GALATASARAY UNIVERSITY
INSTITUTE OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS

THE ROLE OF INVESTOR SENTIMENT IN RISK-RETURN TRADEOFF: TURKISH STOCK MARKET

MASTER'S THESIS

Can Boran AKDAL

Supervisor: Assoc. Prof. Bilge ÖZTÜRK GÖKTUNA

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ABBREVIATIONS

AAII	American Association of Individual Investor
ANOVA	Analysis of variance
BIST	Istanbul Stock Exchange
CBOE	Chicago Board Options Exchange
CBRT	Central Bank of the Republic of Turkey
CCI	Consumer Confidence Index
CDS	Credit Default Swap
CEFD	Closed-End Fund Discount
CMB	Capital Markets Board of Turkey
CSD	Central Securities Depository of Turkey
e.g.	*exempli gratia*
EMH	Efficient Market Hypothesis
Eq.	Equation
et. al.	*et alia*
etc.	*et cetera*
FSI	Financial Stress Index
i.e.	*id est*
Fig.	Figure
KMO	Kaiser-Meyer-Olkin
MCSI	Michigan Consumer Sentiment Index
NYSE	New York Stock Exchange
PCA	Principal Component Analysis
PLS	Partial Least Squares
RISE	Risk Appetite Index
RSCI	Real Sector Confidence Index

S&P	Standard & Poor's
TCMA	Turkish Capital Markets Association
TED	Treasury-Eurodollar
TURKSTAT	Turkish Statistical Institute
SVI	Search Volume Index
VECM	Vector Error-Correction Model
VIX	Volatility Index

LIST OF SYMBOLS

ACC	Number of investment accounts
α	Regression constant
ß	Regression coefficient
*BIST*100	BIST-100 index price
c	Change ratio
ce	Error-correction term
CCI_T	Consumer confidence index of Turkish Statistical Institute
CCI_HT	Consumer confidence index of Bloomberg HT
d	Differance
EXC	Exchange rate
FOR	Ratio of net foreign stock purchases to market capitalization
ITD	Investment trust discount
NIPO	Number of initial public offerings
R	Return
RIPO	Average first-day return of initial public offerings
RISK	Proxy for the overall market risk
SENT	Investor sentiment index
SHARE	Equity share in new issues
TRAD	Trading volume
TURN	Share turnover
u	Error term

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ABSTRACT

We take side with researchers of behavioral finance and aim to confirm its postulates by providing a humble effort in order to explain the excess stock market returns with investor sentiment. Risk-return tradeoff is established considering the premises of the efficient market hypothesis, where rational investors have the same level of risk perception and the amount of risk they bear is compensated with an equivalent raise in expected returns. However, this relationship is violated repeatedly through a history full of bubbles and market crashes. In order to explain such anomalies in this regard, scholars have also used behavioral approaches. Investor sentiment is one possible interpretation of the consistent mispricing. Following relevant literature, we build an investor sentiment index to observe its power of predictability in the Turkish stock market. We use this index in the risk-return setting expecting to describe what the risk fails to explain.

Probably the most crucial and frequently asked questions in finance are those related to asset valuation. Reducing the complexity by the elimination of area-specific matters, the most difficult question converges to "How to determine the fundamental value of a financial asset in order to exploit under- and overvaluations?". Moving forward, it comes down to "How to gain utility?" and eventually to "How can I be satisfied?". Taking from here, we put focus on the subjectivity. Even while asking financial questions, one cannot depart from their self; therefore, relying on fallacious assumptions like the rational man hypothesis leads us to not-so-accurate results describing financial behavior. Each individual is different in their aims, needs, values, intellectual and cognitive abilities, but what is common with them is that they are all prone to systematic errors in their financial judgments. This is a widely discussed topic in behavioral finance, where the inclusion of behavioral elements is argued to enhance the explanation and forecasting capability of risks.

Historically, the assumption of rationality has overshadowed the role of investor psychology in financial research even though prominent scholars of the area have warned against its omission. Through the incorporation of behavioral psychology into finance, a significant progress towards a more realistic understanding is observed. We follow the line of thought originating from the descriptive analysis of individuals (Kahneman and Tversky, 1979) and of stock market traders as well. Black (1986) claims that noise (irrationality) is inherent to financial markets and sews market inefficiency. Fluctuations due to noise traders, who are essentially sentiment-driven traders, are traditionally claimed to be exploited by arbitrageurs, so the prices converge to their fundamental values. De Long *et al.* (1990) oppose this idea and claim that the mispricing can be persistent as a result of limits-to-arbitrage.

The mispricing impairs the risk-return balance, hence it implies the need to explain excess returns. The concept of investor sentiment stems from this necessity. It cannot be directly observed or measured, so is proxied by various variables. Baker and Wurgler (2006) use six of them to build a composite investor sentiment index and find out that the sentiment affects the cross-section of returns. Even if the full disclosure on investor sentiment has not been made yet, most of the researchers link high investor sentiment to low returns. A large portion of related literature is on cross-section of returns, but it is also shown that sentiment affects the market as a whole. Of course, small and volatile stocks are facing a higher risk of mispricing. In the same fashion, markets with higher volatility are prone to the detrimental effects of high and low sentiment periods.

Our framework consists of BIST-100 returns, RISE index as an overall market risk, and the investor sentiment proxies or their composition as an index. In the asset pricing models of finance, risk-return relationship is analyzed by relating the market risk premium and a stock-specific risk sensitivity to the expected return of stocks. As we study the market returns, a market-wide risk factor is necessary. Market risk premium is strongly correlated to the overall market risk, which can also be proxied by the option implied volatility. We use the RISE index, which is an implied volatility derived from options, to refer to overall market risk. Deemed as the Turkish version of VIX, RISE is also called the risk appetite index. There are different versions of RISE available, and we chose the one that refers to the qualified investors since it provided the best fit to the theory and our expectations.

For the proxies we use, we first consider Baker and Wurgler (2006) and include closed-end fund discount rate (CEFD), share turnover (TURN), number of initial public offerings (IPO), average first-day return of IPOs (RIPO), and equity share in new issues (SHARE). Since the closed-end funds are not traded in Turkey, we use the investment trust discount (ITD) for the same purpose (Canbaş and Kandır, 2007). We also considered the change in the trading volume (TRAD), exchange rate (EXC), number of investment accounts (ACC), and the ratio of net foreign stock buys to market capitalization (FOR).

Those above are indirect measures of investor sentiment, which are aimed to measure some other effects. There are also direct measures that use surveys and questionnaires that aims to measure investors' and consumers' sentiment. Consumer confidence indices (CCI) are widely researched in their relation to stock or market returns. There are also abundant number of researches concerning its power to proxy investor sentiment. It is obvious that it reflects some form of sentiment, but in countries where consumers are not frequent participants of the stock market, using CCI as a barometer to measure investor sentiment may be a useless try. However, there are many factors including the culture or the development level of the stock market, which may increase the possibility that CCI levels may reflect investor sentiment. This very much depends on the context. Further clarification is needed to determine its country-specific effect. That is the reason why we also use CCI as a direct proxy, but later also as an indirect proxy beside others.

We perform linear regression analyses to investigate the effect of investor sentiment and use the risk factor as a control variable. For our variables to be used in regression, they have to have some properties, which should be in parallel to assumptions of linear regression. First of all, they must not have a unit root, i.e. we should secure that the variables are stationary. Data should be continuous and observations should be independent, variables should not be closely correlated, significant outliers in the data poses a risk, so it is best to avoid using such data. Even though there should not be multicollinearity between variables, they should also possess a linear relationship. Lastly, for the pre-estimation, variables should be free from heteroscedasticity. For our investor sentiment index, we also check for the Kaiser-Meyer-Olkin test and Bartlett's test of sphericity. Lastly, the residuals from linear regressions should be normally distributed. Despite having acceptable test results, the composite indices did not perform very well. However the regressions with their constituents could provide expected results.

We analyzed the data to check if it suffers from the abovementioned issues. We eliminated the ones that could not pass the test and used the following proxies for the rest: Difference of ITD, ACC, EXC, difference of CCI, change in TRAD, and FOR. Using these variables we performed regression analyses with various settings. Inclusion of one variable could lead to make another insignificant, or vice versa. We determined the best sentiment proxies to describe part of the excess return, the return that is not coming from the risk as described by the traditional finance.

The raw prices of indices usually contain unit roots, i.e. they usually have trend. For the detrending, log returns of prices is used in general, but we decided to stay with the plain difference, since it provided us a clean return series. Another way to get rid of the issues and prepare the data for future analysis is to detrend them, which is basically taking the difference of a variable.

For the values that are stationary only in their difference, cointegration tests may be applied. We know that the raw prices are usually moving with a direction. We used Johansen cointegration and by using the vector error correction model (VECM) we came up with the error correction term. This term could be perceived as the stationary parts of the problematic variables combined, so we used it in regressions to test if it works as a sentiment index.

To sum up, we have used various proxies to determine the contribution of investor sentiment to the risk-return tradeoff. With the help of VECM, the sentiment is proven to be effective on returns when proxied by the combination of seven variables we have proposed. The enhancement in explainability of returns with the addition of investor sentiment index is 5%, and it raises to 37% when its constituent proxies are put into regresion individually. The results show that a proper configuration of proxies help explain the excess return.

Our contributions to the literature are as follows: Instead of relating the investor sentiment directly to market returns as conventionally done, we analyzed its effect in the context of risk-return tradeoff by proxying the risk factor. Besides widely used measures of sentiment to analyze BIST-100, we also considered the seldom used ‘number of investment accounts’ as a sentiment proxy. For the best of our knowledge, its effect on returns has not been confirmed for the Turkish stock market before. Lastly, we made our contribution to the ongoing debate on the sentiment-return relation. Investor sentiment is a negative return predictor and CCI can only be considered as a proxy in combination with other proxies when analyzing the BIST-100 index returns.

Drawbacks of this study include the lack of a robustness test. As there are no direct or indirect measures of investors’ sentiment that have found common acceptance in the literature, the significance of our results cannot be compared to a rigid proxy. Another problem is the potential lack of including important proxies for sentiment. This is partly due to unavailability of data for our sample period, but mostly due to the lack of finding good-quality data.

RÉSUMÉ

Nous prenons le parti des chercheurs de la finance comportementale et notre but est de confirmer ses postulats par procurant un effort modeste afin d'expliquer la bourse excessive qui rembourse avec sentiment de l'investisseur. Compromis du risque-rendement est établi en considérant les prémisses d'une hypothèse d'efficience du marché, où des investisseurs rationnels a le même niveau de risque perception et le montant de risque, qu'ils supportent, est compensé avec une augmentation équivalente dans rendement attendu. Cependant, la relation est violée à plusieurs reprises à travers une histoire qui est remplie par plein des bulles et d'effondrement du marché. Afin d'expliquer tels anomalies dans ce point de vue, savants aussi utilisaient approche comportementale. Sentiment de l'investisseur est des interprétations possibles de l'erreur incessante de l'évaluation inexacte du prix. Suivant littérature pertinente, nous construisons un index du sentiment de l'investisseur pour observer son pouvoir de prévisibilité dans la bourse excessive turque. Nous utilisons cet index dans l'établissement attendu du risque-rendement pour décrire ce que le risque omet d'expliquer.

Probablement, les questions les plus cruciales et fréquemment posées dans finance sont celles qui sont rapportées à l'estimation des actifs. Diminuant la complexité par l'élimination des matières du domaine particulier. Le plus difficile question converge à 'Comment l'on détermine la valeur fondamentale des actifs financiers afin d'exploiter sous-surévaluation?' En avançant, cela réduit à "Comment l'on gagne utilité?" et finalement à "Comment puis-je être satisfait?" Prenant d'ici, nous mettons accent sur la subjectivité. Même, en posant des questions financières, on ne peut pas quitter de leur soi, alors, comptant sur supposition fallacieuse comme hypothèse d'homme rationnel nous dirige vers des résultats pas-très-précis qui décrivent comportement financier. Chaque individu est différent dans leur buts, besoins, valeurs, capacités intellectuelles et cognitives, mais ce qui est commun avec eux est qu'ils sont tous sujettes aux erreurs systématiques dans leurs jugements financiers. Il s'agit d'un sujet qui est largement discuté dans finance comportementale où l'inclusion des elementes est débattue pour améliorer l'explication et la capacité de prévoir des risques.

Historiquement, la supposition de rationalité éclipsait le rôle de la psychologie des investisseurs dans recherche financière, même si savants principaux du domaine étaient avertis contre sa négligence. À travers l'incorporation de la psychologie comportementale en finance, un progrès significatif vers plus réalistique compréhension est observée. Nous suivons le raisonnement, provenant de l'analyse descriptive des individus et également des boursiers (Kahneman et Tversky, 1979). Black (1986) affirme que l''hasard (irrationnel) est inhérente aux marchés financiers

et il coud inefficacité du marché. Fluctuation, en raison des agissant au hasard, qui sont essentiellement conduits par le sentiment, sont traditionnellement allégués d'être exploités par arbitragistes, donc les prix convergent à leurs valeurs fondamentales. De Long et al. (1990) opposent cette pensée et réclamation que l'évaluation inexacte du prix peut être persistant en tant qu'un résultat de limites à l'arbitrage. L'évaluation inexacte du prix nuit à l'équilibre du risque-rendement, cela implique désormais le besoin d'expliquer des remboursements excessifs. Le concept de sentiment de l'investisseur découle de cette nécessité. Cela ne peut pas être directement observé ou mesuré, donc est calculé approximativement par variable divers. Baker et Wurgler utilise six d'eux pour construire un index composite du sentiment de l'investisseur et pour découvrir que le sentiment affecte section transversale de remboursement.

Notre cadre consiste des rendements BIST-100, index RISE en tant qu'un risque global du marché et des représentation du sentiment de l'investisseur ou leur composition en tant qu'un index. Dans l'évaluation des modèles financiers des actifs, la relation du risque-rendement est analysé en liant la prime de risque du marché et une sensitivité de risque spécifique de réserve au rendement attendu des réserves. Comme nous étudions rendement du marché, une facteur de risque de l'échelon du marché est nécessaire. La prime de risque du marché est fortement corrélée au risque global du marché, qui peut aussi être relayé par l'option impliquée de volatilité. Nous utilisons l'index RISE qu'est une volatilité impliquée dérivée des options pour référer au risque du marché. Cela est présumé que RISE en tant que version turque de VIX est aussi appelée l'index de propension au risque.

Pour les représentations que nous utilisons, nous d'abord considérons Baker et Wurgler (2006) et incluons taux réduit de fond fermé (CEFD), roulement d'actions (TURN), nombre d'offre publique initiale (IPO), premier jour remboursement moyenne d'IPOS (RIPO) et l'action participative dans nouvelles émissions (SHARE). Comme fonds fermés n'est pas échangés en Turquie, Nous utilisons, taux réduit de confiance de l'investissement pour le même objectif (Canbaş et Kandır, 2007). Nous avons aussi considérés le change dans le volume d'échanger (TRAD), taux d'échange (EXC), nombre des comptes des investisseurs (ACC) et le ratio de l'achat d'action net des affaires étrangères à la capitalisation de marché (FOR).

Ceux ci-dessus sont des mesures indirectes de sentiment de l'investisseur qui sont objectivés de mesurer quelques autres effets. Il y a aussi des mesures directes que les sondages et les questionnaires utilisent et qu'ils objectivent de mesurer le sentiment de l'investisseur et des consommateurs. L'index de confiance de consommer (CCI) sont largement cherchés dans leur relations à bourse ou à rendement du marché. Il y a aussi nombre abondant des études concernant leur pouvoir de représenter le sentiment de l'investisseur. Cela évident qu'il reflète certaines formes de sentiment, mais dans les pays où consommateurs ne sont pas des participants fréquents de la bourse, d'utiliser CCI en tant qu'un baromètre pour mesurer sentiment de l'investisseur peut être un tentative non utile. Cependant, il y a plusieurs facteurs, y compris la culture ou le niveau de développement de la bourse.qui pourrait augmenter la possibilité que CCI niveaux pourrait refléter le sentiment de l'investisseur. Ce dépend beaucoup du contexte. Il faut que la clarification avancée détermine son pays-spécifique effet. C'est la raison pour laquelle, nous utilisons également CCI en tant qu'une représentation directe, mais aussi en tant qu'une représentation indirecte en dehors des autres.

Nous effectuons des analyses de régression linéaire pour examiner l'effet de sentiment de l'investisseur et utilisons le facteur du risque comme une variable de contrôle. Pour que notre variable soit utilisée dans régression. Ils doivent avoir certaines propriétés, qui doivent être en parallèle aux supposition de régression linéaire Tout d'abord, il faut qu'ils n'aient pas de racine unitaire, c'est-à-dire, nous devons assurer que des variables sont stables. Data doit être permanent et des observations doivent être indépendantes, variables ne doivent pas être étroitement corrélées, aberrations significatives posent le risque, donc c'est le meilleur d'éviter de l'utilisation de tel data. Même si, il ne doit pas y être multicolore entre variables. Ils doivent aussi posséder une relation linéaire. Dernièrement, pour le pré-estimation variable doivent être libre d'hétéroscédasticité. Pour notre index du sentiment de l'investisseur nous également recherchons le test de Kaiser-Meyer-Olkin et le test de sphéricité de Bartlett En conséquence, les résidus des régressions linéaires doivent être normalement distribués Malgré ayant test résultats acceptable, l'index composite n'a pas effectué très bien. Cependant, la régression avec leurs constituants fournit les résultat attendus.

Nous avons examiné le data pour vérifier si c'est souffert des questions susmentionnées. Nous avons éliminé les uns qui ne pouvaient pas passer les test et nous avons utilisé les représentations suivantes pour le reste. Différence de IDD, ACC, EXC, différence de CCI, change dans TRAD. et FOR. En utilisant ces variables, nous avons effectué l'analyse des régressions avec des établissements diverses. Inclusion d'un variable pourrait diriger de faire une autre insignifiante ou vice versa. Nous avons déterminé la meilleure sentiment représentation afin de décrire la partie du remboursement excessif. Le remboursement qui ne vient pas du risque en tant qu'il est décrit par la finance traditionnelle.

Le prix brut d'index contient souvent les racines unitaires, c'est à dire ils ont souvent tendance, pour les décompositions, logarithme du remboursement du prix est utilisé en général, mais nous avons décidé à continuer avec la différence pleine, comme cela nous a fournit une série du remboursement clair. Une autre façon de se débarrasser de la question de préparer data pour l'avenir est de les éliminer qu'est essentiellement prenant la différence d'une variable

Pour les valeurs qui sont stables dans seulement leurs différences, cointégration tests pourraient être appliqués Nous savons que les prix bruts déplacent souvent avec une direction. Nous avons utilisé Johansen cointégration et en utilisant correction modèles du vecteur de l'erreur (VECM). Nous avons trouvé le term d'erreur correction. Ce terme pourrait être perçoit en tant que les parties instables des variables combinées problématiques, donc nous l'avons utilisé dans régression de vérifier si cela marche en tant qu'un sentiment index.

En résumant, nous avions utilisé des représentations diverses pour déterminer la contribution du sentiments des investisseurs au risque rendement À l'aide de

VECM, le sentiment est prouvé d'être effectif sur des remboursements quand il est représenté par la combination de sept variables que nous proposons. L'augmentation dans le pouvoir d'expliquer avec ajout du sentiment de l'investisseur est 5% et elle accroît à 37% quand ses représentations constituantes sont mis individuellement en régression. Les résultats montrent que la configuration propre des représentation favorise d'expliquer excès de rendement.

Notre contributions à la littérature sont comme suivantes: Au lieu de lier le sentiment de l'investisseur directement aux rendements du marché, comme l'on conventionnellement fait, nous avons analysé son effet dans le contexte du risque-rendement par représentant le risque facteur. Les mesures de sentiment sont largement utilisés pour analyser BIST-100, en outre, nous avons aussi considéré 'nombre des comptes des investisseurs', qui sont rarement utilisés, en tant qu'une représentation de sentiment. Pour le meilleure de notre savoir, son effet sur remboursement n'avait pas été confirmé avant pour la bourse turque. Dernièrement, nous avons fait notre contribution au débat actuel sur la relation sentiment-remboursement. Sentiment des investisseur est un prédicteur négatif du remboursement et CCI peut seulement être considéré comme une représentation dans la combination avec des autres représentations en analysant l'index du remboursement BIST-100.

Inconvénients de cette étude incluent le manque d'un test de robustesse. Comme il n'y a aucune mesure directe ou indirecte du sentiment de l'investisseur qui avait trouvé un fondement commun dans la littérature, la signification de nos résultats ne peut pas être comparée par une représentation rigide. Un autre problème le manque potentiel, y compris, représentation importante pour le sentiment. Cela partiellement en raison de l'indisponibilité de donnée pendant notre exemple période, mais plutôt en raison du manque de trouver des données de bonnes qualités.

ÖZET

Davranışsal finans araştırmacılarının yanında yer almak suretiyle, piyasadaki fazla getirileri yatırımcı duyarlılığı ile açıklayarak mütevazı bir çabayla onların sunduğu esasları doğrulamayı amaçlıyoruz. Risk-getiri ödünleşmesi, etkin piyasa hipotezinin iddia ettiği üzere, rasyonel yatırımcıların aynı seviye risk algısına sahip olduğu ve taşıdıkları risk miktarının ise beklenen getirilerle karşılandığı durumlarda oluşmaktadır. Ancak, bu ilişki tarih boyu oluşan balon ve piyasa çöküşleri ile tekrar tekrar ihlal edilmiştir. Bu konuya dair benzeri anomalileri açıklamak üzere bilim insanları da davranışsal yaklaşımları kullanmıştır. Yatırımcı duyarlılığı, sürekli yanlış fiyatlandırmanın olası bir yorumudur. Biz ilgili literatürü takip ederek, bunun Türkiye hisse senedi piyasasını tahmin edilebilir kılmaktaki gücünü gözlemlemek için bir yatırımcı duyarlılığı endeksi oluşturuyoruz. Risk getiri kurgusu içinde, riskin açıklayamadığı durumu tasvir etmek için bu endeksi kullanıyoruz.

Muhtemelen, finansta en sık sorulan ve en önemli olan sorular varlık değerlemesiyle ilgilidir. Alan spesifik maddeleri elimine edip karmaşıklığı azalttığımızda, bu soruların en zoru “Eksik ya da fazla değerlemeden faydalanmak için bir varlığın gerçek değerini nasıl belirleriz?” olur. Devamında, “Nasıl yarar elde edilir?” ve son olarak “Nasıl tatmin olabilirim?” soruları gelir. Buradan yola çıkarak, odağımıza öznelliği koyuyoruz. Finansal sorular sorarken dahi, kişi kendinden uzaklaşamaz; bu sebeple, rasyonel insan hipotezi gibi yanlış önermelere güvenmek bizi finansal davranışı niteleyen, aslında çok da doğru olmayan sonuçlara yönlendirir. Her birey amaçları, ihtiyaçları, değerleri, entelektüel ve bilişsel yetenekleri bakımından farklıdır, ancak ortak olan, hepsinin finansal yargılarında sistematik hatalara yatkın olmalarıdır. Bu, davranışsal finans alanında, risklerin açıklama ve tahmin etme kabiliyetini arttırmak için davranışsal unsurların dahil edilmesinin konu alan yaklaşımların odak noktasında yer alır.

Alanın önde gelen bilim insanları, finansal araştırmalarda yatırımcı psikolojisinin rolünün göz ardı edilmesine karşı uyarıda bulunmuştur buna rağmen tarihsel olarak rasyonellik varsayımı bu durumu gölgede bırakmıştır. Davranışsal psikolojinin finans alanına dahil edilmesiyle birlikte daha realistik bir anlayışa doğru önemli bir ilerleme gözlemlenmiştir. Biz, bireylerin ve borsa tacirlerinin betimleyici analizinden doğan bir düşünce biçimini takip ediyoruz (Kahneman ve Tversky, 1979). Black (1986), gürültünün (irrasyonalite) finansal piyasalara içkin olduğunu ve piyasada verimsizlik yarattığını öne sürmüştür. Geleneksel olarak arbitrajcıların (temelde duygu güdümlü tacirler olan) gürültü tacirlerinin neden olduğu dalgalanmalardan yararlandığı, ve bunun da fiyatların temel değerlerine yaklaşmasını sağladığı fikri benimsenir. De Long ve diğ. (1990) bu fikre, yani arbitraj üzerinde sınırların olmadığı varsayımına karşı çıkmakta ve yanlış fiyatlandırmanın sınırlı

arbitrajın yol açtığı kalıcı bir sorun olabileceğini iddia etmektedir. Yanlış fiyatlama risk-getiri dengesini bozar, bunun sonucu olarak fazla getiriyi açıklama ihtiyacı doğar. Yatırımcı duyarlılığı kavramı bu zorunluluktan doğmuştur. Doğrudan gözlemlenemeyen ya da ölçülemeyen duyarlılık ölçütleri, bu sebepten ötürü türlü mikro ya da makro değişkenler aracılığıyla temsil edilir. Baker ve Wurgler (2006) bileşik bir yatırımcı duyarlılığı endeksi oluşturmak için bunlardan altı tanesini kullanır ve duyarlılığın yatay kesit getirilerini etkilediğini bulur. Hisse bazında ve eş zaman diliminde değerlendirildiğinde, bazı hisselerin diğerlerinden daha fazla getiri sağladığı görülmüştür. Örneğin, küçük piyasa değerine sahip firmaların hisseleri ile oynaklığı yüksek olan riskli varlıklar fiyatlamada meydana gelebilecek gürültü tacirlerinden kaynaklanan bozulmalara karşı daha duyarlıdır. Aynı şekilde risk ve oynaklıkları daha yüksek piyasalardaki borsa endeksleri de yüksek ve düşük duyarlılık periyotlarının verdiği zarara karşı daha duyarlıdır.

Kurmuş olduğumuz çerçeve BIST-100 endeks getirilerini, piyasadaki riske ilişkin RISE endeksini, yatırımcı duyarlılığı vekillerini ve de onların endeks biçimindeki bileşimlerini içeriyor. Finansta varlıkların fiyatlandırılması modelinde risk getiri ilişkisi risk primi ve her bir hisse senedine özgü olan hisse seneti duyarlılığı da beklenen hisse senedi getirisine ilişkilendirilerek çözümleniyor. Piyasa gelirleri üzerine çalışmakta olduğumuz için, geniş piyasa risk unsurları kaçınılmaz. Piyasa risk primi, geçici örtük opsiyonlar vasıtasıyla vekalet edilebilen genel piyasayla güçlü bir biçimde ilişkili. Genel piyasa riskine işaret etmek için, opsiyonlardan türemiş örtük bir geçiciliği ortaya koyan RISE endeksini kullanıyoruz. VIX endeksinin Türk versiyonu sayılan RISE, risk iştah endeksi olarak da adlandırılıyor.

Kullandığımız temsilciler için, öncelikle Baker ve Wurgler'i göz önünde bulunduruyor ve kapalı uçlu yatırım fonları iskontosu (CEFD), hisse senedi değişim hızı (TURN), ilk halka arz sayısı (NIPO), halka arzların ilk gün ortalama getirisi (RIPO) ile tüm senet ihraçlarında hisse senedi payı (SHARE) vekillerini analize dahil ediyoruz. Türkiye'de kapalı uçlu yatırım fonları işlem görmediğinden, yatırım ortaklığı iskontosunu (ITD) aynı maksatla kullanıyoruz (Candaş ve Kandır, 2007). Bunun yanı sıra, işlem hacmindeki değişim (TRAD), döviz kuru (EXC), yatırım hesaplarının sayısı (ACC) ve net yabancı hisse senedi alımlarının piyasa değerine oranını (FOR) vekil olarak değerlendirmeye alıyoruz.

Yukarıda sayılan yatırımcı duyarlılığı vekilleri aslında başka ekonomik faktörleri ölçmek için hesaplanmış değerlerdir. Yatırımcıların ve tüketicilerin duyarlılığını doğrudan ölçmeyi amaçlayan, anket ve soru cevap yöntemini kullanan ölçümler de bulunmaktadır. Türlü ülkelerdeki beklenti anketlerinden hazırlanan Tüketici Güven Endeksleri (CCI), hisse senedi ya da piyasa getirileri ile olan ilişkisi dahilinde birçok çalışmaya konu olmuştur. Ayrıca bir vekil olarak yatırımcı duyarlılığını temsil etme gücüne ilişkin pek çok araştırma mevcuttur. Açıktır ki bu endeks bazı duyarlılık biçimlerini yansıtmaktadır, fakat tüketicilerin sıklıkla hisse senedi piyasasına katılımcı olarak dahil olmadığı ülkelerde, yani tüketici ve yatırımcı arasında göz ardı edilemeyecek kadar bir fark bulunan ülkelerde, yatırımcı duyarlılığını ölçmek için tüketici güven endekslerini kullanmak faydasız bir girişim olabilir. Ancak, bu endekslerin seviyelerinin veya seviyelerindeki değişimlerin yatırımcı duyarlılığını yansıtma olasılığını artırabilecek faktörler de bulunur. Bunlar arasında borsa kültürü, hisse senedi piyasasının gelişim düzeyi gibi pek çok unsur vardır. Kullanımı bu faktörler göz önüne alınarak değerlendirilmelidir. Ülkelerin kendine özgü etkilerini daha açık bir biçimde belirlemek için konu üzerinde daha çok çalışma yapılması gerekmektedir. Bu nedenle, biz Türkiye İstatistik Kurumu (TURKSTAT) tarafından yayımlanan tüketici eğilim anketlerine dayalı olarak hesaplanmış olan ve mevsimsellikten arındırılmamış olan TURKSTAT ve Bloomberg HT güven endekslerini doğrudan bir vekil olarak alıyor, fakat daha sonra diğer bağımlı değişkenlerle birlikte regresyon analizi kapsamında dolaylı bir vekil olarak kullanıyoruz.

Yatırımcı duyarlılığının etkisini araştırmak ve risk faktörünü kontrol değişkeni olarak kullanmak için doğrusal regresyon analizleri yapıyoruz. Regresyonda kullanılacak değişkenlerimizin, doğrusal regresyon varsayımlarına ters özellikler taşımamasıgerekir. Öncelikle, değişkenlerin hiçbirinde birim kök bulunmamalıdır, yani değişkenlerin durağan olduğunu güvence altına almalıyız. Zaman serileri kullandığımız için verilerin sürekli olması koşulu sağlanmış oluyor, fakat gözlemler ya da ölçülen değişkenler bağımsız olmalı, diğer değişkenlerle yakından ilişkilendirilememelidir. Değişkenlerde normal dağılım sınırları dışında kalan veriler regresyonun ve korelasyon analizinin güveniliriliği açısından risk teşkil eder; bu nedenle böyle verileri kullanmaktan kaçınmak en iyi yol olabilir. Eğer bu mümkün değilse Değişkenler ciddi bir korelasyon olduğu durumda bunların kullanımından kaçınmak gerekse de, aralarında asgari düzeyde doğrusal bir ilişki olduğu saptanmalıdır. Son olarak, doğru bir ön tahmin yapabilmek için, değişkenlerdeki hataların varyanslarının zaman içinde değişmemesi, daha doğrusu, bir trende sahip olmaması gerekmektedir. Yatırımcı duyarlılık endeksimiz için Kaiser-Meyer-Olkin testi ve Bartlett'in küresellik testini de uyguluyoruz. Bunlar değişkenlerin boyut indirgeme metotlarıyla kullanılıp kullanılamayacağını gösterir. Son olarak, doğrusal regresyonlardan kalanlar, yani regresyondaki hata terimi, normal dağılım eğrisine benzer özellik göstermelidir. Bizim çalışmamızda kabul edilebilir test sonuçlarına ulaşılmasına rağmen, bileşik endeksler beklendiği kadar iyi performans göstermedi. Ancak, bu yatırımcı duyarlılık endekslerini oluşturan değişkenler bir faktörizasyon yoluyla birleştirilmeyip regresyonlara tek tek sokulunca, BIST-100 endeksi üzerinde literatürde de iddia edilen ölçüde bir etkide bulunduğu görülebilir.

Yukarıda belirtilen sorunlardan biri ya da birkaçından muzdarip olup olmadığını kontrol etmek için verileri analiz ettik. Homojenlik, çok kutupluluk, hataların normal dağılımı, korelasyon vb testleri geçemeyen değişkenleri eledik ve geri kalan hesaplamalar için şu vekilleri kullandık: ITD, ACC, EXC, CCI değişimi, TRAD ve FOR değişim oranı. Bu değişkenleri kullanarak çeşitli düzenlemelerle regresyon analizleri yaptık. Bir değişkenin dahil edilmesi, başka bir değişkenin önemsiz hale gelmesine neden olabilir veya bunun tersine tahmin etme yeteneğinde artış da sağlayabilir. Geleneksel finans tarafından tanımlanan riskten getiri ilişkisinde öngörülmemiş olan fazla getirinin en azından bir kısmını açıklamak için en iyi yatırımcı duyarlılığı temsilcilerini belirledik.

Endekslerin ham fiyatlarının birim kökler içermesi sık rastlanan bir durumdur. Bu şu demek oluyor: Zaman serisi genel bir eğilim izliyor, yani devamında yapılacak analizlere eklenebilmesini gerektiren durağanlığa sahip değil. Borsa endeksleri üzerinden yapılan risk getiri analizlerinde sıklıkla logaritmik getiri kullanılır. Bu sayede zaman serilerinde durağanlık sağlanmış olur. Ancak biz sadece iki ardışık ay arasındaki farkı kullanarak analize soktuğumuz BIST 100 endeks fiyatlarının gerekli koşulları sağladığını ve logaritmik getiriyle benzer sonuçlar verdiğini gördüğümüz için, logaritma işlemini kullanmadık. İstatistiki analizde veya teoride gerekli görüldüğü yerlerde ilgili değişkenin gecikmeli değerlerini kullandık. Böylelikle bah birim kök içermeyen veriler de elde etmiş olduk

Ham hallerinde birim kök içeren, ama önceki döneme göre farklarında birim kök içermeyen değişkenler için eşbütünleşme testleri uygulanabilir. Ham fiyatların genellikle bir yöne doğru hareket ettiğini biliyoruz. Johansen eşbütünlemesi ve vektörel hata düzeltme modelini (VECM) kullanarak hata düzeltme terimini bulduk. Bu terim, sorunlu olduğu için analiz kapsamı dışına alınan değişkenlerin durağan olan kısımları olarak algılanabilir. Bu yüzden bir duyarlılık indeksi olarak çalışıp çalışmadığını test etmek için regresyonlarda kullandık.

Özetlersek, yatırımcı duyarlılığının risk-getiri ödünleşmesine katkısını belirlemek için çeşitli vekiller kullandık. VECM'in yardımıyla, duyarlılığın önerdiğimiz yedi değişkenin birleşimi ile vekalet edildiğinde getiriler üzerinde etkili olduğu kanıtlanmıştır.

Yatırımcı duyarlılık endeksinin kontrol regresyonuna eklenmesiyle getirilerin açıklanmasındaki artış %5, vekil bileşenlerinin tümünün ayrı ayrı eklenmesiyle de artış %37 olarak ölçülmüştür. Sonuçlar, uygun bir vekalet bileşiminin fazla getiriyi açıklamaya yardımcı olduğunu göstermektedir.

Literatüre katkımızı şöyle özetleyebiliriz: Yatırımcı duyarlılığını, konvansiyonel olarak yapıldığı gibi, piyasa getirisi ile doğrudan ilişkilendirmek yerine etkisini risk faktörü için vekil kullanarak risk-getiri ödünleşmesi bağlamında analiz ettik. BIST-100'ü konu alan analizlerde sıkça kullanılan bazı vekillerin yanı sıra 'yatırım hesaplarının sayısı' gibi pek az kullanılan bir vekili de çalışmaya dahil ettik. Bildiğimiz kadarıyla Türkiye'deki borsa getirisi üzerindeki etkisi daha önce teyit edilmemiştir. Son olarak, duyarlılık-getiri ilişkisi üzerine süregelen tartışmaya katkı sunmuş olduk. Literatürdeki bazı sonuçları teyit ederken bir kısmıyla ilgili bulmuş olduğumuz farklı sonuçları belirttik. Bulgularımıza göre yatırımcı duyarlılığı negatif bir getiri prediktörüdür ve tüketici güven endeksi BIST-100 endeks getirisini değerlendirirken yalnızca öteki vekillerle birlikte kullanıldığında vekalet özelliği kazanır.

Çalışmadaki eksikliklere gelince, en önemli problem bir sağlamlık testinin olmayışı olarak görünmektedir. Literatürde ortak kabul gören doğrudan veya dolaylı yatırımcı duyarlılığı ölçütleri olmadığından, bulgularımızın anlamlılığı uygunluğu kanıtlanmış bir vekilin tesiriyle karşılaştırılamamıştır. Bir öteki sorun ise bazı önemli vekillerin analizde yer almayışı olarak görülebilir. Bu kısmen örneklem dönemimizde ilgili verilerin bulunmamasından, fakat çoğunlukla da kaliteli veri bulmakta yaşanan sıkıntıdan kaynaklanmaktadır.

CHAPTER 1: INTRODUCTION

It has always been desired to foresee the future. One can make much gain out of this capability, such a gain that is not limited to having a prosperous life, but that could even extend to claiming one's prophecy. In a deterministic world, if a superior mind had all the available data, they would have known what would come next. Let aside the discussion whether the world is deterministic, it is obvious that one can never hold full information on the determinants of the topic of interest. That is why people do approximations when having need to decide on daily problems or when they try to understand the mechanics of natural/social phenomena.

Scientists build models to replicate the real life, and while doing so, various assumptions are made inevitably, in the hope that they will not violate truthfulness. It is the same in economics and finance. A model is first proposed with assumptions to imitate the real-life economic event. The assumptions are gradually eased, thanks to the cumulative nature of scientific information and research, and the accuracy of the model to reflect what is real is exceled.

In hard science, things are more straightforward. If a man jumps out of a window, one could determine his velocity approximately when he touches the ground, using some assumptions. Relaxing the assumptions and relying on computational modeling, one could almost exactly know the velocity. Even if no models are used, relying on many experiments and some computer power, it could be determined with big data approach. A camera and few lines of codes even work. The effort to understand the person poses a true challenge. What is the motivation of such a behavior, why a person would do that, if we had his twin brother brought by the same window, would he also jump off? Understanding human nature, if such a thing exists, is a hard pursuit.

Is it not interesting that countless number of highly trained economists fail to foresee a crisis approaching, and all one could do is to list reasons why that happened after what has occurred? It is also funny that if many expect it coming, it may not occur due to that common expectation. When human factor is considered, forecasting is difficult. Traditional finance does indeed takes the human factor into account. However, to analyze the human decision process, it employs a normative approach. A so-called rational person (like everyone else) acts according to their best interest and their decisions are consistent with the law of probability. Is it really so?

When you toss a coin and ask your friend: Head or tail? There is 50% chance that they say “tail” and they would be correct 50%. Do this fifty more times and ask each time. It is a good chance that they will not answer the same. But why? If the probabilities are the same, why would one change their response? Either way one would have expected to be correct only half the times. What is logical? Is it to respond the same all the time? Does it even make sense to answer to a head-or-tail question? Or, think about the lotteries. The decision under uncertainty is indeed a popular subject of experiments carried out by Kahneman and Tversky. They present two options to participants; for instance, they would either choose a gain of $80, or they would opt for a 85% chance of winning $100. Despite the expected gain (the monetary expectation) of the latter is higher (0.85 to 0.80), most of the respondents choose the sure gain (Kahneman and Tversky, 1982).

Say that we design an experiment, in which the numbers of heads and tails in a coin-tossing sequence are equal, as if we repeat the act infinitely many times. A normative approach would conclude that it does not matter how one responds, it is always 50% chance to win. We may define two types of persons here and conclude that a risk-averse person would go for the same answer all the time in order to secure the win half the times, and the risk-taker person would change their decision in between in order to gain the win more than half the times, with a cost of increased risk of equal probability to win less than half the times. Here comes the risk-return tradeoff.

Risk-return tradeoff is one of the main subjects studied in finance. Its validity is strictly tied to premises of traditional finance, which assumes a rational agent that has full access to all relevant information and processes it according to Bayes rule. Agents have necessary intellectual and mathematical abilities to calculate probabilities and to use them as a ground for their decision; moreover, they make necessary updates when new information is available. In short, an economical agent takes decisions considering the risk involved.

Inspired by Manktelow (2012), we can picture how the Bayesian belief revision works using the following example: John and Paul are looking for Ringo to get ready for their gig. They know that on a Saturday night Ringo is found at the Cavern Pub 80% of the time. They arrive there and from the outside they see half the pub, but he is not in that half. Is there still 80% chance that Ringo is inside? According to Bayesian John, no! He updates his prior belief, does the math, and comes up with a posteriori probability of 67%. This is what a Bayesian rational agent would basically do. If we move further in this example and see how a rational John would behave to maximize his utility, we could roughly estimate that John would get into the pub to check if Ringo were there inside, given the cost of further search etc.

Traditional finance theories dominate the literature, but their unrealistic assumptions have long been questioned. The failure of classical theories became evident with ongoing financial crises, where prices deviated from fundamentals contrary to hypotheses of classical finance. After October 1987 market crash (Black Monday), doubts on the validity of market efficiency have risen (Bathia and Bredin, 2013). Alternative explanations, such as investor sentiment, are widely used to analyze the Black Monday, the Internet bubble in the 1990s and the 2008 financial crises (Huang *et al.*, 2015).

Addressing the presumptions of rational finance there arise two questions: First, do economical agents behave so? Are they really rational beings or does their behavior depend also on other factors? Second, is it true that one cannot gain more than they risk? The answer to the first question is “No”. They are not rational, and assuming so hampers the possibility to arrive meaningful, realistic conclusion and reduces the usage of the models built. The answer to the second question is "No" as well. The mechanism does not always work so. It is evident that in the long-term S&P 500 yields excessive return compared to the given risk levels.

Abovementioned problems result in violations of the principals of the risk-return trade-off and lead to anomalies, i.e. unexpected consequences. Solving puzzles that follow up necessitates the inclusion of agents who depart from rationality. As behavioral finance is a response to the classical approach, pointing the contrast between these approaches will be explanatory to grab its essence. Here are the main differences between traditional and behavioral finance, as stated by Sharma (2014):

i. Behavioral finance recognizes that investors usually display irrationality and they can be emotional in their behaviors, whereas, traditionally they are always rational conforming to the efficient market hypothesis.

ii. Regarding complete information, behavioral finance challenges the classical assumptions and claims that the investors do not have the equal opportunity to reach the information, and that stock prices does not always reflect all available information.

iii. Traditional finance does not consider demographic distinctions, while behavioral finance takes age, gender, education level etc. into account.

iv. Concerning financial crises and bubbles, traditional view is such that in an efficient market they would not occur. This approach is a direct consequence of the assumption of investor rationality. Since that assumption is rejected in the behavioral approach, the crises and bubbles can be better analyzed.

v. Behavioral finance is related to a larger number of disciplines, in addition to economics, finance and investing, which are traditionally of interest. Among those are psychology, sociology, social psychology, behavioral economics and behavioral accounting as put forward by Ricciardi (2006). Psychology deals with behaviors and cognitive processes, and how they take effect given the individual's own state related to their surroundings. How people decide and their psychology in the meantime affect their rational judgments, which cannot be dismissed in financial research. Sociology and social psychology study human in social settings and how they interact with social groups. A person's psychology and their decisions are affected by social relationships, e.g. herd behaviour.

Taking into account the contributions of the behavioral approach, anomalies in the risk-return tradeoff can be justified to some degree, for instance via the inclusion a sentimental trader. Behavioral finance argues that asset prices may deviate from their fundamental. Behavioral finance relaxes the assumption of rational agents. A behavioral agent makes decisions not based on probabilities, but rather on heuristic biases. The deviation of prices can be permanent because the market prices the risk, which is often referred as the sentiment risk.

The phenomenon of investor sentiment relies on the premises of the behavioral finance, and in recent years it finds its usage in the financial research as a behavioral measure. It describes the prospects of investors on future returns that are not justified by economic fundamentals. Investor sentiment does not only affect the prices, but since may result in a consisting mispricing, it is also used as an indicator predicting stock market crises (Zouaoui *et al.*, 2011).

We take side with researchers of behavioral finance and aim to confirm its postulates by providing a humble effort in order to explain the excess stock market returns with investor sentiment. Risk-return tradeoff is established considering the premises of efficient market hypothesis, where rational investors have the same level of risk perception and the amount of risk they bear is compensated with an equivalent raise in expected returns. However, this relationship is violated repeatedly through a history full of bubbles and market crashes. In order to explain such anomalies in this regard, scholars have also used behavioral approaches. Investor sentiment is one possible interpretation of the consistent mispricing. Following relevant literature, we build an investor sentiment index to observe its power of predictability in the Turkish stock market. We use this index in the risk-return setting expecting to describe what the risk fails to explain.

In the literature, developed markets are analyzed more frequently, especially the USA. Reasons may be manifold, but the possibility of having high-quality data for longer periods of time, the fact that markets reflect fundamentals better, and the availability of numerous financial instruments may be cited to name a few. The volume of research on developing markets has increased in the last ten years, yet in comparison to developed markets low amount of relevant studies have been carried out on Turkish stock market. Most of the research on sentiment relates investor sentiment directly to the market or stock returns. Instead, we take a risk factor to relate to returns and later we include the sentiment factor. We aim to detect the effect of investor sentiment in the risk-return relationship, i.e. in a sense; we regard it as a risk to be priced.

The thesis is organized as follows: The following chapter provides a theoretical background. We explain the foundations of traditional and behavioral finance, and mention of the risk-return tradeoff. We show how the prices are determined by the traditional view using asset-price models, and later, mention of their deficiencies. Investor sentiment, what the behavioral view has to offer to address those deficiencies, is explained. We elaborate relevant concepts without delving into much detail. This chapter functions as a general literature overview. The third chapter addresses prior research regarding the relationship between investor sentiment and stock/market returns. It also focuses on risk and its effect on this relationship. The fourth chapter describes the data used and our methodology. The steps taken to build the investor sentiment index are detailed and the risk proxy is explained. Descriptive and inferential statistics are provided to confirm the reliability of data. Necessary treatment is discussed. The regression framework follows. The fifth chapter involves the regression analysis and the discussion of its implications. Robustness tests to validate our approach end the chapter. The sixth chapter summarizes our research and addresses its limitations. We also provide some suggestions regarding further studies.

CHAPTER 2: THEORETICAL BACKGROUND

This chapter focuses on the theoretical basis this research is built upon. It is vital to have a basic grasp on the traditional approach of finance to appreciate the need to involve behavioral elements. The same applies to the concept of investor sentiment, which is based on the premises of behavioral finance. After an overview of two distant approaches, we elucidate the concept of investor sentiment.

2.1 Traditional Finance

The traditional finance analyzes the financial market using models that has rational agents, who make optimal financial decisions. The term 'Homo Economicus' is coined to describe such an agent. Contrary to 'Homo Sapiens', it refers to rational traders, who are assumed to be identical, update their belief correctly in Bayesian way when exposed to new information and they make choices that maximize their utility, consistent with the notion of the expected utility theory. It rests on four principles: cancellation, transitivity, dominance, and invariance (Tversky, 1986). If an agent prefers A over B, any external situation that affect both of the options can be discarded, so the agent still prefers A. This is the cancellation principle. Transitivity of preference is the assumption that agents assign values to each option which is independent from others so that they can prefer the option with the highest utility, as the dominance principle suggests. Invariance tells that agents prefer the same choice when the problem is stated in a different representation.

So, at one side of the coin, i.e. micro-finance, there is the assumption of 'Homo Economicus'. The other side describes the medium, where those rational agents meet: the market.

The backbone of the macro-finance theory is the efficient market hypothesis, which is theorized by Fama (1965) and Samuelson (1965) based on the theory of random walks in stock prices. Although their interpretation of the underlying mechanism and its significance differs, they both assume rational expectations of traders. Propositions of the hypothesis are the nonexistence of "free lunch" in the market, the inclusion of all available information in prices, the correctness of price, and the existence of arbitrage opportunities. That is to say that traders cannot make constant gains by exploiting prices, since transient periods of undervaluation or overvaluation are corrected by rational arbitrageurs who incorporate new information into prices (Delcey, 2019).

Three forms of market efficiency are proposed. In the weak form, the historical prices are reflected at the current price and it is impossible to consistently gain abnormal returns just by analyzing past prices. In the semi-strong form, prices reflect all published information besides past returns, so one cannot take advantage of studying all public information to constantly make a profit. The strong form indicates the efficient market as it was first described. No tools or public/insider information can help an investor earn superior returns because prices include all the information. Luck would be the primary determinant of success in case of no over- or undervaluation.

Proponents of traditional finance are well aware of the irrational side of humans. However, what those claim is that rational agents who seize the arbitrage opportunities compensate for the irrational behavior of agents. Thus, at the end of the day, market corrects itself and those who do not take a rational position will be eliminated. Noise traders may also be manipulated before the market corrects itself. From a micro perspective, Piccione and Spiegler (2014) proposed a model where a large trader supplies assets to a market comprising arbitrageurs and two noise speculators who are a noise trader and a naïve speculator. They show that the large trader can activate the sentiment of noise traders by causing price fluctuations and motivate them to trade; as a result, win over the loss of noise traders and eventually the price reaches an equilibrium.

In conclusion, classical financial economics is based on two foundations: First, individual investors who behave rationally; second, market efficiency.

2.2 Asset Pricing Models

Various models to determine asset prices have been proposed based on abovementioned assumptions, which can help investors build an optimal portfolio. Asset pricing models are introduced and employed to construct a portfolio that is risk- and volatility-reduced. In order to achieve that, risk and volatility is related to the market return. Even though there are plenty of approaches on how to improve a portfolio, four among them are mostly cited by academics and widely used by finance professionals. A brief characterization of their essence is sufficient for our purposes.

2.2.1 Markowitz's Modern Portfolio Theory (MPT)

The pioneering theory of Markowitz (1952) describes the process of selecting a portfolio for rational traders. It is assumed that investors are risk-averse and they take into account only the mean and variance of their investment return. Investors seek a solution for the maximization problem, where minimum variance and maximum return is desired. The Markowitz approach is also called "mean-variance model", and "modern portfolio theory". According to the model, one can reach an optimal mixture of assets by diversification.

$$ER_C = R_F + (\sigma_C/\sigma_P)\left(ER_P - R_f\right) \quad (1)$$

where *f* denotes risk-free asset, p is the risky asset, *c=p+f* refers to all assets, R_f is the return of a risk-free asset, R_P is the return of risky assets, σ is the standard deviation, and ER_C is the expected return for a security.

2.2.2 Capital Asset Pricing Model (CAPM)

CAPM, theorized by Sharpe (1964) and Lintner (1965), introduces systematic risk (i.e. volatility, market risk - measured via ß) and unsystematic risk (i.e. specific risk) in order to make a better estimate of the market return. Investors are risk-averse, markets are efficient and other MPT premises are preserved except treating risks. It is an equilibrium model, where the equilibrium is satisfied when all investors has the same risk-return expectation. Although the model may provide insights to interpret aggregate returns, it is used generally for individual stocks. The relationship between risk and return is established as follows:

$$ER_i = R_f + \beta_i\left(ER_m - R_f\right) \tag{2}$$

where *m* denotes market, i is each individual stock, $(ER_m - R_f)$ is the market risk premium and β is the relative risk contribution relative to the overall market, which is expressed as the ratio of the covariance of market and stock returns to the variance of market returns, i.e. $\beta = cov(R_i, R_m)/var(R_m)$. The return of risk-free asset is generally assumed to be the return of treasury bills.

Cross-section of returns is taken into account in CAPM and the risk factor in the risk-return scheme is proxied by the risk premium. Risk premium refers to the return compensation of an investor to bear a specific level of risk. It is obtained via the adjustment of the market risk premium by the stock-specific beta, which displays the sensitivity of a stock to the market premium. Resultant risk factor is supposed to reflect the systematic risk, i.e. the market risk.

2.2.3 Three-Factor Fama-French (F-F) Model

E. F. Fama, a Nobel laureate economist and the co-developer of efficient market hypothesis and K. French proposed the incorporation of two more factors in CAPM scheme to better describe the stock returns (Fama and French, 1993).

$$ER_i = R_f + \beta_{1,i}(ER_m - R_f) + \beta_{2,i}E(SMB) + \beta_{3,i}(HML) \qquad (3)$$

where *SMB* (Small Minus Big) is the returns of value-weighted portfolios and reflects the size affect and *HML* (High Minus Low) is the returns on zero-investment portfolios and relates to the book-to-market equity ratio**.** Authors also consider two bond-market related factors, but omit them as they fail to explain the differences in cross-sectional returns. Yet, the model is open to further inclusions.

2.2.4 Arbitrage Pricing Theory (APT)

APT is an alternative to CAPM and addresses some of the weaknesses of the latter. The assumptions that markets are efficient are corrected so that markets might now misprices securities. Moreover, instead of solely calculating the expected market return, APT also addresses non-company factors, therefore includes a variety of risk factors:

$$ER_i = R_f + \beta_{1,i}RP_1 + \beta_{2,i}RP_2 + \cdots + \beta_{n,i}RP_n \qquad (4)$$

where RP is the risk premium of a systematic factor, as described in previous equations.

Among weaknesses of this theory are the preservation of the assumption of investors with identical expectations and the necessity to properly define ß’s for a meaningful forecast (Ross, 1976; Roll and Ross, 1980).

Asset-pricing models may also be called risk-return models. Risk-return relationship is a major facet in modern financial research both in classical and behavioral senses. Those models generally assume that the more risk investors bear, the more return they would expect, that is, asset prices are determined by a risk-return tradeoff. Criticisms are usually centered on market anomalies, which are yet to be explained. To elucidate the true mechanism, researchers proposed many variations of the four main theories, but none of them is decisively backed up by solid empirical evidence.

To sum up, we may acknowledge a consensus on the risk-return relationship. Despite the inner criticism coming from the traditional perspective in claim that the relationship is insignificant or reversed, the idea that higher return comes only at an expense of increased risk is well-established in the literature and in the field.

2.3 Anomalies & Puzzles

However, when analyzing the stock market, a number of anomalies are observed that violate the premises of classical finance. These anomalies undermine the risk-return tradeoff by demonstrating that, at times, “free lunch” in the market exists. Those anomalies are deemed as puzzles that need to be solved. Three of the most striking, as elaborated by Barberis and Thaler (2003) are the equity premium, volatility, and predictability puzzles.

Certain anomalies in the risk-return trade-off are attributed to investor sentiment by various researchers such as price clustering (Blau, 2018) and price resolution hypothesis.

Yu and Yuan (2011) suggests the inclusion of investor sentiment while observing risk and return in order to solve this puzzle. According to them, the ambiguity stems from not taking into account the investors' psychology.

2.4 Behavioral Finance

Behavioral finance is the latest major advancement in finance. It aims to put a more realistic perspective into the financial research by offering a descriptive definition of traders and markets.

Behavioral finance is closely related to behavioral psychology. As Anlaş (2017) conveys, John D. Watson was first to incorporate behavioralism into psychology in the early twentieth century. On the other hand, human psychology is emphasized by economists as early as the late 1700s, for instance by Adam Smith (Smith, 1759).

The research concerning behavioral aspects in finance/economics started to increase in the 1990s and gained momentum after 2000s. According to the Web of Science database, number of finance/economics articles published on behavioral topics increased tenfold in the last twenty years, reaching to 1595 in 2018.

Behavioral finance does not assume rational traders; rather it acknowledges the normal human behavior, which is deemed to be 'irrational' in the literature. The term irrational trader indicates an agent whose decisions is influenced by their emotions; hence violate the behavior code of a rational one. Irrationality, in this context, does not imply an absence of reason, but the lack of a rational basis in financial perspective. It can be used interchangeably with bounded rationality, which finds a greater use in economics.

The expected utility approach defines utility over final wealth position. In their seminal paper that introduces prospect theory, Kahneman and Tversky (1979) provide examples in an attempt to disprove assumptions of expected utility theory. At one of their experiment the respondents are asked to choose between definitive and probable gains, each having the same end wealth position. The majority chooses the definitive win. When the question is reversed to a loss scenario, they prefer a probable loss. This experiment stands as evidence against the expected utility theory by demonstrating that the utility is defined over the loss-gain position.

Criticism on the assumption of traditional finance goes way back before the birth of behavioral models. Friedman (1953) challenged the criticism claiming that the trade made by rational arbitrageurs is enough to drive the prices back to normal (Barberis and Thaler, 2003).

Although the arguments such as of Friedman (1953) are partly correct when it comes to exploiting any good investment opportunities, those opportunities are rather risky and costly in the case of mispricing, so cannot be deemed as 'good'. Even if we could say so, the existence of noise traders is effective enough to limit the arbitrage as explained by De Long *et al.* (1990). Noise traders, i.e. irrational traders, pose a risk that in the short-run the mispricing may not be corrected, resulting in losses for arbitrageurs.

Two pillars of behavioral finance are psychology and limit-to-arbitrage, as put by Shleifer and Summers (1990).

2.4.1 Psychology: Decision making

Instead of classical assumptions on decision-making process, which accounts for an integral part of the rationality hypothesis, behavioral finance intends to draw a more realistic picture of humans concerning their financial behaviors. It borrows some terminology from psychology and thus forms a basis on which financial decisions of people are described. Making judgments under uncertainty is a difficult task. In order to simplify this, people rely on biases, which stem from certain heuristics.

Heuristics. Heuristics can be defined as cognitive short cuts an individual use in the process of decision making and they lead to biases. In parallel with the search cost in the microeconomic theory, arriving to a conclusion and finally making a decision has a cost. Be it consciously or not, an optimization process is in effect and putting a preference considering the costs, so simplifying the decision, is indeed rational even if the preference does not stem from economic fundamentals. The process being somehow rational does not mean, however, that those mental short cuts are, per se, rational.

Some commonly referred heuristics are *representativeness*, *availability*, and *anchoring* as put by Tversky and Kahneman (1974).

In order to evaluate the probability of an event, people may consider related events they believe to represent it and their conclusion might not be based on the essential information on that very event, but on a related event. This is called the *representativeness heuristic.*

For instance, without any related prior information except that Germany is closing down its nuclear plants, one may presume that France would be doing the same, considering the similarities between two countries, however, omitting the real dynamics of the issue. Or take Spud for example. He is 1.7 meters tall. When asked if he is a basketball player or a jockey, many would guess wrong and answer “jockey”. In fact, Spud Webb was actually an NBA player who had won the slam-dunk contest in 1986!

Availability describes the act of an individual, who assesses probability or frequency of an event to occur, giving a greater probability to ones that recently took place or had taken place previously, but with a great frequency –so that it is easier to recall.

Crimes committed by Syrian refugees often take place in the media, leading many to think that they engage in crime more often than Turkish citizens. However, statistics show the opposite. Likewise, one may think that a shark attack is a serious risk, while the lifetime odds of death from a shark attack is 1 in 8 millions for an average American. It is 1 in 1180 for drowning![1]

Anchoring, also known as focalism, is a phenomenon that describes the propensity of individuals to use 'an anchor' as a starting point for their estimates. This starting point may be an initial piece of information that comes from the formulation of the problem and it is used as a reference point even if it is irrelevant to the problem.

Scott and Lizieri (2012) conduct an experiment where participants were asked to write down the last three digits of their phone number as a price in thousands of pounds. They received some visual and textual information about some houses and were subsequently asked to estimate the sale price of the houses. As results show, their estimates were influenced by the 'anchor', the number they wrote on a piece of paper.

Biases. Heuristics mentioned above and such lead to biases that influence an individual's decisions. Many forms of biases are discussed in the literature; here we include only a few to put it into perspective as categorized by Calderon (2018).

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[1] https://www.businessinsider.com/shark-attack-death-statistics-2017-5

[2] Qiu and Welch (2004), for instance, claim that is not a good proxy, because it does not correlate well with the direct USB/Gallup measure or with other sentiment proxies.

[3] We may confirm this by comparing volatilities (standard deviations to be exact) of the log returns of BIST-100, S&P SmallCap 600 and S&P 500 indices. S&P SmallCap 600 roughly covers the US stocks that have smaller market capitalization and S&P 500 covers those with largest

People may tend to overestimate their knowledge and capability in their financial decisions. This is called *overconfidence bias*, and may result in actions such as excessive trading, besides making wrong decisions. *House money effect* portrays the case when investors make decisions under the influence of prior gains or losses.

Loss aversion describes the state of putting losses a heavier weight than gains. A person who prefers not losing a certain amount of money over gaining the same amount poses a typical example. *Endowment effect* emerges as a consequence, a bias that tells that people overvalue what they have compared to that of the same value they do not possess. If they were to sell an asset, they would demand more money than they would have paid to buy it. *Status quo bias* defines another tendency related to *loss aversion*. It is the preference to stick to the current position and prior decisions. Investors suffering from *myopic loss aversion* focus heavily on the short-term and evaluate their portfolio frequently to see the outcomes. They are also more sensitive to losses and these combined lead to omitting long-term gain possibilities.

Mental accounting addresses investors' perception of their money. They psychologically allocate their money based on where they plan to spend it or from where it is gained. What typically follow are the *sunk cost fallacy* and the *disposition effect*. The former describes the reluctance to retreat from an investment that causes loss or the act of spending even more on an initial investment to prevent it from going to waste. The latter refers to the action of keeping a stock losing value for too long and selling another one, which is lucrative, too early.

Heuristics and biases may be regarded as the counterpart of Bayesian theory (Çelik, 2012), which defines a normal and assumes the investors adhere to that. The behavioral counterpart casts light on investors' actual behavior by analyzing it in a descriptive way. Provided examples find place in every aspect of life, financial decisions being no exception. Besides, their inclusion in finance theory provides benefits beyond its use as a justification for investor sentiment, because they do not affect only the noise traders, i.e. sentimental traders, but also professionals.

2.4.2 Limits-to-arbitrage: Deviation from fundamental price

Proponents of the efficient market hypothesis (EMH) argues that even if the market involves agents departing from rationality (noise traders), arbitrageurs (rational traders) seize the opportunity caused by mispricing and eventually the prices are corrected and noise traders are driven out of the market. This approach neglects limitations imposed by the risk taken and the cost of transactions.

The prices are unpredictable. So when arbitrageurs sell short thinking that a specific asset is overvalued, they bear the risk caused by the unpredictability. If the asset's price continue rising, at least during the time of the contract, they will have to buy it more expensive in the end (Shleifer and Summers, 1990).

2.5 Investor Sentiment

Investor sentiment is a term used in finance to describe the mood of investors who are not assumed to be rational in economic sense. The difference between the objective expectancies and the perception of irrational traders on future returns and risks is another way to define investor sentiment. High levels of sentiment are referred as optimism, and low levels as pessimism.

Humans' tendency to behave in a way that is derived from emotion rather than reason is no different for investors even if they are professional; they make decisions not always based on concrete facts but also on how they perceive them. In other words, they are not immune to cognitive shortcuts. So, when such behavior is no longer incidental but rather recurring, it poses a risk in the financial market that needs to be priced (Lee *et al.*, 2002).

Investor sentiment, especially during high-sentiment periods, causes prices to deviate from fundamental values. The need to consider sentiment in asset pricing stems from the fact that the deviation can be long-standing and should not be omitted. Especially, stocks of small-cap growth companies that are non-dividend paying, highly volatile, and young are more sensitive to the effects of sentiment (Baker and Wurgler, 2007).

Sentiment affects the cross-section of prices, i.e. the price of a given stock. Baker and Wurgler (2006) states that investor sentiment can also be used to forecast the aggregate stock market, but its capability therefor is rather limited. However, intuition is that if the sentiment is market wide, it should also affect the aggregate return, e.g. the index prices (Huang *et al.*, 2015; Lee *et al.*, 2002). Samuelson (1998) argues that markets may be “micro” efficient, but there is no persuasive evidence of market “macro” efficiency. This leads us to conclude that investor sentiment could be even more promising predicting the aggregate return. After all, market inefficiency and the usefulness of investor sentiment go hand in hand.

Investor sentiment finds its use also in the classical asset valuation schemes. For instance, its inclusion as a sixth factor to five-factor Fama-French Model is proven to perform better in US markets (NYSE) (Dhaoui and Bensalah, 2017).

The literature on investor sentiment is closely related to that of noise traders. Noise traders are unsophisticated investors who make financial decision not necessarily based on concrete facts, but also on perceptions and emotions, i.e. beliefs. In fact, the concept of investor sentiment stems from the notion of noise trading. Black (1986) was the first who came up with the idea that noise is inherent to financial markets. Indeed, as he put forward, noise is what makes financial markets possible. The simple logic is the following: If a trader knows what both sides of the trade know (informational symmetry), he or she cannot exploit any information and make gain. So, for a model to make sense, noise trading should be included. Also De Long *et al.* (1990) acknowledged the risk posed by noise traders. They conclude that noise traders induce unpredictability, which drives away arbitrageurs -at least limits their aggressiveness, so the mispricing can be persistent. Moreover, unorthodoxly, they claim that noise traders can survive the market.

We rely on proxies as a gauge for investor sentiment. Plenty of them are proposed in the literature, which can be categorized by means of measurement: Direct, indirect, and alternative methods providing direct measures of sentiment.

2.5.1 Direct (survey-based) measures

Direct measures refer to survey-based data. Two widely used indices help obtain a sentiment for the US stock market. One is the American Association of Individual Investor (AAII) index, which is based on a questionnaire survey that measures how investors perceive the future of the market. The other one is the Michigan Consumer Sentiment Index (MCSI), in which participants are surveyed via telephone interviews.

2.5.2 Indirect (market-based) measures

Indirect measures refer to macro- and microeconomic variables that are not aimed to reflect sentiment in the first place. They are hypothesized to be, intuitively or theoretically, related to market return and investor psychology. Widely used investor sentiment proxies are those used by Baker and Wurgler (2006): closed-end fund discount rate (CEFD), share turnover, number of initial public offerings (IPO), average first-day return of IPOs, dividend premium, and equity share in new issues. They regularly publish their composite index in Wurgler’s website and it has become a benchmark in the literature.

A word on nomenclature: Proxy is defined as “the agency, function, or office of a deputy who acts as a substitute for another” in the Merriam-Webster Dictionary. The investor sentiment index we build works as a proxy for investor sentiment. On the other hand, each measure that constitutes the sentiment index is a proxy itself for the sentiment, too. In what follows, we refer each constituent as a proxy and their combination as the index to avoid any ambiguity.

Trading Index, which is also called the Arms Index, is used by Yoshinaga and Castro (2012). It is the ratio between the average volumes of declining stocks to advancing ones and used as a measure of the market perception.

Option implied volatility indices are also used as a sentiment proxy. They are also called risk appetite indices, as the option prices gives an idea of how investors react to the perceived future risks posed by the forthcoming volatility. A widely used example is to such indices is VIX, the volatility index, which is provided by the Chicago Board Options Exchange (CBOE) (Smales, 2017).

In their cross-sectional study, Wu *et al.* (2016) use credit default swap (CDS) and treasury-Eurodollar (TED) spread, and Mbanga *et al.* (2019) uses Financial Stress Index (FSI) as investor sentiment proxies, in addition to VIX.

The share of repo holdings in the portfolios of mutual funds (Anlaş, 2017) and odd-lot sales-to-purchases ratio is (Brown and Cliff 2004) among others that find usage in order to proxy the sentiment.

A popular approach to make an investor sentiment estimation is by forming a composite sentiment index. In this method, an index is constructed via a combination of various indicators by employing some dimensionality-reduction methods such as the principal component analysis (PCA) or the partial least squares (PLS) is commonly used to form a sentiment index. The reason for doing so is to reduce the dimensionality and to eliminate common effects of sentiment proxies, i.e. to classify them, so as to provide a concise independent variable for further analysis.

2.5.3 Alternative direct measures

This approach is also a direct measure of sentiment, but instead of relying on surveys, it captures the sentiment from individual’s behaviour on the internet, in a fashion used to capture investor attention, or it derives the sentiment from newspaper columns or financial reviews via textual analysis. Since this method is based on data analytics and demands constructing a proper algorithm, computer scientists mostly use it. Analyzing internet search volume data (search volume index (SVI) by Google), text-based methods like sentiment analysis, opinion mining that captures a sentiment from tweets, reviews etc. are some examples (Da *et al.*, 2011; Da *et al.* 2015; Joseph and Zhang, 2011).

CHAPTER 3: LITERATURE ON INVESTOR SENTIMENT

Perhaps the most influential study in the investor sentiment literature is that of Baker & Wurgler (2006). They challenge the traditional view that investor sentiment does not play a role in the stock returns. They form a composite sentiment index via principal component analysis (PCA), which has since become a standard, and show that investor sentiment, indeed, is an important factor to explain returns. For small stocks which are harder to price and arbitrage, they identified a negative relationship between the sentiment index and returns. The case of high sentiment violates the principle that higher risk (regarding small stocks) comes with a higher expected return as compensation.

Lee *et al.* (2002) propose a scheme where the effect of investor sentiment on both the excess return and the conditional volatility is modeled. They use Investors' Intelligence sentiment index as investor sentiment proxy and employed a GARCH-in-mean model to relate sentiment to Dow Jones, S&P 500 and NASDAQ indices. They find that investor sentiment and volatility are negatively correlated, i.e. a bearish sentiment results in a higher volatility. Among three indices NASDAQ is found to be more sensitive to sentiment shifts, as expected, since this index contains many stocks that are generally newer and more volatile. A critical result of their study is that higher excess return is related to a decrease in conditional volatility, which is imposed by bullish shifts in the sentiment. The positive relationship between sentiment and returns implies a contradiction with Baker and Wurgler (2006)'s findings on cross-sections, but on the other hand, as the lower risk causes higher returns, they are also in opposition to the premise of the risk-return tradeoff. A relevant study by Yu and Yuan (2011) point out that during low-sentiment periods the market return and the conditional volatility is positively correlated, but the correlation is nearly flat for high-sentiment regime. This signifies the disruptive effect of high sentiment on the risk-return relationship.

The effect of noise traders on returns was a phenomenon agreed upon in behavioral finance. However, no decisive conclusions can be made regarding the dynamics. Effects of investor sentiment change drastically depending on markets, stocks and indices, risk levels and especially on proxies chosen. Extreme levels of sentiment, particularly the high-sentiment periods, are proven to be influencing returns.

According to Lemmon and Portniaguina (2006), for example, the forecasting ability of investor sentiment as proxied by CCI is limited to small stocks and stocks that have low institutional ownership. However, in contradiction to general findings, the effect of investor sentiment may not be confined to small, risky stocks. Bathia and Brendin (2013) use survey-based consumer confidence indices to establish a relation between sentiment and stock market returns for G7 countries. Their results show that investor sentiment has a greater influence on value stocks rather than on growth stocks.

Another study that relates investor sentiment to the cross-section of returns considers also the risk premium (Wu *et al.*, 2016). They used the standard Fama-French model to investigate the effect of investor sentiment, as proxied by the volatility index (VIX), credit default swap (CDS), and the treasury-Eurodollar (TED) spread, on the three risk premiums (market, size, and value). In essence, stock returns are influenced by the sentiment and the three proxies have different impacts on risk premiums. He *et al.* (2019) analyze the effect of risk premium and investor sentiment on aggregate returns and find that both have a positive influence on market returns.

Fisher and Statman (2000) divide investors into three groups: Individuals, newsletter writers, and Wall Street strategists represent small, medium, and large investors, respectively. Sentiments of all groups and their combination are found to be negatively related to S&P 500 returns, but the relationship is statistically insignificant for medium investors. An interesting outcome of their research is about actual investment decisions of individuals. Their high sentiment leads to lower returns, but their portfolios indicate otherwise showing that the relation is positive but statistically insignificant.

Huang *et al.* (2015) confirm the effect of investor sentiment on aggregate stock market returns in the USA. They build an aligned sentiment index by using the PLS method in the hope that it eliminates the error and noise so that they retain only the return-related components. Investor sentiment is found to have a greater predictive power on aggregate returns when PLS is employed. They show that the method of Baker and Wurgler (2006) is applicable to time-series analysis and the effect of sentiment on aggregate returns is in parallel to their findings for cross-section of returns.

Compared to more developed markets in Western Europe and in the US, Central European markets are claimed to be more susceptible to the influence of investor sentiment. In their cross-sectional study, Corredor (2015) found that investor sentiment, as proxied by CCI, influences stock prices. In comparison to the most developed markets in Europe, sentiment has a significantly greater ability to forecast returns.

Yoshinaga and Castro (2012) found that investor sentiment is an important variable to explain stock prices for the Brazilian market. They formed a sentiment index using PCA and using the analysis of variance (ANOVA) verified the relationship between sentiment and the cross-section of stock prices. After a positive sentiment period, small, riskier and younger firms have lower returns according to their results. After a negative sentiment period, the negative relationship is attenuated for the age and market value factors, and reversed for the risk factor. When the joint effect of sentiment and risk of the portfolio is analysed, risk itself is not found to be a significant factor on the stock returns, only the sentiment is significant. They also estimated an asset pricing model, in which the sentiment index is included, and concluded that the inclusion of a behavioral variable is useful for a better estimation.

Investor sentiment as proxied by CEFD, mutual fund flows, and the ratio of net stock purchases of foreign investors to BIST market capitalization has a capability to predict future returns (Canbaş and Kandır, 2007). However, in another study where they replace stock purchases of foreign investors with odd-lot sales-to-purchases ratio, share of equity issues in aggregate issues, repo shares of in mutual fund portfolios, and BIST turnover ratios, investor sentiment loses its forecasting capability Canbaş and Kandir (2009). Contrarily, returns are found to be influencing investor sentiment.

Kaya (2018) follows the approach of building an investor sentiment index and analyzes BIST-100 index returns. According to the results, investor sentiment is a positive return predictor for the aggregate market.

Bolaman and Evrim Mandacı (2014) find that CCI is a valid proxy for investor sentiment when examining the returns of BIST-100 at crisis period between December 2003 and December 2012. CCI is claimed to have a long-term relationship with returns. However, Köse and Akkaya (2016) argues that the effect of CCI starts to vanish after 2008 crisis and from 2010 on only the Real Sector Confidence Index (RSCI) shows an effect on the Turkish stock market. In addition to that, Korkmaz and Çevik (2009) find that BIST-100 returns have an effect on RSCI, too. According to the study of Eyüboğlu (2018a), the effect of RSCI is for short-term on BIST sector index returns, and for the long-term the causality direction the opposite.

CHAPTER 4: DATA AND METHODOLOGY

We study BIST-100 monthly index returns covering the time span between 01.01.2008 and 31.12.2018. The range is determined considering the availability of data. Historical prices of market indices are obtained from *Investing.com*, RISE index, our risk measure, is provided by CSD (Central Securities Depository of Turkey), and financial data used as sentiment measures are gathered from Capital Markets Board of Turkey (CMB), Turkish Capital Markets Association (TCMA), Central Bank of the Republic of Turkey (CBRT), and BIST (Turkish stock market).

For statistical procedures, econometric analyses and visual presentations Microsoft Excel and STATA are used.

In the following sections we describe what our variables are and why we use them. We inspect the data to make sure that the assumptions of linear regression are fulfilled and pertinent measures of sentiment proxy can be compiled into a single index. After examining the quality of the data, we end the chapter by constructing the design from which the relations are inferred.

4.1 Investor Sentiment Proxies

There is no straightforward way to measure or calculate the investor sentiment, so it is estimated using proxies. It is deduced either via direct methods such as survey-based approaches or via indirect methods, that is, a combination of various sentiment proxies.

4.1.1 Direct measures

We use the Consumer Confidence Index of Bloomberg HT (CCI), which is calculated from the data provided by Survey of Expectations of TÜİK on a monthly basis. We use seasonally unadjusted data, because it is expected to reveal more about the sentiment. Investor sentiment as proxied by CCI is used as a signal that depicts the expectations of consumers.

As Doms and Morin (2004) point out, expectations of consumers may not be continuously updated, and when updated, it may take imperfect information into account. News media is a crucial factor that shapes consumer sentiment. This process is realized through three channels: First, latest economic data and opinions of professionals are presented by the news media., Second, the tone and volume of the economic reports send a signal to consumers, Third, a greater volume of news on economy urges consumers to update their expectations. In their study they found that at certain times the consumer sentiment is driven away from economic fundamentals.

Household participation to the stock market is higher in developed countries so consumer sentiment is more widely used there as a proxy for investor sentiment. However, there is an advantage using CCI in countries such as Turkey, where news coverage is a prominent tool to shape individuals' preferences and expectations. Rational basis of consumer confidence is more likely to be replaced by irrational elements. Therefore we assume that CCI is an appropriate proxy for consumer sentiment.

One potential issue using CCI, as mentioned, is that it may fail to monitor investors' sentiment if consumers are not widely participating in the market. Also, attendants to surveys may not pay attention to questions.

Qui and Welch (2004) compare two sentiment proxies that measure consumer confidence, i.e. UBS/Gallup investor sentiment surveys and MCSI, and claim that multicollinearity rules out any sampling issues. Following the same approach, we compare CCI from TURKSTAT with CCI provided by Bloomberg HT. Despite the fact that they come from the same source, they are calculated in a different fashion. Due to the strong multicollinearity ($r=.678$, $p<.01$), we may exclude any problems regarding mentioned issues.

4.1.2 Indirect measures

Proxies that we have considered are listed below:

1. **The Investment Trust Discount (ITD)**

In the literature, closed-end fund discount (CEFD) is generally used as a sentiment proxy after Lee *et al.* (1991) concluded with supporting evidence that it is useful as a sentiment measure, validating Zweig (1973)'s initial thought. While this claim is also challenged[2], following Baker and Wurgler (2006), and Bathia and Bredin (2013) we consider it as a sentiment proxy.

CEFD, defined as the difference between the net asset value of a fund and its market price, is expected to be inversely related to sentiment since a higher CEFD means that the investors do not trust the market. This implies a bearish sentiment.

CEFD is supposed to be a good measure since individual investors mostly hold closed-end fund shares. CEFD is deemed to be a negative sentiment factor, i.e. an increase in CEFD, indicating pessimism, is correlated to a decrease in asset returns (Qiu and Welch, 2004).

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[2] Qiu and Welch (2004), for instance, claim that is not a good proxy, because it does not correlate well with the direct USB/Gallup measure or with other sentiment proxies.

One potential issue is that the effect of CEFD on returns is found to be significant prevalently for small stocks in the literature. Since we are dealing with the BIST-100 index, which comprises big stocks, it is necessary to justify our position.

Compared to big ones, small stocks are more volatile -so riskier, and thus has potential to be more lucrative. The reason that we include CEFD as a measure for sentiment proxy is that BIST index in Turkey is more volatile compared to e.g. S&P 500, so it rather resembles to those risky small stocks[3].

In Turkey, the closed-end funds are not traded, so instead we use the investment trust discount following Kaya (2018). The value-weighted index of discount of investment trusts is calculated as follows (Lee *et al.*, 1991):

$$ITD_t = \sum_{i=1}^{n_t} W_i DISC_{it} \tag{5}$$

where W_i is the ratio of net asset value (NAV) of an investment trust to total NAV of investment trusts ($NAV_{it}/\sum_{i=1}^{n_t} NAV_{it}$), $DISC_{it}$ is the discount rate ($100\times (NAV_{it} - SP_{it})/NAV_{it}$), SP_{it} is the stock price of fund *i* at the end of period *t*, and n_t is the number of investment trust whose data are available at end of period *t*.

[3] We may confirm this by comparing volatilities (standard deviations to be exact) of the log returns of BIST-100, S&P SmallCap 600 and S&P 500 indices. S&P SmallCap 600 roughly covers the US stocks that have smaller market capitalization and S&P 500 covers those with largest capitalization. Between 02/10/2012, when S&P 600 was first calculated, and 31/12/2018 BIST-100 was about 71% and 42% more volatile than S&P 500 and more volatile than S&P 600.

2. BIST Trading Volume and Share Turnover (TRAD & TURN)

Share turnover is the ratio of trading volume and market capitalization. Considering the overall market, it shows the rate of circulation, which gives a hint of the optimism/pessimism of investors. Cross-sectionally, it indicates how easy or difficult to sell a specific stock. Baker and Wurgler (2006) used NYSE share turnover in the view of Baker and Stein (2004), who suggested that liquidity, and turnover as well, is useful as a sentiment index. Both measures are strongly related to market prices. Optimistic investors tend to show higher participation in the market, therefore, increase the liquidity. Higher investor attention due to increased liquidity implies the overvaluation of stocks, and thus low market returns.

The difference of trading volume or its change respective to the previous period may well serve as a sentiment indicator since it reflects the investor attention, which is might be related to the sentiment.

It is crucial to note that NYSE turnover is no longer used by Baker and Wurgler as stated in Wurgler's website, because the increasing use of high-frequency trading made it lose the meaning it once had in our context.

Data is obtained from Capital Market Factsheets of TCMA and Monthly Statistical Bulletins of CMB.

3. Equity Share in New Issues (SHARE)

Equity share in new issues is the ratio of the market values of equity shares to all security issues registered with the CMB at the given month. Data is obtained from the Monthly Statistical Bulletins provided by the CMB.

The equity share is expected to increase when sentiment is positive, and it is a strong predictor of future market returns according to Baker and Wurgler (2000).

4. Number of Investment Accounts (ACC)

An increase in the number of investors may be interpreted as a signal of increasing investor attention. It is safe to attribute a larger portion of this increment to individual retail investors, i.e. noise traders. Therefore, as a sentiment measure we consider the number of investor accounts, supposing that the number of professional investor accounts remain more or less steady. We expect a positive correlation between the appetite to trade and sentiment.

Even though the relation between investor attention and investor sentiment lacks definitive proof, attention is a necessary condition for sentiment. On the other hand, attention helps the available information to be embedded into prices, thus increases the market efficiency. Da *et al.* (2011) finds that the attention derived from search volume index (SVI) exhibits a low correlation to sentiment, but also claims that the extreme negative sentiment can be inferred from the textual analysis of news articles.

As a conclusion, considering that liquidity affects sentiment (Baker and Stein, 2004), number of investor accounts is correlated to future returns (Choi *et al.*, 2013), and the investor attention may cause changes in sentiment (Mbanga et al., 2019), we decide to add this attention-related proxy to our index in case it does not possess a serious correlation to other variables.

The growth rate of investment accounts is previously used as a positive sentiment proxy by Qiang and Shu-e (2009).

5. Number of Initial Public Offerings (NIPO)

Initial public offerings (IPOs) has many benefits for companies. In summary, publicly traded companies have better financing sources by reaching a large number of investors, benefit from an easier access to capital markets, gain reputation, and may use advantages of an increased liquidity.

6. Average First-Day Return of Initial Public Offerings (RIPO)

First-day return of IPOs is calculated as follows:

$$RIPO_t = \frac{1}{NIPO_t} \sum_{i=1}^{NIPO_t} RIPO_{it} \tag{6}$$

where $NIPO_t$ is the number of IPOs at the period *t*, $RIPO_{it}$ is the first-day return of firm *i* at the period *t* ($PCLO_{it}/PINIT_{it} - 1$), $PCLO_{it}$ is the first-day closing price and $PINT_{it}$ is the initial offering price of firm *i* at the period *t*

7. Exchange Rate (EXC)

We use the levels and difference of USD/TRY exchange rate. Although the exchange rate is widely used as an economic factor, it also affects the sentiment of investors.

Heiden *et al.* (2013) claims that institutional investors' sentiment can identify the medium-run returns in the EUR/USD market and individual investors' sentiment on this regard seems more like a noise. Plakandaras *et al.* (2015), on the other hand, finds that investor sentiment can be a possible predictor of the future evolution of exchange rates. So we include it as a lagging indicator.

8. Ratio of Net Foreign Stock Purchases to Market Capitalization (FOR)

A good portion of investors in the Turkish stock market are foreigners. The difference between buys and sells of foreign investors is said to have an explanatory power on the level and direction of returns (Canbaş and Kandir, 2009).

4.1.3 Forming the Investor Sentiment Index

As described in the literature, we form composite investor sentiment indices, whose constituents are supposed to indicate investor sentiment as well as affecting the return. Lags and differences are already specified in the indices and this structure forbids the use of changes in the index during regression analysis. Therefore, only the levels of indices are considered.

Orthogonalization. An orthogonalization procedure is usually applied in the literature when it comes to treating sentiment proxies. The idea behind is that the sentiment index has both rational and irrational components as a consequence of employing business cycle and market-related variables. It is desired to have an index comprising less of a rational portion in order to reflect the irrational side of expectations. Although it is not possible to fully refrain from macroeconomic influences, orthogonalization helps to an extent. Various macroeconomic variables to use for this purpose include but not limited to inflation rate, industry production index, exchange rates of currency etc.

Despite its common use, we do not opt to use this method. First of all, the regression analyses include the risk factor, which is supposed to be reflecting macroeconomic conditions. Once it is proved that regression assumptions are not violated, e.g. no multicollinearity between independent variables, regression works in a way that it isolates the effects of each of those variables. The procedure might statistically have a meaning, but is not more than wishful thinking to be able to have a separate fully irrational investor sentiment. In fact, Baker and Wurgler (2006) use this approach to build the index, but also point out that this is a second-order issue, and the procedure does not qualitatively affect the sentiment index.

After all, the concept of investor sentiment does not assume an ever-erroneous investor, it merely postulates that investors are prone to systematic behavioral misjudgements. So, of course, behaving rationally is also “normal”.

Principal Component Analysis (PCA). PCA is a way of factorization in order to reduce the dimensionality of variables. By employing PCA, we expect to remove what variables have in common and obtain independent factors comprising eigenvalues of those variables in order to have a cleaner measure of sentiment. The sum of eigenvalues is equal to the number of variables and the eigenvalue of each component tells the portion of cumulative information contained therein. The addition of each eigenvalue to the resulting index increases its explanatory power; however, the number of components needed to adequately represent the full effect depends on our judgment and is somewhat subjective. Generally, the decision is made by observing the scree plot and the cumulative proportion of explanation after including each component. Visually, the shape of an elbow in the scree plot implies the number to choose. It is also suggested that the number we seek is the one after the eigenvalues drop below 1. A more objective judgment is to choose as much components needed as to reach a desired proportion of the original values to be explained after the reduction. Of course, it would not be wise to use PCA if one explains five variables using four components. We build multiple sentiment indices that consist of various blends of our explanatory variables and through regression analysis we assess their quality. After deciding on how many principal components to include, we form the index from the weighted averages of those components. Necessary requirements for the composite index to be meaningful are fulfilled and it is tabulated in Section 4.3, Data Inspection.

Proposed Investor Sentiment Indices. We form the indices after we control for its constituents. When they are proved to be explanatory for the return, we combine them into a sentiment index to see what this process can contribute to our analysis.

We have used Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity for seeing if proxies are reliable to use at PCA and if they are not, we did not include them in the indices. KMO test is used to measure sampling adequacy. The values are between 0 and 1, and small values signify that the variables have too little in common for a healthy factor analysis. KMO values smaller than 0.50 are unacceptable. We also run the Bartlett test of sphericity. The probability value of Bartlett's statistic smaller than 0.05 shows that the correlation matrix is different than unit matrix, hence the relation between variables is significant (Kaya, 2018). Results are found in.

4.2 Overall Market Risk

Risk-return relationship is predominantly studied using cross-sectional returns. In this stock-wise approach, the systematic risk (market risk) upon certain stocks is associated with their return. As we analyze the aggregate return, stock-specific risk is not of our interest. Instead, we deal with the risk in the market as a whole. Market risk premium of the cross-sectional approach is in strong positive relation with riskiness in the market (Bali, 2015). Both risks refer to the systematic risk inherent to the market and cannot be diversified away.

The RISE Index is used as a proxy for the overall market risk. The Investor Risk Appetite Index (RISE) may be regarded as a Turkish counterpart of the well-known VIX index and is provided by the partnership of CSD and Özyeğin University since December 2012. It differs by means of measurement. Instead of using options, it is calculated by normalizing the change of investors' portfolio values with BIST-100 prices. Index data is available starting from November 28, 2005 onward, and it is obtained from CSD. The index is published weekly on Fridays, and by converting it to a monthly basis we assume that the effect of residuary days can be neglected in a time-span of 11 years.

RISE will function as a base regression to which we add other independent variables to assess their contribution. Theoretical framework that justifies the link between overall market risk and the VIX is provided by Bali et al. (2015). They compare the VIX, the option implied riskiness, and physical measures of riskiness, and show that the VIX is highly persistent and it is correlated well with the physical measures of riskiness (in the range of 0.61-0.88).

Overall market risk is supposed to be determined by macroeconomic factors. Çelik *et al.* (2017) acknowledges gross domestic product (GDP), exchange rate, money supply, foreign exchange reserves and inflation among macroeconomic variables that affect RISE.

Among the calculated RISE indices, we choose the one that represents the difference of qualified investors risk appetite since it has the best predictability on returns.

4.3 Data Inspection

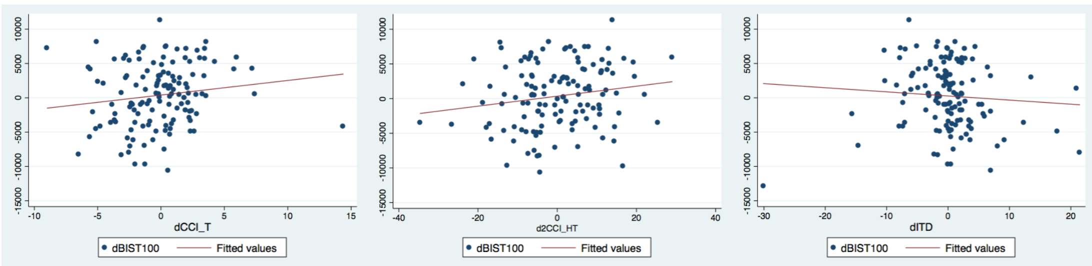
Here we present details of our data in order to prove its usefulness for further analysis. Key assumptions of linear regression are linear relationship, multivariate normality, little multicollinearity (better none), no autocorrelation, and homoscedasticity. So, our data is expected to satisfy those assumptions. Moreover, there are specific requirements in case multiple variables are fused into one sentiment index.

Before addressing those requirements, we present a general overview. Basic features of the data are described in Table 4.1. Here displayed are the variables as we use them, i.e. with lag, difference or change. Plain versions with no lag or difference is provided in Appendix A, Table A.1. Mean, mode and median are measures of central tendency and show the distribution of data. Skewness shows the lack of symmetry in the probability distribution, and kurtosis shows how heavy or light tailed the variable is, compared to the normal distribution.

Table 4.1: Summary statistics of the data

	Obs	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
dBIST-100	132	270.6996	4698.321	-12840.57	11348.62	-.2423278	2.583192
RISK	132	45.64394	11.38777	18	71	-.0843821	2.594544
dCCI_T	131	-.1579333	3.044303	-8.983097	14.36617	.6630296	6.406724
d2CCI_HT	130	.1091231	10.74399	-34.60701	28.98499	-.1406652	3.305645
dITD	132	-.0277235	5.970283	-30.10312	21.43244	-.2971534	9.518313
cTRAD	132	3.15206	20.36684	-32.50108	61.24017	.7480454	2.974426
cTURN	132	.0248498	.2059647	-.3474075	1.042118	1.244819	6.394479
cSHARE	121	51.70291	402.0924	-.9997456	4374.604	10.4272	112.3028
logSHARE	125	-3.68568	2.304142	-9.499441	-.000016	-.4083241	2.687587
dACC	132	1809.636	8178.578	-17717	42950	1.61524	8.24677
NIPO	132	.9318182	1.483719	0	8	1.890933	6.927664
RIPO	52	-.8242692	.53902	-3.05	1.1	.166518	10.93983
dEXC	132	.0179886	.077716	-.1484001	.3431001	1.023489	5.307825
FOR	131	-.0000192	.0025293	-.0068858	.0069832	-.1762765	3.561923
cFOR	129	-.8249233	5.749248	-34.57863	33.44005	.1568781	22.01012

For a visual inspection, we provide scatter plots that depicts the relation between potential proxies and the market return.



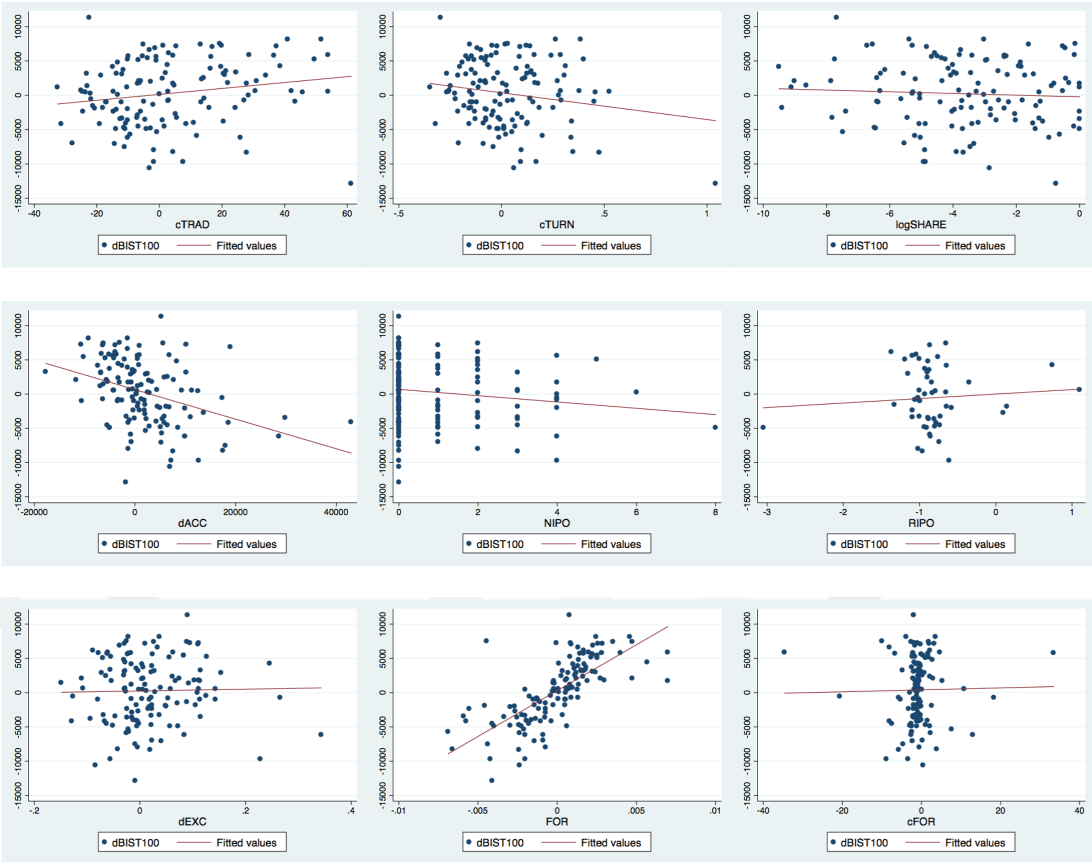


Figure 4.1: Scatter plots of proxies vs return From left to right and top to bottom: dCCI_T, d2CCI_HT, dITD, cTRAD, cTURN, logSHARE, dACC, NIPO, RIPO, dEXC, FOR, cFOR.

The relations are somehow visible from Fig. 4.1, but before moving on it is necessary to statistically show the relation. It is also required that the sentiment proxies should not be significantly correlated to each other in order to justify their inclusion.

Correlations are calculated via Pearson correlation coefficients. In order to use Pearson's correlation, the variables should be normally distributed and not suffer from heteroscedasticity. Moreover, outliers should be kept to a minimum or better removed.

Besides, we have to make sure that our time series are stationary, i.e. they do not possess unit roots, to be able to make estimations using them. For that purpose, we employ Augmented Dickey-Fuller unit-root test. The results show that BIST100, RISK, TURN, SHARE, NIPO, AND RIPO are stationary and has no unit roots, while for the others, this is secured by using their differences. Full results are available in Appendix A, Table A.2.

We use the LM test for ARCH to make sure that none of our variables suffer from heteroskedasticity. The null hypothesis "H_0: no ARCH effects" is rejected for ITD, TRAD, TURN, ACC, and EXC, among which TURN and SHARE has heteroscedasticity also for their differenced values (Appendix A, Table A.3).

Table 4.2 shows the correlations among variables, which possess no heteroscedasticity and nonstationarity as tested above. Variables determined to be suitable for further analysis is listed in Table A.4 of Appendix A. Ideal outcome should depict good correlation between independent variables and return, and less correlation among explanatory variables.

Table 4.2: Pearson correlation coefficients

	Return	RISK	dCCI	dITD	cTRAD	cTURN	logSH.	dACC	NIPO	RIPO	dEXC
RISK	0.6603***	1.0000									
dCCI	0.1416	0.2438***	1.0000								
dITD	-0.0762	-0.0632	-0.1461*	1.0000							
cTRAD	0.1869**	0.2909***	0.2321***	-0.2131**	1.0000						
cTURN	-0.1710**	0.0413	0.1499*	-0.2246***	0.9153***	1.0000					
logSHARE	-0.0598	0.0488	0.2092**	-0.0055	0.0859	0.0794	1.0000				
dACC	-0.3759***	-0.2601***	0.0534	0.0268	-0.0601	0.0563	0.0895	1.0000			
NIPO	-0.1457*	-0.1099	0.0983	0.1953**	-0.1271	-0.0745	0.1087	0.1232	1.0000		
RIPO	0.0811	0.0052	0.1506	-0.0708	0.3661***	0.3150**	0.0931	0.1516	0.1137	1.0000	
dEXC	0.0213	0.0714	0.0037	0.0294	0.1086	0.1150	-0.0808	-0.0149	-0.1015	0.1812	1.0000
FOR	0.7182***	0.5071***	0.0632	0.0086	0.2041**	-0.0799	-0.0821	-0.4447***	-0.0681	0.0542	0.0160

Note: $*: \rho > 0.1$ $**: \rho > 0.05$ $***: \rho > 0.01$

The coefficients both range from -1 to 1, for Pearson and Spearman, -1 meaning perfect negative correlation, 1 perfect positive correlation, and 0 no correlation. As observed from Table 4.2, the highest correlation is between risk and return, as expected. For the correlation between sentiment proxies, we take this table as reference and act accordingly in the regression analysis. If the correlation between variables is high, we prefer not to use them together, but do not refrain from including in the regressions. Post-estimation diagnostics are helpful to determine whether the collinearity possess a problem. On the other hand, proxies are expected to be correlated to returns.

Note that, using statistics one can only examine correlations. Correlation does not imply causality and causality is on the table only when the relation is backed up by economic theory.

CHAPTER 5: RESULTS AND ANALYSIS

As we seek to find the effect of investor sentiment on risk-return relationship, we initially relate market risk and return to identify the explanation capability of the risk variable. Later on, we incorporate the sentiment indices, which were built from various proxies in different settings, such as time lags and difference conditions. By means of this we decide what structures provide a better explanation of market returns and discuss the results. As for the market returns, using the log difference of prices, i.e. $ln(P_t) - ln(P_{t-1})$ is the conventional approach. However, we stick to the plain difference of BIST-100 prices since using log returns does not make any further contribution for our purposes, they essentially give the same results. Any difference we observe is indicated.

We present examplary results in a gradual manner to reflect our steps to achieve the final judgment. The final regression is analyzed in more detail, but results, post-estimation diagnosis etc. for the others can be found in the Appendix B and Appendix C.

First of all, we set the control regression and show how much the risk, our control variable, can explain returns:

$$R_t = \alpha + \beta_1 . RISK_t + u_t \tag{7}$$

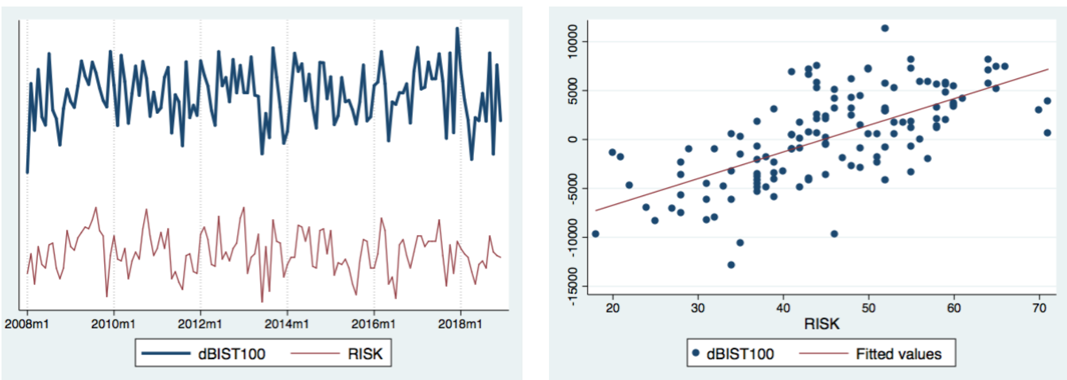
where α is the constant, β_1 is the regression coefficient for *RISK*, u is the error term, and t is the period of time. The regression results are provided here, in Table 5.1, since others are evaluated in comparison to this baseline.

Table 5.1: The Effect of Risk on BIST-100 Returns

Source	SS	df	MS		
Model	1.2607e+09	1	1.2607e+09	Number of obs =	132
Residual	1.6310e+09	130	12546343.3	F(1, 130) =	100.48
				Prob > F =	0.0000
Total	2.8917e+09	131	22074215.7	R-squared =	0.4360
				Adj R-squared =	0.4316
				Root MSE =	3542.1

BIST-100	Coef.	Std. Err.	t	P > | t |	[95% Conf. Interval]	
RISK	272.415	27.17591	10.02	0.000	218.6507	326.1792
_cons	-12163.39	1278.154	-9.52	0.000	-14692.07	-9634.717

As observed from Table 5.1, risk seems related to returns, as expected. The adjusted R^2 of 0.4326 presents a good percentage of explainability. The high RMSE is due to large variations between the values of variables. The model-to-residuals ratio is ~0.77, and the F number is around 100. The scaled line plot in Fig. 5.1a provides a visual depiction of the relation between risk and return, and from the scatter plot in Fig. 5.1b we can observe the degree of relation as the exact corresponding points are shown along with the fit line.



(a) (b)

Figure 5.1: Visual depiction of the relation between risk and return. (a) Line plot, (b) Scatter plot.

Once the risk-return trade-off is established, we move forward to include sentiment indices to assess their contribution. First we incorporate the consumer confidence indices into the risk-return regression as an independent variable.

$$R_t = \alpha + \beta_1.RISK_t + \beta_2.dCCI\_T + u_t \tag{8a}$$

$$R_t = \alpha + \beta_1.RISK_t + \beta_2.ddCCI\_HT + u_t \tag{8b}$$

where $dCCI\_T$ is the difference of CCI of TURKSTAT, and $ddCCI\_HT$ is the second difference of CCI_HT, the CCI of Bloomberg HT. We did not include levels of CCI values and the first difference of CCI_HT, since they either are nonstationary or they show ARCH effect.

Results show that none of them significantly contribute to explaining returns. Adjusted R^2 is found to be 0.4286 and 0.4396 for Eq. 8a and Eq. 8b, respectively. Moreover, neither CCI has a coefficient with significant t-value. From here we can infer (1) Sentiment has no effect on returns, (2) CCI is not a proxy for sentiment. For now, we neglect (1) and focus on (2). So, knowing that CCI alone is not explanatory, we consider it as an independent variable among indirect proxies. The distinction between indirect and direct proxies is in the way they are measured, not about their usage; therefore, it is fine to do so, even though in the literature only a few choose this way. The difference of CCI from TURKSTAT is included in the analysis from now on, since it is harder to economically make sense the second differences.

$$\begin{aligned} R_t = \alpha + \beta_1.RISK_t + \beta_2.dCCI\_T_t + \beta_3.cTRAD_t + \beta_4.FOR_{t-1} + \beta_5.cTURN_t \\ + \beta_6.logSHARE_t + u_t \end{aligned} \tag{9}$$

where c denotes the change, d the difference, and log the natural logarithm.

Above regression is meant to describe the effect of sentiment proxies when indirect and direct ones are combined. Results point an impressive adjusted R^2 of 0.8091 (see Appendix B, Table B.1, Eq. 9). Yet, when we check the Granger causality, only FOR_{t-1} is found to possess a significant relation to the return. Note that, possible arrangements to provide similar results are manifold. For example, when we replace FOR_{t-1} with $dFOR_{t-1}$, then add $dACC_{t-1}$, we come up with an adjusted R^2 of 0.8174, with all coefficients being significant (Appendix B, Table B.1, Eq. 9b). When $dITD$ is added further, adjusted R^2 stays around the same level, but $dITD$ does not have a significant coefficient (see Appendix B, Table B.1, Eq. 9c).

Next, we check if neglecting CCI results in diminishing explanatory power. For Eq. 10, adjusted R^2 decreased to 0.7975 and for the following two variations, the decrease is even more slight.

What comes next is to build a composite sentiment index by employing PCA with the variables we have used. We examine both cases where CCI is included or not. For now, we remove $cFOR_t$ from Eq. 9 (Appendix B, Table B.1, Eq. 9d) since its omission provides a more robust result. The resulting regression provides an adjusted R^2 of 0.8034, but the residuals are not normally distributed, which is not a critical problem. If we neglect CCI, the resulting adjusted R^2 is 0.7901. Detailed results can be found in Table B.1 of Appendix B, and the post-estimation diagnostics in Table C.2 of Appendix C (Eq. 9d & Eq. 9e).

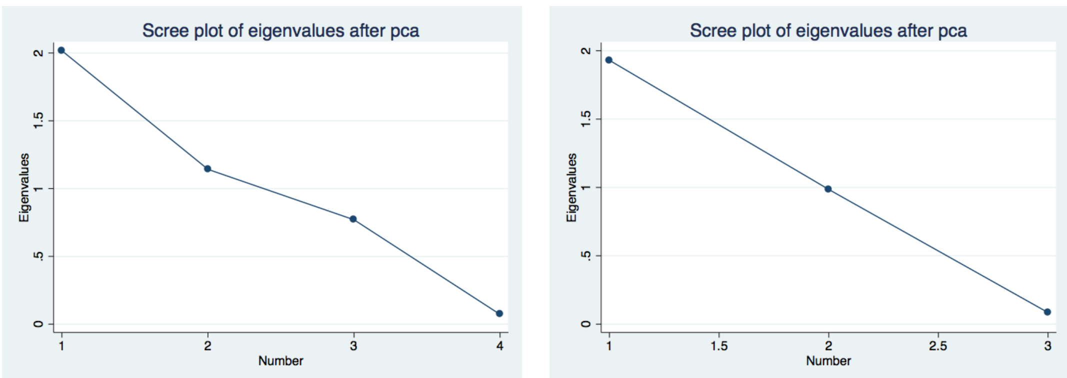


Figure 5.2: Scree plots of eigenvalues after PCA. SENT1 (left) and SENT2 (right).

To decide on the number of components in the PCA, we view the screeplots (Fig. 5.2) and check the cumulative portions of principal components to reflect the effect of constituent proxies (Table 5.2).

Table 5.2: Cumulative explanation portions of principal components. SENT1 (left) and SENT2 (right)

SENT1		SENT2	
Component	**Cumulative**	**Component**	**Cumulative**
Comp1	0.5042	Comp1	0.6433
Comp2	0.7897	Comp2	0.9718
Comp3	0.9821	Comp3	1.0000
Comp4	1.0000		

For both SENT1 and SENT2, we find that two principal components are enough to explain the variables. The variables that make up the sentiment index are tested via Bartlett's test for white noise if they are suitable to use in PCA. For 95% confidence interval they are proven to be useful. For results of the test see Appendix A, Table A.4. Second criterion to assess the health of PCA is the KMO measure. It is 0.5025 and 0.5040 for SENT1 and SENT2, respectively.

After their formation, we put the contemporaneous and lagged sentiment indices into regression equations as follows:

$$R_t = \alpha + \beta_1.RISK_t + \beta_2.SENT1_t + u_t \tag{10a}$$

$$R_t = \alpha + \beta_1.RISK_t + \beta_2.SENT1_{t-1} + u_t \tag{10b}$$

$$R_t = \alpha + \beta_1.RISK_t + \beta_2.SENT2_t + u_t \tag{11a}$$

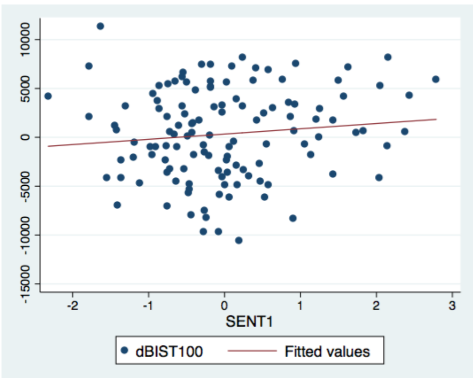
$$R_t = \alpha + \beta_1.RISK_t + \beta_2.SENT2_{t-1} + u_t \tag{11b}$$

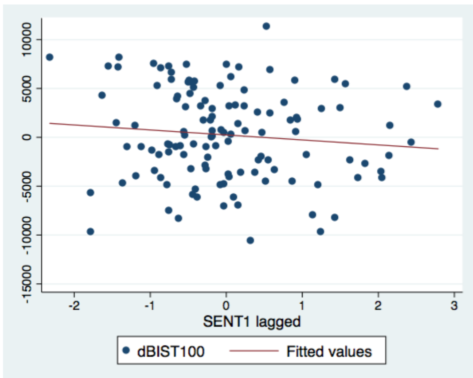
The results are depicted in Table 5.3. Indices provide only a minor improvement compared to the control regression except the contemporaneous SENT1, which is found to be insignificant.

Table 5.3: Brief results for SENT1 and SENT2

	t-statistic	P>|t|	Adjusted R^2
$SENT1_t$	-1.12	0.264	0.4605
$SENT1_{t-1}$	-2.33	0.021	0.4523
$SENT2_t$	-2.11	0.037	0.4730
$SENT2_{t-1}$	-1.87	0.064	0.4429

Scatter plots of sentiment indices in comparison to returns show the insignificance of the contemporaneous SENT1, since the line fit has a positive slope even though its coefficient has a negative value (Fig. 5.3). The results show that the effect of investor sentiment on returns is negative.





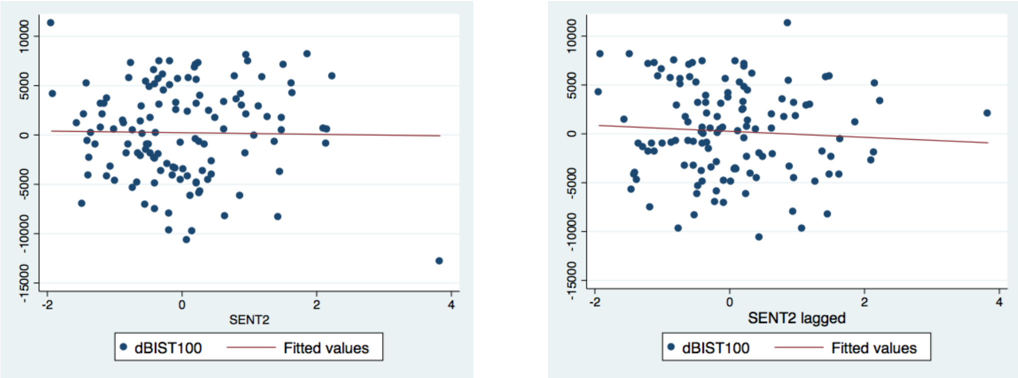


Figure 5.3: Scatter plots of sentiment indices and their lags.

CCI, ITD, ACC, and EXC are, as described before, nonstationary. The fact that their first difference becomes stationary makes them suitable for a vector error-correction model (VECM), along with BIST-100 prices.

We first run Johansen cointegration and determine the rank for the VECM. Next, we use the error term extracted from the VECM as a sentiment index comprising abovementioned nonstationary proxies. We can estimate the error term without CCI (ce1) or with CCI (ce2) as follows (see Table B.3-B.6 in Appendix B for details):

$$ce1 = BIST100 - 3538.218 \times ITD + 3831.209 \times EXC + 0.0140735 \times ACC \quad \text{(12a)}$$

$$\begin{aligned} ce2 = BIST100 - 2180.892 \times ITD - 87754.07 \times EXC + 0.5981084 \times ACC \\ - 8423.227 \times \mathrm{CCI\_T} \end{aligned} \quad \text{(12b)}$$

When we check the estimation results of both VECM models, we realize that t-statistics for constituent variables in Eq. 12a are not significant in 95% confidence interval (see Table B.4 in Appendix B). So for further analysis, we consider using Eq. 12b alone or complementary to SENT2, which does not include CCI. However, for neither case can we find meaningful results. The constituents of SENT2 are mixed with ce2 into a composite index, but this does not work either.

The best result we can come up with is by implementing ACC and CCI_T into the regression via VECM next to some other proxies. The conditions for VECM are checked as above and the new error-correction term is built as follows:

$$ce3 = BIST100 - 0.4087741 \times ACC + 5430.561 \times CCI\_T \tag{13}$$

This term is then added to the following regression:

$$\begin{aligned} R_t = \alpha + \beta_1.RISK_t + \beta_2.cTRAD_t + \beta_3.cTURN_t \\ + \beta_4.logSHARE_t + \beta_5.dITD_t + \beta_6.FOR_{t-1} + \beta_7.ce3_t + u_t \end{aligned} \tag{14}$$

All the variables are found to be significant in the regression above with an adjusted R^2 of 0.8096 (see Eq. 14 in Appendix B & C for details). Now we form the sentiment index with those variables by using PCA. KMO measure is 0.5440.

$$R_t = \alpha + \beta_1.RISK_t + \beta_2.SENT3_t + u_t \tag{15}$$

Above regression with the investor sentiment index that conveys effects of seven proxies has significantly lower adjusted R^2 compared to Eq. 14 (0.4807 vs. 0.8096), but it still shows a minor improvement compared to the control regression. This proves the explanatory capability of investor sentiment on returns. This sentiment index has a significant t-statistic, and as the post estimation diagnostics show, this regression is the most robust one among all we have considered. It has no heteroskedasticity or collinearity problems, residuals are normally distributed with no severe outliers (see Appendix C, Table C.2 for detailed diagnosis results). The estimated regression equation is as follows:

$$R_t = -13596.5 + 302.4615 \times RISK_t - 1262.419 \times SENT3_t \tag{16}$$

As expected, risk is positively related to return. This is confirmed here, and further we find that an increase in the investor sentiment decreases BIST-100 index returns. This result contradicts to that of Lee *et al.* (2002) and Kaya (2018), who find a positive relationship between sentiment and aggregate returns for US and Turkey, respectively. We show that the relation is indeed negative as parallel to the cross-sectional analysis of Baker and Wurgler (2006), supporting the findings of Huang *et al.* (2015).

The signs of proxy coefficients for the regression in Eq. 14 are tabulated below so that we can observe whether their effect on returns is positive or negative (Table 5.4):

Table 5.4: Signs of proxy coefficients

	$cTRAD$	$cTURN$	$logSHARE$	$dITD$	$L.FOR$	ACC	CCI_T
$dBIST100$	+	-	-	-	-	-	+

As to our findings, SHARE and TURN are contrarian predictors of market returns, which confirms Baker and Wurgler (2006). However, ITD does not have the same sign as the sentiment index, opposing their findings for CEFD. Interestingly, we find that CCI and investor sentiment index has different signs, so different effects on the return. This shows that CCI alone is not a proper sentiment proxy when used alone.

As described step by step, we have used various proxies to determine the contribution of investor sentiment to the risk-return trade-off. With the help of VECM, the sentiment is proven to be effective on returns when proxied by the combination of seven of ten explanatory variables we have proposed. Exclusion of proxies related to IPOs is due to the low number of monthly IPOs. The mean of

NIPO is 0.9318182, where no offerings is the most frequent observation. As a consequence, RIPO can be calculated only for 52 months, out of 132. So, they both are removed from consideration. The results show that a proper configuration of proxies help explain the excess return.

CHAPTER 6: CONCLUSION

To sum up, we investigated the risk and return relationship in this thesis. Risk, as proposed by the asset pricing models, forms a trade-off with the returns. For a higher gain, an investor must be willing to bear more risk. The relationship fails to explain certain market anomalies, that is why we used the concept of investor sentiment, expecting that it can explain some portion of anomalies such as the excess return.

We formed a sentiment index to find how it affects returns, given that risk is another independent variable, we seek to find its contribution. We first analyzed the data to check if it suffers from the abovementioned issues. We eliminated the ones that could not pass the test and used the following proxies for the rest: Difference of ITD, ACC, EXC, difference of CCI, change in TRAD, and FOR. Using these variables we performed regression analyses with various settings. Inclusion of one variable could lead to make another insignificant, or vice versa. We determined the best sentiment proxies to describe part of the excess return, the return that is not coming from the risk as described by the traditional finance.

The raw prices of indices usually contain unit roots, i.e. they usually have trend. For the detrending, log returns of prices is used in general, but we decided to stay with the plain difference, since it provided us a clean return series. Another way to get rid of the issues and prepare the data for future analysis is to detrend them, which is basically taking the difference of a variable.

For the values that are stationary only in their difference, cointegration tests may be applied. We know that the raw prices are usually moving with a direction. We used Johansen cointegration and by using the vector error correction model (VECM) we came up with the error correction term. This term could be perceived as the mixture of variables.

Our contributions to the literature are as follows: Instead of relating the investor sentiment directly to market returns, as done conventionally, we analyzed its effect in the context of risk-return tradeoff by proxying the risk factor. Besides widely used measures of sentiment to analyze BIST-100, we also considered the seldom used 'number of investment accounts' as a sentiment proxy. For the best of our knowledge, its effect on returns has not been confirmed for the Turkish stock market before. Lastly, we made our contribution to the ongoing debate on the sentiment-return relation. Investor sentiment is a negative return predictor and CCI can only be considered as a proxy in combination with other proxies when analyzing the BIST-100 index returns.

Drawbacks of this study include the lack of a robustness test. As there are no direct or indirect measures of investors sentiment that have found common acceptance in the literature, the significance of our results cannot be compared to a rigid proxy. Another problem is the potential lack of including important proxies for sentiment. This is partly due to unavailability of data for our sample period, but mostly due to the lack of finding good-quality data.

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APPENDIX A: PRE-ESTIMATION DIAGNOSTICS

Table A.1: Descriptive statistics of plain variables

	Obs	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
BIST-100	132	70319.82	21509.69	24026.59	119528.8	-0.0622784	2.705837
RISK	132	45.64394	11.38777	18	71	0.0843821	2.594544
CCI_T	132	70.91435	6.10336	55.65735	83.19334	-0.3706795	2.501707
CCI_HT	132	87.93818	16.43813	55.478	122.007	0.0614584	2.048417
ITD	132	20.80212	12.49419	-11.2214	43.40399	0.0112979	2.147682
TRAD	132	75454.55	40155.98	17363.35	211029.8	1.22113	4.206282
TURN	132	13.94252	3.352725	7.787973	26.80137	1.004399	4.732764
SHARE	125	0.1488808	0.2602242	0.0000749	0.999984	2.161014	6.636514
ACC	132	1059967	51254.59	938291	1186133	0.015466	3.11746
NIPO	132	0.9318182	1.483719	0	8	1.890933	6.927664
RIPO	52	-0.8242692	0.53902	-3.05	1.1	0.166518	10.93983
EXC	132	2.063111	0.7437	1.1616	3.919	0.9209352	2.712285
FOR	131	-0.0000192	0.0025293	-0.0068858	0.0069832	-0.1762765	3.561923

Table A.2: Testing the stationarity of data

Variables	Test statistic	1% Critical Value	Variables	Test statistic	1% Critical Value
BIST100	-1.362	-3.500	**cTURN**	-16.591	-3.500
dBIST100	-12.045	-3.500	**SHARE**	-6.607	-3.503
RISK	-8.748	-3.500	**dSHARE**	-15.394	-3.505
CCI	-2.709	-3.500	**d2SHARE**	-18.953	-3.507
dCCI	-10.073	-3.500	**cSHARE**	-10.868	-3.505

CCI_HT	-2.835	-3.500	**logSHARE**	-8.142	-3.503
dCCI_HT	-10.054	-3.500	ACC	-0.999	-3.500
d2CCI_HT	-14.785	-3.500	**dACC**	-10.445	-3.500
ITD	-2.809	-3.500	**d2ACC**	-20.337	-3.500
dITD	-13.803	-3.500	**NIPO**	-8.136	-3.500
d2ITD	-22.421	-3.500	**RIPO**	-5.691	-3.716
TRAD	-2.296	-3.500	EXC	1.374	-3.500
dTRAD	-17.565	-3.500	**dEXC**	-9.733	-3.500
cTRAD	-15.280	-3.500	**d2EXC**	-17.377	-3.500
TURN	-4.701	-3.500	**FOR**	-12.452	-3.500
dTURN	-16.275	-3.500	**dFOR**	-21.898	-3.501
d2TURN	-24.147	-3.500	**cFOR**	-11.065	-3.501
Note: Test statistic smaller that 1% Critical Value means that the null hypothesis of H_0: unit root exists is rejected at 1% significance level. Fonts in bold denote variables for which the null hypothesis is rejected.					

Table A.3: Testing the homoscedasticity of data

Variables	chi^2	Prob > chi2	Variables	chi^2	Prob > chi2
BIST100	0.675	0.4113	**cTURN**	0.006	0.9395
dBIST100	0.232	0.6299	SHARE	13.897	0.0002
RISK	0.779	0.3774	dSHARE	3.656	0.0559
CCI_T	74.110	0.0000	d2SHARE	25.580	0.0000
dCCI_T	0.870	0.3509	**cSHARE**	0.010	0.9223
CCI_HT	55.317	0.0000	**logSHARE**	2.421	0.1198
dCCI_HT	2.925	0.0872	ACC	120.261	0.0000
d2CCI_HT	0.002	0.9634	**dACC**	0.019	0.8904
ITD	54.228	0.0000	d2ACC	18.346	0.0000
dITD	0.393	0.5305	**NIPO**	0.099	0.7530
d2ITD	21.314	0.0000	**RIPO**	0.412	0.5209

TRAD	66.252	0.0000	EXC	124.489	0.0000
dTRAD	25.311	0.0000	**dEXC**	0.497	0.4808
cTRAD	0.262	0.6088	d2EXC	9.455	0.0021
TURN	29.726	0.0000	**FOR**	2.450	0.1176
dTURN	8.135	0.0043	dFOR	63.000	0.0000
d2TURN	32.574	0.0000	**cFOR**	0.278	0.5981

Note: Null hypothesis is that H_0: no ARCH effects. P>0.1, P>0.05, and P>0.01 denotes significance at 10%, 5%, and 1% significance levels, respectively. Fonts in bold denote variables for which the null hypothesis is rejected.

Table A.4: The form of variables as used in the analysis

Variable	Description
d.BIST100	Difference in BIST100 (BIST100 returns)
RISK	Risk proxy
dCCI_T	Difference in Consumer Confidence Index (TURKSTAT)
d2CCI_HT	Second difference in Consumer Confidence Index (Bloomberg HT)
dITD	Difference in Investment Trust Discount
d2ITD	Second difference in Investment Trust Discount
cTRAD	Chance in Trading Volume
cTURN	Change in Turnover Rate
cSHARE	Change in Share of Equity Issues in Total New Issues
logSHARE	Natural logarithm of Share of Equity Issues in Total New Issues
dACC	Difference in Number of Investment Accounts
NIPO	Number of Initial Public Offerings
RIPO	First-day Return of Initial Public Offerings
dEXC	Difference in Exchange Rate
FOR	Foreign Net Purchases / Market Capitalization
cFOR	Change in Foreign Net Purchases / Market Capitalization

Table A.5: Suitability of data for PCA

Regression	Bartlett test of sphericity			Kaiser-Meyer-Olkin Measure of Sampling Adequacy
	Chi-square	dF	p-value	
SENT1	249.496	6	0.000	0.502
SENT2	223.034	3	0.000	0.504
SENT3	235.912	15	0.000	0.544

Note: The null hypothesis for Bartlett's test is H_0: The intercorrelation matrix not different that identity matrix.

APPENDIX B: RESULTS

Table B.1: Regression results for proxies

t value for:	**C**	**(8a)**	**(8b)**	**(9)**	**(9b)**	**(9c)**	**(9d)**	**(9e)**	**(14)**
RISK	10.02***	9.74***	9.83***	4.49***	4.53***	4.59***	4.13***	4.52***	4.91***
dCCI		-0.30		-1.65†	-1.87*	-2.00**	-1.83*		
d2CCI_HT			1.56†						
L.FOR				-2.16**					-2.80***
L.dFOR					-1.78*	-1.95*			
cTRAD				14.12***	14.36***	13.99***	14.24***	13.04***	13.41***
cTURN				-14.44***	-14.68***	-14.34***	-14.58***	-13.87***	-14.44***
logSHARE				-2.19**	-2.28**	-2.14**	-2.07**	-1.96*	-2.02**
L.dACC					2.08**	2.02**			
dITD						-1.25			-2.48**
ce3									1.77*
_cons	-9.52***	-9.16***	-9.26***	-5.05***	-5.18***	-5.19***	-4.69***	-4.86***	-5.40***
Model / Residual	0.77	0.78	0.81	4.51	4.81	4.90	4.30	3.92	4.57
F Number	100.48***	49.75***	51.60***	87.19***	77.72***	68.54***	101.54**	117.69**	75.71***
Adj R-squared	0.4316	0.4286	0.4396	0.8091	0.8174	0.8183	0.8034	0.7901	0.8096

<u>**Note:**</u> *,**,*** indicates significance (P>|t|) at levels of 10%, 5%, and 1%, respectively.

†: p-values are slightly higher than 0.1

Table B.2: Regression results for sentiment indices

t value for:	**C**	**SENT1**	**L.SENT1**	**SENT2**	**L.SENT2**	**SENT3**
RISK	10.02***	10.20***	10.01***	10.64***	9.94***	10.76***
SENT1		-1.12				
L.SENT1			-2.33**			
SENT2				-2.11**		
L.SENT2					-1.87*	
SENT3						-2.36**
_cons	-9.52***	-9.67***	-9.52***	-10.17***	-9.45***	-10.27***
Model / Residual	0.77	0.88	0.86	0.93	0.83	0.96
F Number	100.48***	53.50***	51.37***	56.65***	49.89***	57.92***
Adj R-squared	0.4316	0.4605	0.4523	0.4730	0.4429	0.4807

Note: *,**,*** indicates significance (P>|t|) at levels of 10%, 5%, and 1%, respectively.

Table B.3: Cointegrating rank of a VECM (without CCI)

Johansen tests for cointegration

Trend:	none	Number of obs =	130
Sample:	2008m3 - 2018m12	Lags =	2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	16	-2870.436	.	40.5413	39.89
1	23	-2858.4017	0.16902	16.4726*	24.31
2	28	-2853.2536	0.07615	6.1764	12.53
3	31	-2850.9773	0.03441	1.6239	3.84
4	32	-2850.1654	0.01241		

Table B.4: Vector error-correction model (without CCI)

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
_ce1						
BIST100p	1	.	.	.	.	.
ITD	-3538.218	783.7819	-4.51	0.000	-5074.403	-2002.034
EXC	3831.209	13507.17	0.28	0.777	-22642.35	30304.77
ACC	0.0140735	0.0256441	0.55	0.583	-0.0361881	0.0643351

Table B.5: Cointegrating rank of a VECM (with CCI)

Johansen tests for cointegration

Trend:	none	Number of obs =	130
Sample:	2008m3 - 2018m12	Lags =	2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	25	-3188.4436	.	63.4513	59.46
1	34	-3174.4208	0.19405	35.4058*	39.89
2	41	-3164.3493	0.14354	15.2627	24.31
3	46	-3159.1185	0.07732	4.8012	12.53
4	49	-3157.5252	0.02421	1.6146	3.84
5	50	-3156.7179	0.01234		

Table B.6: Vector error-correction model (with CCI)

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
_ce2						
BIST100p	1	.	.	.	.	.
ITD	2180.892	1078.48	2.02	0.043	67.11043	4294.673
EXC	-87754.07	18661.28	-4.70	0.000	-124329.5	-51178.63
ACC	0.5981084	0.1871737	3.20	0.001	0.2312548	0.9649621
CCI	-8423.227	2422.392	-3.48	0.001	-13171.03	-3675.425

APPENDIX C: POST-ESTIMATION DIAGNOSTICS

Table C.1: Post-estimation diagnostics

STATA code	Null Hypothesis	C	(8a)	(8b)	(9)
		***p*-values**			
estat archlm	H_0: no ARCH effects	0.8864	0.6838	0.7648	0.5466
estat hettest	H_0: Constant variance	0.5835	0.7977	0.7918	0.0354
estat imtest, white	H_0: homoskedasticity	0.5562	0.7205	0.4867	0.0003
estat durbinalt	H_0: no serial correlation	0.2773	0.2956	0.1433	0.3325
linktest	H_0: model is specified correctly	0.200	0.200	0.166	0.124
ovtest	H_0: model has no omitted variables	0.0755	0.1235	0.1672	0.0000
swilk r*	H_0: residuals normally distributed	0.60997	0.75688	0.62287	0.08573
sktest r**	H_0: residuals normally distributed	0.6955	0.7158	0.7801	0.0782
collin	Mean VIF	1.00	1.06	1.01	4.74
	Tolerance (~)	1.0000	0.94	0.99	0.21
	Condition Number	8.1693	8.4606	8.1998	14.4386
iqr r	Number of severe outliers	0	0	0	0
	Percentage of severe outliers	0.00%	0.00%	0.00%	0.00%
	Number of mild outliers	3	2	1	4
	Percentage of mild outliers	2.28%	1.52&	0.77%	3.26%

Note: Null hypothesis is rejected if P>0.1 (10% significance), P>0.05 (5% significance), P>0.01 (1% significance). P-values are calculated via F or t distribution or via chi-squared or normal distribution.

Description of tests:

estat archlm	LM test for ARCH
estat hettest	Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
estat imtest, white	White's test for homoskedasticity
estat durbinalt	Durbin's alternative test for autocorrelation

linktest	Link test for model specification
ovtest	Ramsey regression specification-error test (RESET) for omitted variables
swilk r	Shapiro-Wilk test for normal data
sktest r	Skewness/Kurtosis tests for normality (D'Agostino test)
collin	Collinearity Diagnostics
iqr r	Interquartile Range, outliers test

Table C.2: Post-estimation diagnostics (cont.)

STATA code		**(9b)**	**(9c)**	**(9d)**	**(9e)**	**(14)**	**SENT1**	**L.SENT1**	**SENT2**	**L.SENT2**	**SENT3**
		***p*-values**									
archlm		0.3856	0.5037	0.2300	0.7253	0.6505	0.2300	0.6191	0.8756	0.5916	0.9183
hettest		0.0008	0.0020	0.0112	0.0010	0.0254	0.0112	0.7346	0.8685	0.9337	0.7654
imtest		0.0000	0.0003	0.0000	0.0001	0.0123	0.0000	0.6556	0.3693	0.9072	0.5501
durbinalt		0.1111	0.1720	0.6712	0.8320	0.8653	0.6712	0.1471	0.1993	0.1534	0.4235
linktest		0.023	0.027	0.064	0.001	0.006	0.064	0.342	0.022	0.269	0.054
ovtest		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2238	0.0768	0.1815	0.1378
swilk r		0.15008	0.41280	0.06153	0.11065	0.15008	0.06153	0.46605	0.79263	0.71664	0.94775
sktest r		0.0475	0.1008	0.0464	0.0692	0.0475	0.0464	0.4339	0.8566	0.6135	0.8483
collin	VIF	4.28	3.97	5.41	5.69	3.75	5.41	1.01	1.03	1.01	1.06
	tol	0.23	0.25	0.18	0.18	0.27	0.18	0.99	0.97	0.99	0.94
	cond	14.5085	14.5336	14.2909	14.0635	15.1395	14.2909	8.0884	8.3714	8.1327	8.4497
iqr r	sev	0	0	0	0	0	0	0	0	0	0
	sev%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	mild	5	1	3	5	5	3	2	1	2	1
	mild	4.13%	0.83%	2.42%	4.00%	4.13%	2.42%	1.62%	0.80%	1.62%	0.81%

Table C.3: Granger causality for proxies

Granger causality		C	(8a)	(8b)	(9)	(9b)	(9c)	(9d)	(9e)	(14)			
RISK →	BIST100	0.092	0.135	0.216	0.411	0.342	0.361	0.522	0.933	0.590			
dCCI_T →	BIST100		0.263		0.915	0.946	0.925	0.919					
d2CCI_HT →	BIST100			0.134									
L.FOR →	BIST100				0.087					0.095			
L.dFOR →	BIST100					0.154	0.132						
cTRAD →	BIST100				0.560	0.550	0.591	0.429	0.430	0.677			
cTURN →	BIST100				0.184	0.107	0.127	0.142	0.238	0.419			
logSHARE →	BIST100				0.852	0.790	0.827	0.893	0.957	0.887			
L.dACC →	BIST100					0.394	0.359						
dITD →	BIST100						0.126			0.117			
ce3 →	BIST100									0.480			

Table C.4: Granger causality for sentiment indices

Granger causality		C	SENT1	L.SENT1	SENT2	L.SENT2	SENT3
RISK →	BIST100	0.092	0.341	0.287	0.241	0.217	0.229
SENT1 →	BIST100		0.513				
L.SENT1 →	BIST100			0.244			
SENT2 →	BIST100				0.691		
L.SENT2 →	BIST100					0.192	
SENT3 →	BIST100						0.000
BIST100 →	ALL	0.568	0.718	0.915	0.777	0.862	0.609

Note: The table shows p-values. P>0.1, P>0.05, and P>0.01 denotes significance at 10%, 5%, and 1% significance levels, respectively.

CURRICULUM VITAE

Can Boran Akdal was born in Istanbul on the 22nd May, 1989. He went to Vefa High School, and later studied Electrical-Electronical Engineering in Bahçesehir University and Photonics in Friedrich-Schiller University of Jena.

TEZ ONAY SAYFASI

Üniversite	: T.C. GALATASARAY ÜNİVERSİTESİ
Enstitü	: SOSYAL BİLİMLER ENSTİTÜSÜ
Hazırlayanın Adı Soyadı	: Can Boran Akdal
Tez Başlığı	: Risk-getiri ödünleşmesinde yatırımcı duyarlılığının rolü: Türkiye hisse senedi piyasası
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Danışmanı	: Doç. Dr. Bilge Öztürk Göktuna

JÜRİ ÜYELERİ

Unvanı, Adı Soyadı	İmza
Doç. Dr. Bilge Öztürk Göktuna	
Dr. Celalettin Ruhi Tuncer	R. Tuncer
Dr. Serkan Yeşilyurt	

Enstitü Müdürü
Prof. Dr. M. Yaman ÖZTEK