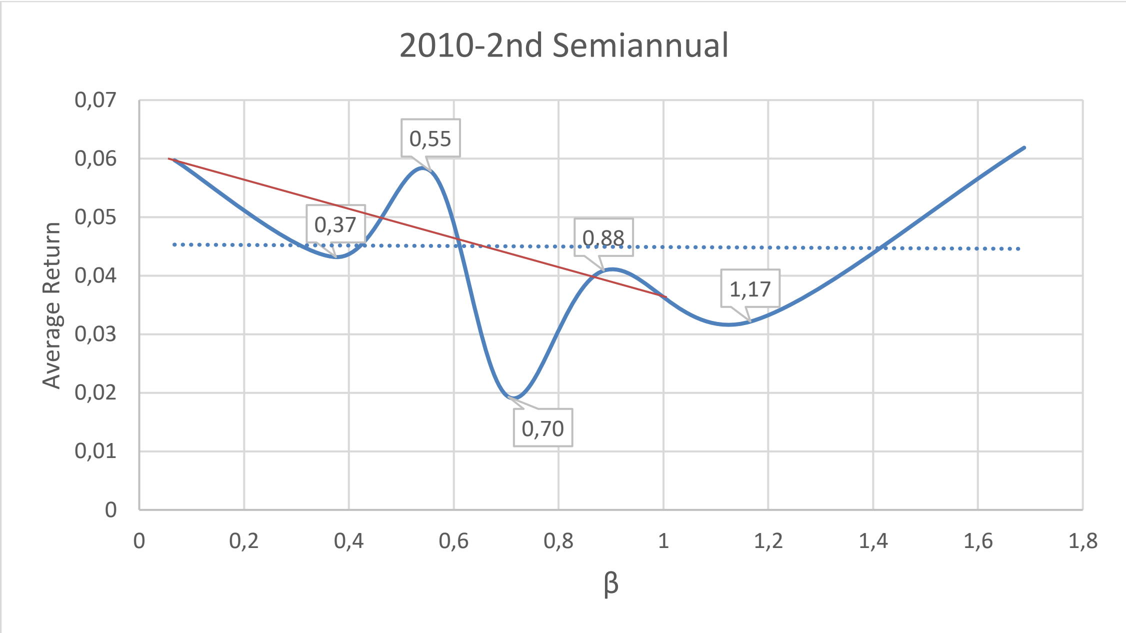

Figure 23: 2010-2nd Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2011-1st semiannual is shown in Figure 24. The rate of return decreases as the beta value increases up to β = 0.50. The same situation is also observed between the values of β = 0.88 and β = 1.13. In this case, there is a beta anomaly among these values. Beta anomaly disappears after β = 1.13.

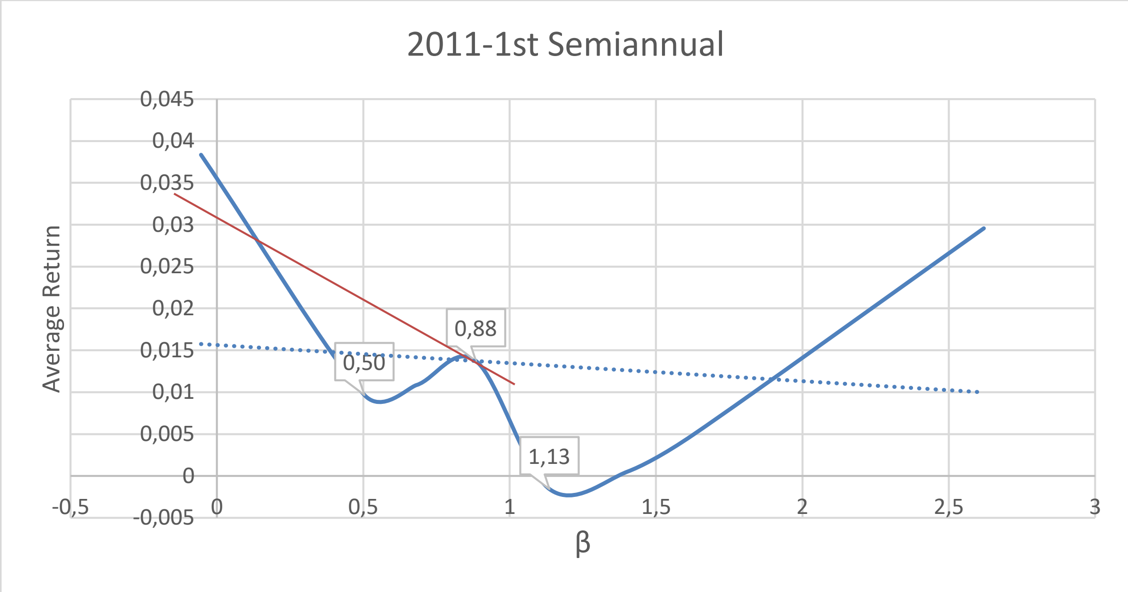

Figure 24: 2011-1st Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2011-2nd semiannual is shown in Figure 25. This period has a different structure in itself. Because the returns within the period have a negative value. The rate of return decreases as the beta value increases up to β = 0.45 - β = 0.64. The same situation is also observed between the values of β = 1.06 and β = 1.44. In this case, there is a beta anomaly among these values. Considering the available data, it can be said that Beta anomaly disappears after β = 1.44.

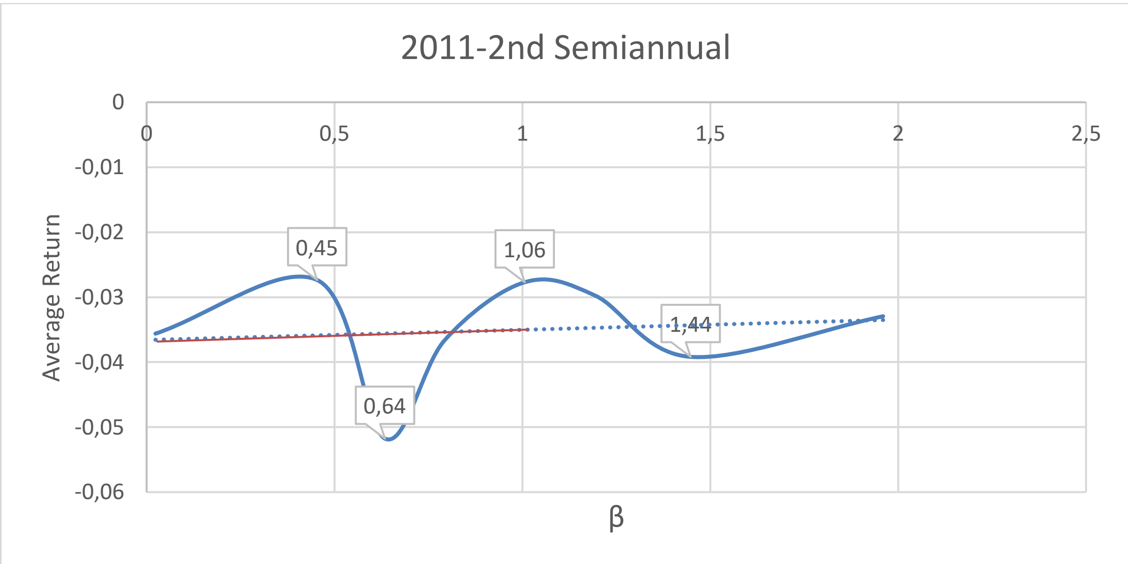

Figure 25: 2011-2nd Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2012-1st semiannual is shown in Figure 26. In this period, there are minimal fluctuations between β = 0.58 - β = 1.40 in terms of return-risk in general terms. However, this situation may not be accepted as a strong indicator of a benign anomaly. After β = 1.40, while the return increases, the beta value also increases. In this case, beta anomaly has disappeared.

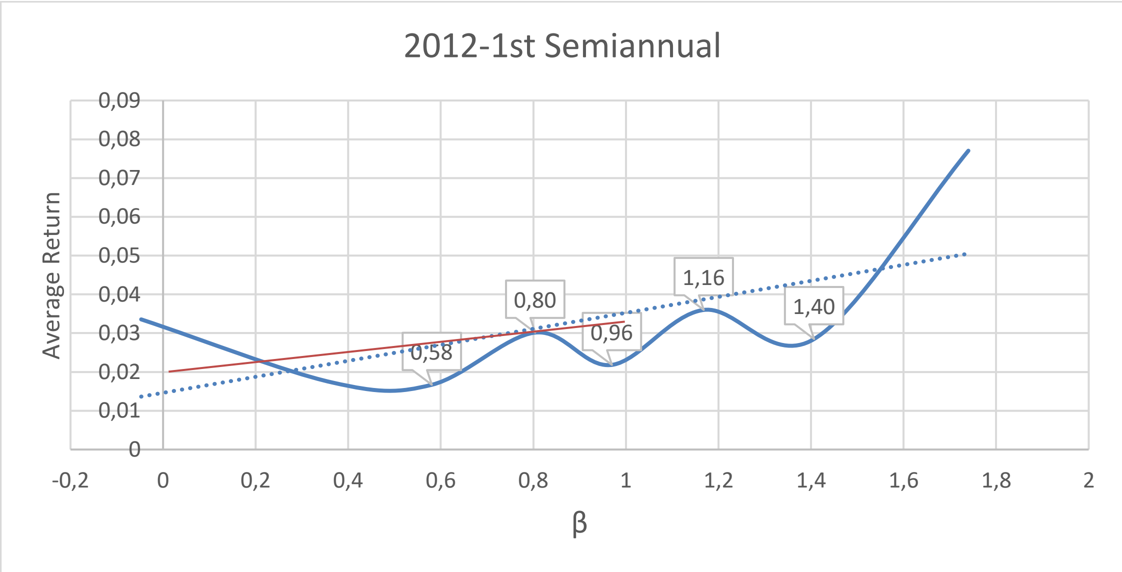

Figure 26: 2012-1st Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2012-2nd semiannual is shown in Figure 27. The rate of return decreases as the beta value increases up to β = -0,27. Also, the same situation is observed β = 0.11- β = 0.31 and β = 0.87 - β = 1.30. In this case, there is a beta anomaly among these values.

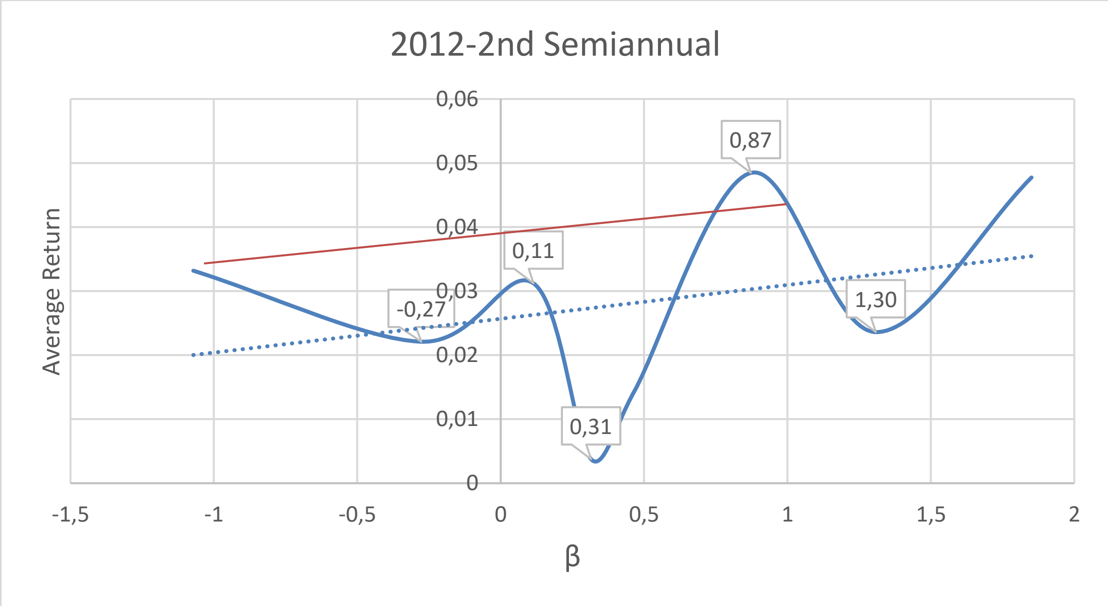

Figure 27: 2012-2nd Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2013-1st semiannual can be seen in Figure 28. Up to β = 0.74, the rate of return generally decreases as the beta value increases. In this case, there is a beta anomaly up to this degree. After β = 0.74, as the beta value increases, the rate of return increases. The rate of return increasing to β = 1.16 follows a horizontal course after this value. As a result, beta anomaly disappears.

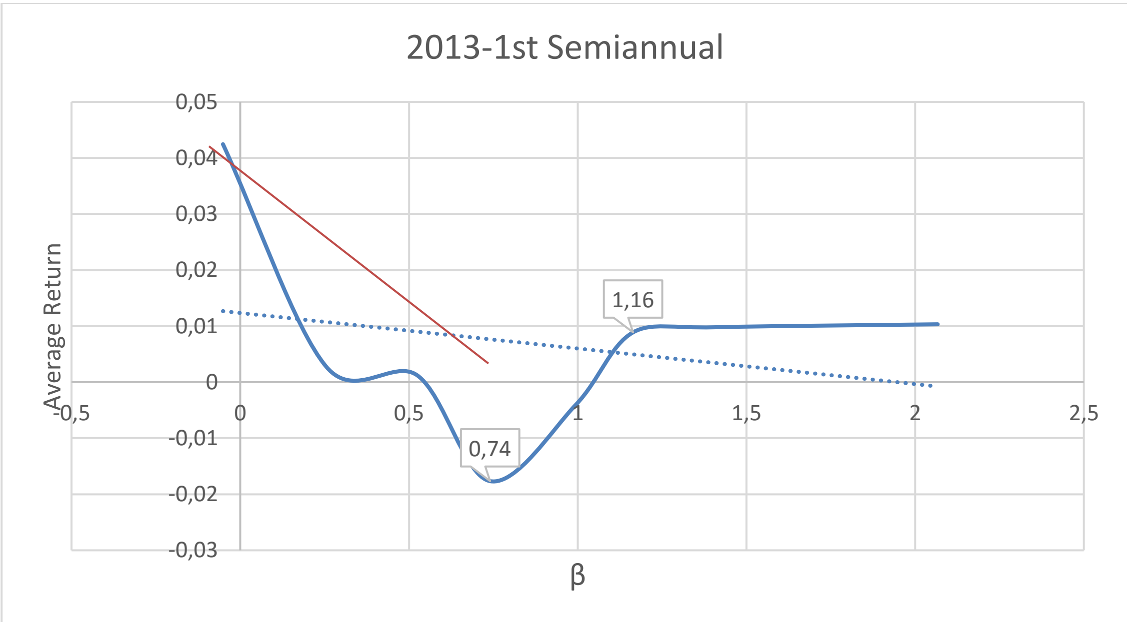

Figure 28: 2013-1st Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2013-2nd semiannual is shown in Figure 29. As can be seen from the figure, while beta value increases until get β = 1.00, the rate of return decreases. A similar situation is observed between β = 1.30 and β = 1.60. As the risk increases, the decrease in the rate of return reveals the existence of a beta anomaly.

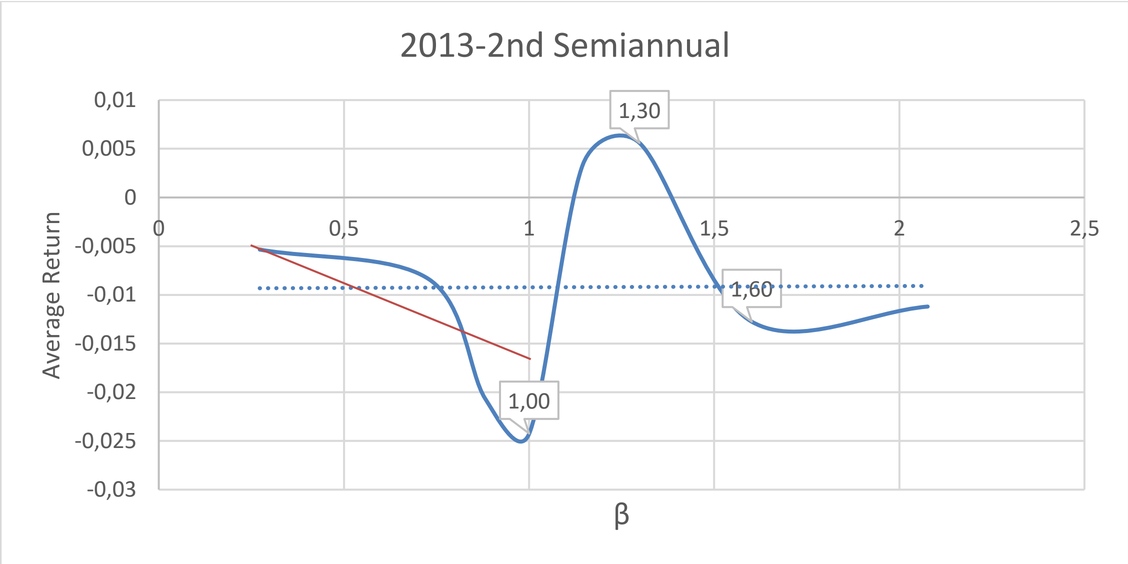

Figure 29: 2013-2nd Semiannual Beta - Return Monthly Change

The graph of return and beta value for 2014 1st Semiannual is shown in Figure 30. The rate of return increases as the beta value increases up to β = 0.03. Also, the same situation is observed between the values of β = 0.63 and β = 0.88. On the other hand, while beta increases between β = 0.03 and β = 0.88, the return is decreasing. In this case, there is a beta anomaly among these values. Beta anomaly disappears after β = 0.88

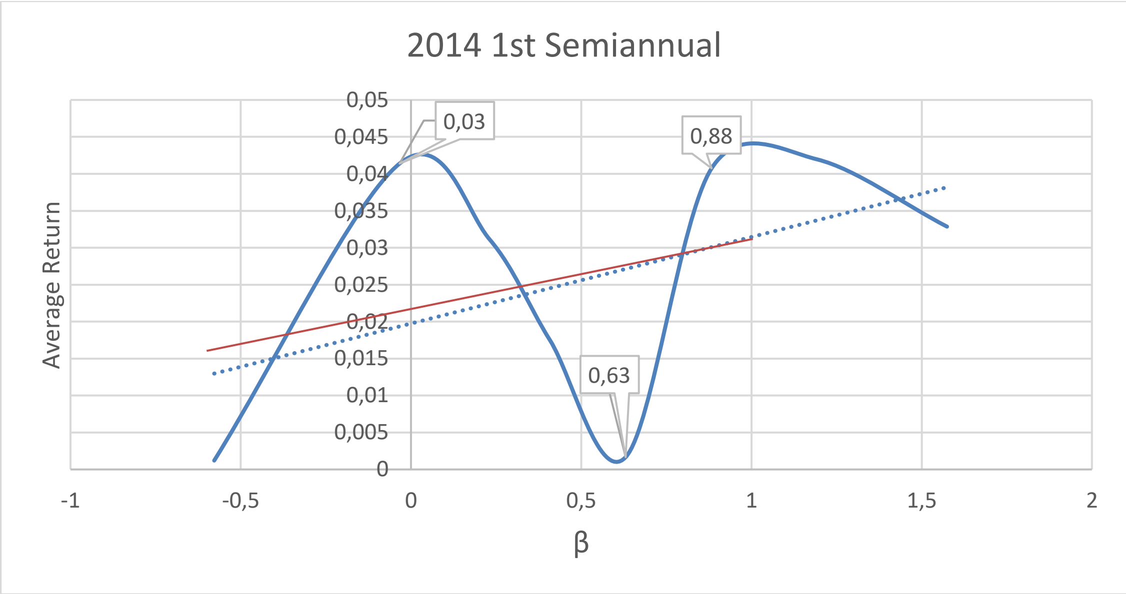

Figure 30: 2014-1st Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2014-2nd semiannual is shown in Figure 31. The rate of return decreases as the beta value increases up to β = 0,47. Also, the same situation is observed β = 0.81- β = 0.99. In this case, there is a beta anomaly among these values.

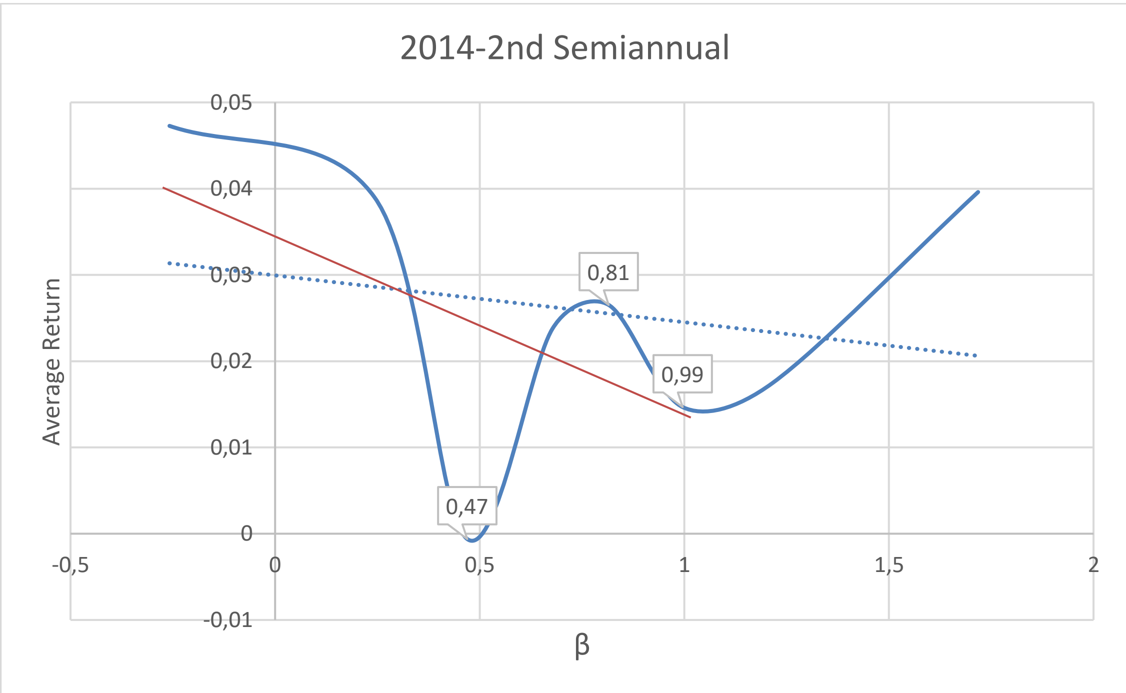

Figure 31: 2014-2nd Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2015-1st semiannual is shown in Figure 32. The rate of return decreases as the beta value increases up to β = -0,07. Also, the same situation is observed β = 0.54- β = 0.80 and β = 1,53 - β = 1.92. In this case, there is a beta anomaly among these values. Beta anomaly disappears after β = 1.92.

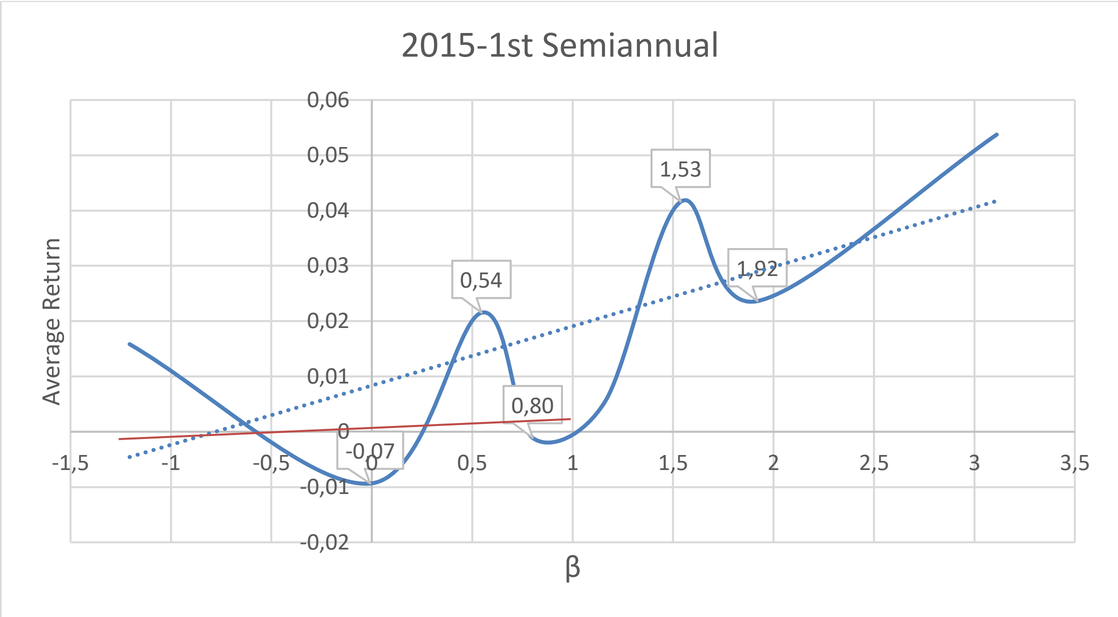

Figure 32: 2015-1st Semiannual Beta - Return Monthly Change

The graph of return and beta value for 2015 - 2nd Semiannual is shown in Figure 33. Although there is a partial difference between β = 0.42 - β = 0.62, the rate of return decreases as the risk increases until β = 1.05. This situation is an indication of the presence of beta anomalies.

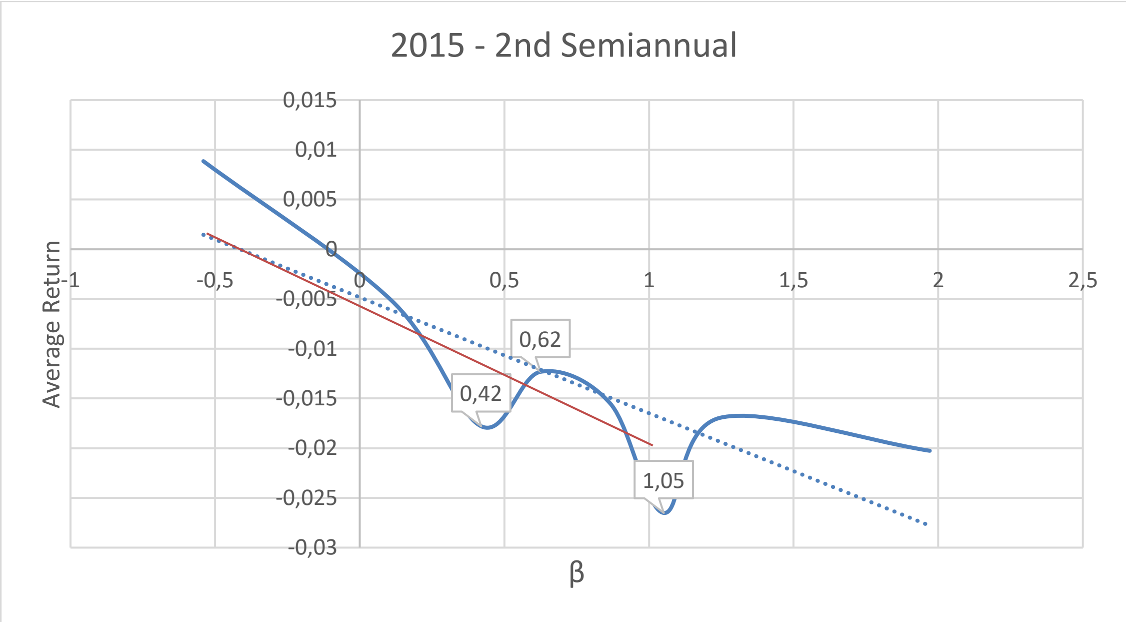

Figure 33: 2015-2nd Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2016-1st semiannual can be seen in Figure 34. Up to β = 0.70 the rate of return generally decreases as the beta value increases. In this case, there is a beta anomaly up to this degree. After β = 0,70, as the beta value increases, the rate of return increases. As a result, beta anomaly disappears.

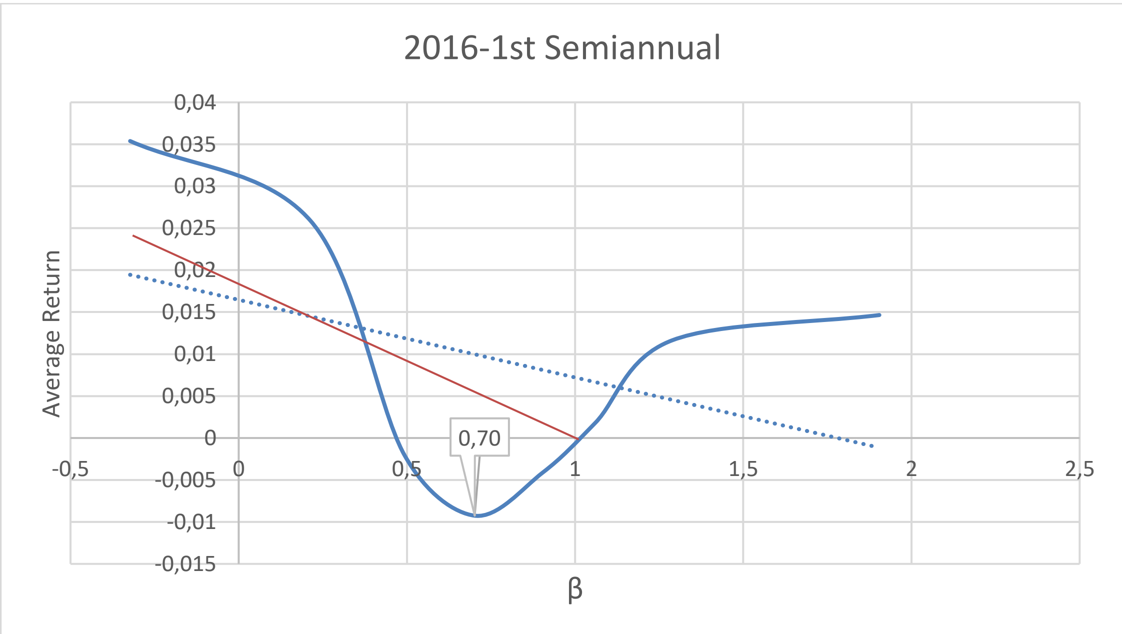

Figure 34: 2016-1st Semiannual Beta - Return Monthly Change

The graph of return and beta value for 2016 - 2nd Semiannual is shown in Figure 35. The rate of return displayed a partial horizontal trend up to β = 1.26. On the other hand, while beta value increased between β = 1.26 and 1.56, the rate of return displayed a decreasing trend. This situation indicates the presence of a beta anomaly. This situation disappears after the value of = 1.56.

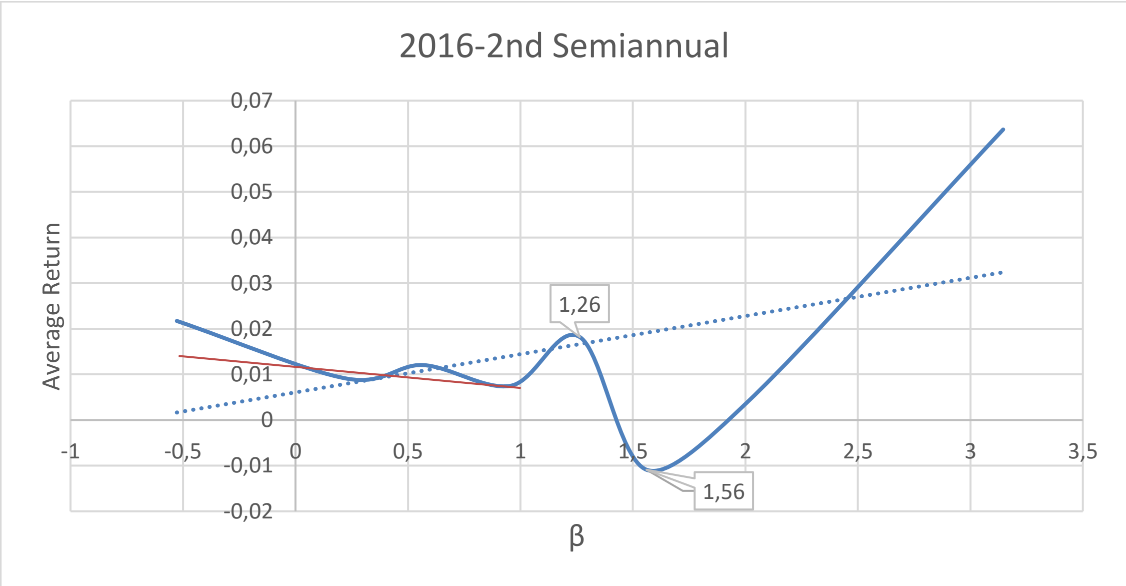

Figure 35: 2016-2nd Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2017-1st semiannual is shown in Figure 36. The rate of return decreases as the beta value increases up to β = 0,59. Also, the same situation is observed β = 1,07- β = 1,48. In this case, there is a beta anomaly among these values. This situation disappears after the value of = 1,48.

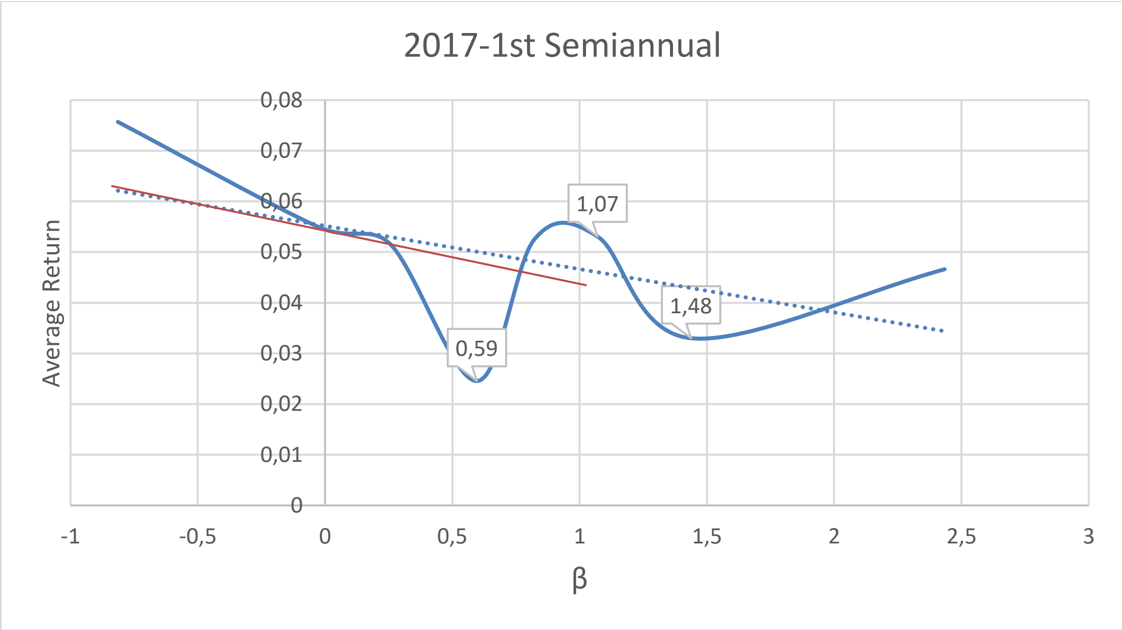

Figure 36: 2017-1st Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2017-2nd semiannual can be seen in Figure 37. Up to β = 1.61 the rate of return generally decreases as the beta value increases. In this case, there is a partial beta anomaly up to this value. After β = 1,61 as the beta value increases, the rate of return increases. As a result, beta anomaly disappears.

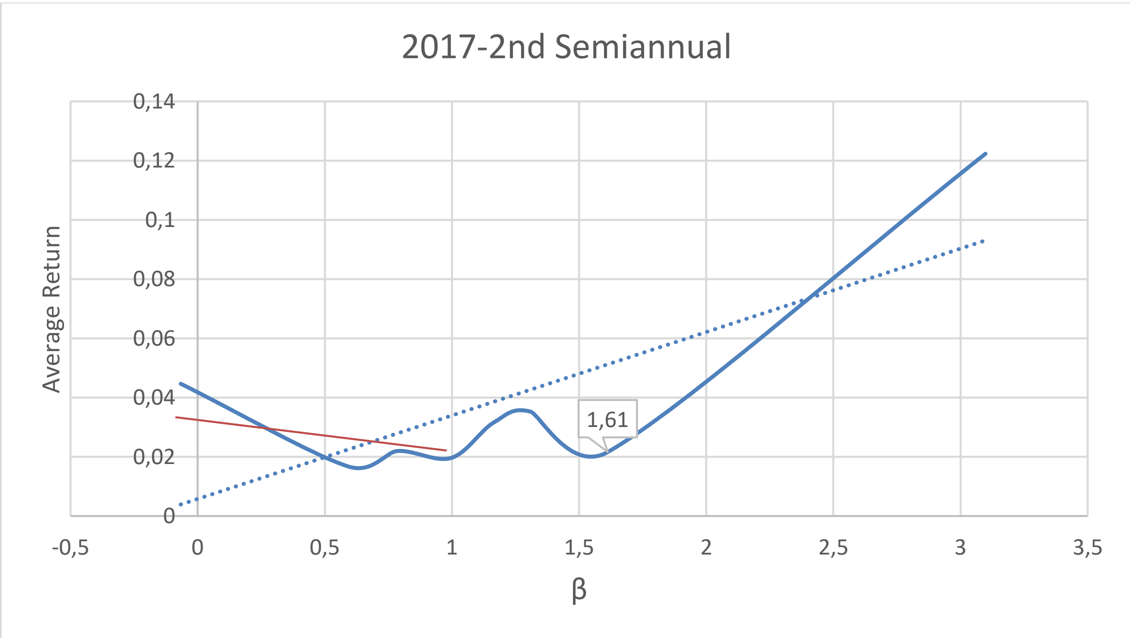

Figure 37: 2017-2nd Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2018-1st semiannual can be seen in Figure 38. This period has a similar trend in the 2017-2nd period. Up to β = 1.32 the rate of return generally decreases as the beta value increases. In this case, there is a beta anomaly up to this value. After β = 1,32 as the beta value increases, the rate of return increases. As a result, beta anomaly disappears.

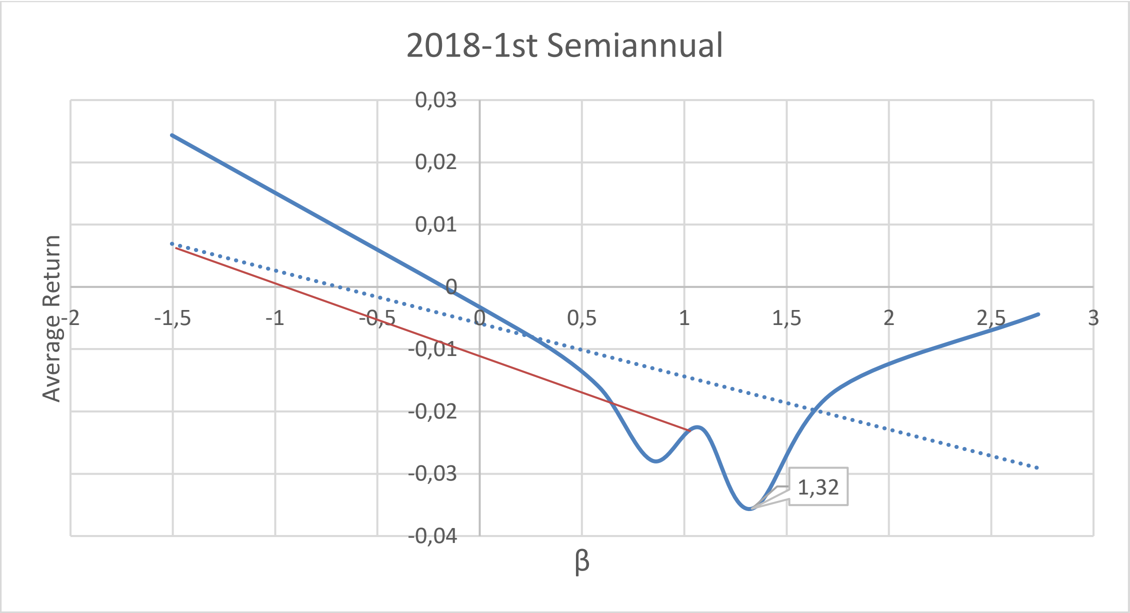

Figure 38: 2018-1st Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2018-2nd semiannual can be seen in Figure 39. Up to β = 0.91 the rate of return generally decreases as the beta value increases. In this case, there is a partial beta anomaly up to this value. After β = 0,91 as the beta value increases, the rate of return increases. As a result, beta anomaly disappears.

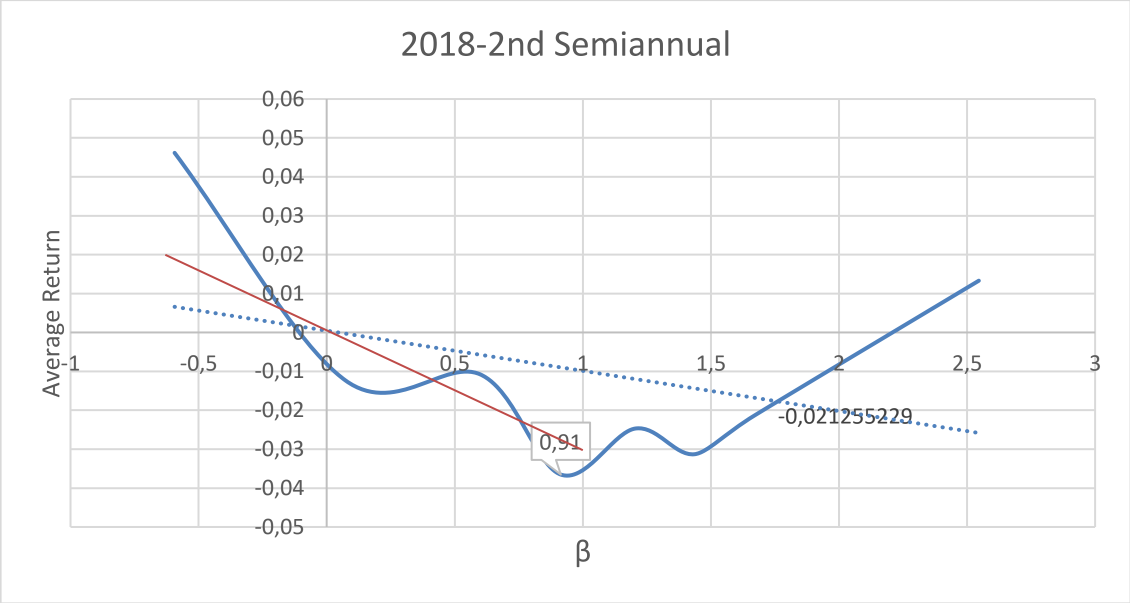

Figure 39: 2018-2nd Semiannual Beta - Return Monthly Change

The graph of return and beta value for 2019-1st Semiannual is shown in Figure 40. As can be seen from the figure, there is a general decrease in the rate of return up to β = 0.48. From this value to β = 0.71, while the risk increases, there is also an increase in return. On the other hand, while the risk decreases between β = 0.71 and β = 1.05, there is an increase in the rate of return. This situation can be considered as an indicator of beta anomaly. After this value, while the risk increases, the return tends to increase. In this case, beta anomaly disappears after this value.

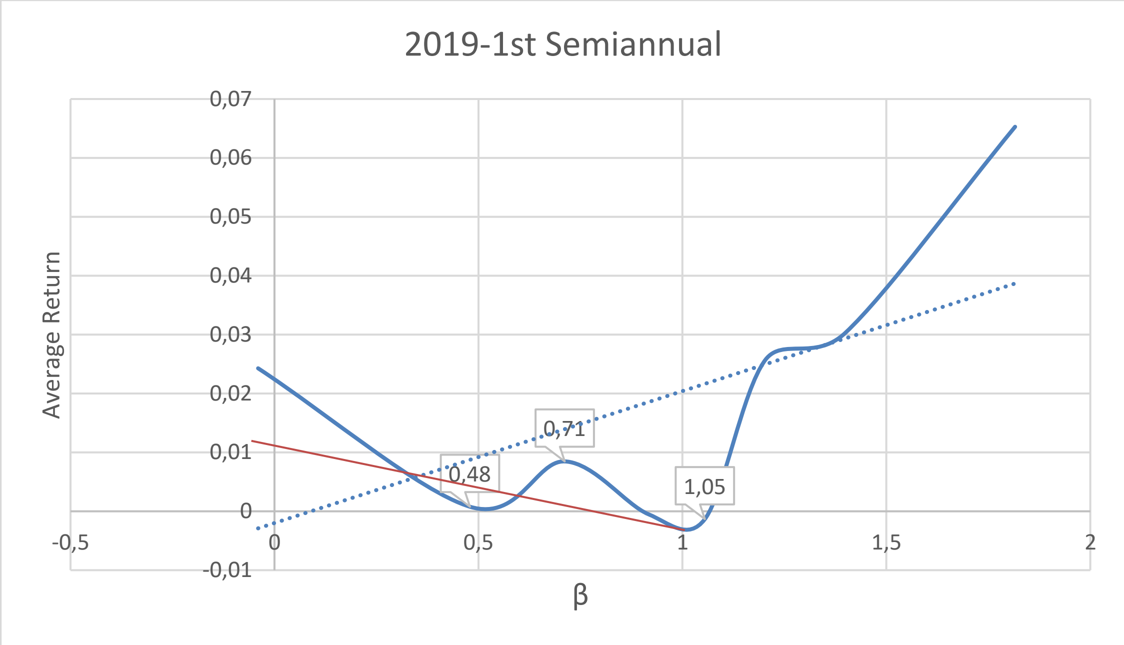

Figure 40: 2019-1st Semiannual Beta - Return Monthly Change

The graph of return and beta value for the years 2019-2nd semiannual is shown in Figure 41. In general, it can be said that the return decreases in a partial sense until β = 0.87, and the rate of return increases after this value. However, it is seen that these increases and decreases remain quite limited. In this case, it is not possible to talk about a beta anomaly.

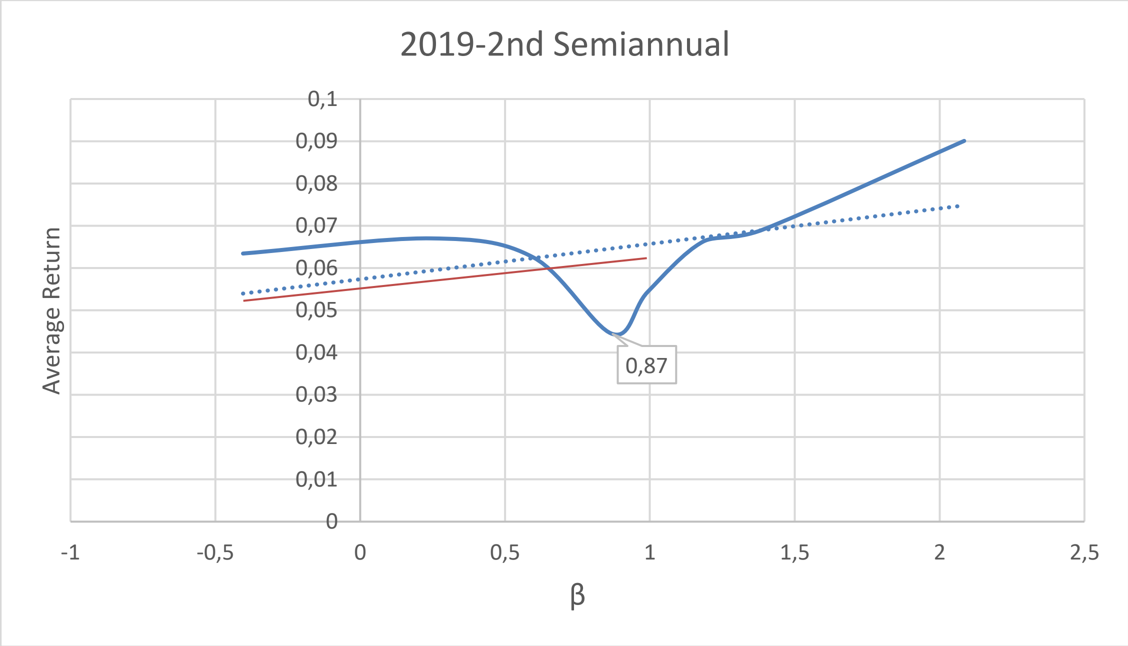

Figure 41: 2019-2nd Semiannual Beta - Return Monthly Change

The results obtained reveal that the semiannual periods between 2010 and 2019 generally have beta anomalies at low-risk values. This shows that these periods are typical for short term investments.

CHAPTER III

CONCLUSION

It is not an expected situation that the performances of stocks in the previous periods will continue this performance in the future periods. It can also be an effective basis for speculating about the performance of stocks for future periods in the long run. It is a more rational way to choose between return and risk when making investment choices. Choosing high-return and low-risk stocks while investing can contribute to the accuracy of the investment. Generally speaking, high-yielding stocks tend to have a higher risk. However, it may be better to choose stocks with high risk but low return.

Stock types are quite high. Accordingly, their returns and risks also vary. A person who wants to earn a high profit accepts the high risk by investing in the stocks of companies with high liquidity rates. However, these risks can of course be reduced when the variables are controlled.

The rise and fall in the value of securities varies depending on the performance of both the market and the companies. Market risk is a broad concept and also known as unsystematic risk. Although investors keep their portfolios diverse to avoid losses, market risk is more dominant. This is because prices change due to multiple factors.

Systematic risk is another risk which affects the conduct of stocks. The performance of the company directly affects the value of the shares in the market. The risks here are largely avoided by diversifying the portfolio. Beta coefficients showing the market price balance are utilized in order to balance these two elements and avoid losses.

Risk can be described as the ambiguity in the capital markets. Market participants willing to increase risk appetite as they see an alpha. Basically, in financial markets, it is the situation where high returns are expected in response to high systematic risk. The fact that large-risky share returns are lower the returns of the small-risk shares is considered as a financial anomaly. This situation is called as low volatility anomaly or beta anomaly in financial literature. In this study, it was investigated whether there was a low volatility anomaly in BIST 100 between 2010-2019.

Within the scope of the study, the presence of beta anomaly was considered for semiannual, 1, 2, 5 and 10 years periods. The results obtained show that there is a beta anomaly within a certain beta value range in each period examined. In other words, it is seen in almost all graphs that as beta value of the portfolio increases, the average portfolio return.

Within the scope of the study, the period 2010-2013 and the period 2014-2019 were considered separately. In the period of 2010-2013, the existence of an anomaly up to a certain risk value is observed in general, after the said risk value, this anomaly disappears. In other words, the higher the risk, the higher the return. On the other hand, in the period of 2014-2019, there is a sweat relationship between return and risk in general. This situation indicates the presence of beta anomaly. This situation shows that the economy had a very fragile structure during this period. In addition, it can be stated that investors avoid risk during these periods.

It is observed that beta anomaly is generally encountered in lower beta values within semiannual. Especially in beta values one or more than one, beta anomaly disappears. This situation reveals that investors can obtain high returns at high risks in the short term. In lower risk values, the increase in risk does not cause an increase in return. In this case, it can be concluded that greater returns can be obtained with higher risks in short-term investments.

The periods discussed in the study can be considered as short and long terms. As a matter of fact, semiannual, annual and 3-year reviews are considered as short-term reviews, while 5 and 10-year reviews are considered long-term. In this case, it is seen that beta anomaly generally does not occur when the beta value is 1 and above by the short term scenario. When looking long term, this situation is not exactly similar. As a matter of fact, the return decreases when the beta value increases too much in the long term. In this case, it can be demonstrated that very low and very high beta values reduce the rate of return in the long run, and therefore beta anomaly occurs.

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İş Yatırım Menkul Değerler A.Ş Equity Prop Trader	2018-2019
İstanbul Portföy Yönetimi A.Ş Associate Fund Manager	2016-2018