A NEW LOOK AT MUTUAL FUND TOURNAMENT HYPOTHESIS USING SPATIAL MODELING

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF SOCIAL SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

SEVGİ EDA TUZCU

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF DOCTOR OF PHILOSOPHY
IN
THE DEPARTMENT OF BUSINESS ADMINISTRATION

APRIL 2015

Approval of the Graduate School of Social Sciences

Prof. Dr. Meliha Altunışık
Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Doctor of Philosophy.

Prof. Dr. Ramazan Sarı
Head of Department

This is to certify that I have read this thesis and that in my opinion it is fully adequate, in scope and quality, as a thesis for the degree of Doctor of Philosophy.

Prof. Dr. Z. Nuray Güner
Supervisor

Examining Committee Members

Assoc. Prof. Dr. Zeynep Önder	(Bilkent U., BA)	
Prof. Dr. Z. Nuray Güner	(METU, BA)	
Assoc. Prof. Dr. Süheyla Özyıldırım	(Bilkent U., BA)	
Assoc. Prof. Dr. Fazıl Gökgöz	(Ankara U., BA)	
Asst. Prof. Dr. Seza Danışoğlu	(METU, BA)	

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last name: Sevgi Eda Tuzcu

Signature:

ABSTRACT

A NEW LOOK AT MUTUAL FUND TOURNAMENT HYPOTHESIS USING SPATIAL MODELING

Tuzcu, Sevgi Eda
Ph.D., Department of Business Administration
Supervisor: Prof. Dr. Z. Nuray Güner

April 2015, 280 pages

Literature indicates that mutual fund investors react strongly to prior fund performance, though this reaction is not symmetric. Many papers suggest that this relation creates incentives for fund managers to change the portfolio risk towards the end of the year in order to be placed among the winners. Contrary findings, on the other hand, highlight the importance of cross correlation and auto correlation in the fund flow data, which may bias the results. Hence, this study investigates the existence of this incentive creating convex association for Turkish mutual fund industry with spatial modeling techniques. I account for the spatial dependence among mutual funds.

Keywords: Mutual funds, spatial econometrics, fund flow, portfolio risk

ÖZ

YATIRIM FONLARINDAKİ TURNUVA HİPOTEZİNE MEKÂNSAL YÖNTEMLERLE YENİ BİR BAKIŞ

Tuzcu, Sevgi Eda
Doktora, İşletme Bölümü
Tez Yöneticisi: Prof. Dr. Z. Nuray Güner

Nisan 2015, 280 sayfa

Literatürdeki çalışmalar, fon yatırımcılarının önceki dönem fon performansına çok duyarlı olduğunu, ancak bunun simetrik olmadığını göstermektedir. iyi getiri sağlayan fonlar arasında yer alabilmek için, dönem sonuna doğru portföy riskini arttırmasına neden olduğunu göstermektedir. Öte yandan, karşıt bulgular, fon akışı verisinde mevcut olan otokorelasyonun ve çapraz kesit korelasyonun öneminden ve yanlış sonuçlar üretme potansiyelinden bahsetmektedir. Bu nedenle, bu tez çalışması, Türkiye'deki yatırım fonları için söz konusu konveks ilişkiyi mekânsal modelleme yöntemleri ile incelemekte ve böylece mekânsal korelasyonu da dikkate almaktadır.

Anahtar Kelimeler: Yatırım fonları, mekansal ekonometri, fon nakit akışı, portföy riski

ACKNOWLEDGMENTS

I wish to express my gratitude to a few people who made possible to complete this Ph.D. program. First and foremost, I would like to express my deepest thanks to my supervisor Prof. Dr. Z. Nuray Güner. She has not only provided guidance and insights throughout this research, but she has also shaped my thoughts and my future academic life. Now, I have an example to follow when I have my own students.

I also would like to thank to Asst. Prof. Dr. Seza Danışoğlu. She has been my committee member and she has always provided me her continuous support and shared her experience. Yet, she has also shown me that I am not alone when I am trying to fulfill the requirements of this program.

In addition, I wish to express my sincere gratitude to Assoc. Prof. Dr. Fazıl Gökgöz. He has always provided me with help and encouragement throughout my research. He also taught me the meaning of “academic family”, which has become one of the most important things in my academic life. I feel myself fortunate for being his student and research assistant.

Throughout my Ph.D., I have also gained life-time friends; Naz Sayarı, Yeşim Aydın and Mehmet Uzunkaya. Without their endless help, it would not be “literally” possible to complete this program.

Last but not least, I wish to thank to my family: When I met my husband, Arcan Tuzcu, I was at my first year. Throughout 7 years that I spent in this program, he has not lost his belief in me. Without his patience and understanding, this thesis would not be possible. Moreover, Cansu Dinçer, my dear sister, and my mother, Aynur Katlı, once again have shown me the importance of having a family. I always feel the support of my father, Adnan Dinçer, with me. They are and always will be with me when I need them the most. I would like to say that without the love and support of my family, I could not keep going to the last.

This study was supported by the national graduate scholarship of Scientific and Technological Research Council of Turkey (TÜBİTAK BİDEB 2211-Yurtiçi Doktora Bursu).

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

One of the most discussed questions in the finance literature is whether active portfolio managers can show consistent performance that compensates fund investors for the management fees. Addressing this issue reveals an interesting structure between new cash flows to the fund and the fund's past performance. Many papers indicate that mutual fund investors react strongly to prior fund performance, though this reaction is not symmetric (Brown, Harlow, & Starks, 1996; Chevalier & Ellison, 1997; Ippolito, 1992; Sirri & Tufano, 1998). More specifically, the flow-performance relation is convex in shape, which results in rewarding the winner portfolios, while not punishing the losers by the same amount (Sirri & Tufano, 1998). As explicitly demonstrated in the study of Chevalier and Ellison (1997), this convex relation can create incentives for risk shifting by the fund managers towards the end of the year in order to be placed among the winners, and to attract new cash and investors to the fund. Busse (2001) and Goriaev, Nijman, and Werker (2005), on the other hand, argue that due to the high level of correlation in daily returns, prior studies provide biased results; in fact the previously found convex relation between fund flow and performance is spurious. Hence, the primary aim of this study is to investigate the existence of this incentive creating convex association for Turkish mutual fund industry with a set of new techniques. By doing so, I attempt to account for both the cross sectional and the spatial dependence among mutual funds. This spatial dependence among mutual fund performances, to the extent of my knowledge, has not been considered as a factor impacting flow-fund performance association in the literature yet.

As the literature suggests, fund managers have to compete with each other to be among winners and to attract more investors to the fund. For instance, Brown et al. (1996) point out a tournament like situation in the mutual fund industry due to the continuous ranking of funds in the market. They indicate that "*the amount of remuneration that a fund receives for winning this tournament depends upon its performance relative to the other participants*" (pg.85). Likewise, Del Guercio and Tkac (2002) note a high degree of autocorrelation among mutual fund flows. They argue that the main reason behind this situation is that some funds draw more cash inflows relative to the others, and they will continue to do so in the future as well. Putting it differently, a fund will be called as a winner, and will receive a higher remuneration/ cash inflow only if it shows a better performance. Due to the high level of autocorrelation in the mutual fund industry, winners of past terms will maintain to be winners in the next term as well. Del Guercio and Tkac (2002) explain this autocorrelation with the herding behavior towards specific funds. Busse (2001) and Goriaev et al (2005) account for the possible consequences of this fund flow-risk autocorrelation in their analysis as well. In this dissertation, I argue that the winner of the tournament is identified according to where the fund is in the space relative to other funds as first suggested by Brown et al. (1996). I also argue that, this location impact causes spatial dependence as well, since the position of a fund according to its risk-return structure in the mutual fund space will be important for the evaluation/reaction of the investors. This is the link that has been left unaccounted for by the papers discussing cash flow structure and fund manager behavior. This dissertation aims to fill this gap by including the spatial interactions in the explanation of tournament behavior.

Another major difference of this dissertation from the existing literature is the fund flow data it possesses. To date, studies investigating this fund flow-performance association have used an estimated flow into or out of the fund. The basic estimation method for the net flow is suggested by Sirri and Tufano (1998) as the net percentage growth when all the dividends are reinvested. It also assumes that all new fund flows occur at the end of the period. This estimation is widely used by many papers such as Chevalier and Ellison (1997); Huang, Wei, and Yan (2007); Huang, Sialm, and Zhang (2011); Ferreira, Keswani, Miguel and Ramos (2012b). Some of these papers also use net dollar growth or percentage change in the number of clients as robustness checks (Del Guercio & Tkac, 2002). However, Turkish mutual fund data provided by the Capital Markets Boards of Turkey contains both the number of shares of a fund and per share total net asset values, from which the actual net fund flow can be obtained. These computed net fund flows are compared to the value of participation certificate account in the annual balance sheets of funds to assure accuracy. This actual fund flow data will allow me to examine the fund flow-performance relation without the presence of estimation errors or some simplifying assumptions, and hence will contribute to the literature.

Spatial econometrics is a branch of techniques that deals with the location based issues in regional science which impedes the use of standard econometric techniques due to spatial effects (Anselin, 1988). These spatial effects or interactions emerge depending on the relative position of the research units in a space. These effects are classified into two types: spatial dependence and spatial heterogeneity. I argue in this dissertation that since the mutual fund managers attempt to maximize their gains from altering the risk-return structure of the fund according to their *relative* positions; the results would be biased unless the methods employed to measure the association between fund flow and past performance consider these spatial effects. This argument is in fact in line with the conclusions reached by both Busse (2001) and Goriaev et al. (2005). These studies state that one cannot be sure about the true structure of the flow-performance relation for mutual funds without taking into account the autocorrelation in the data. Here, one should note that this mentioned autocorrelation that biases the flow-performance association has only one direction throughout the time period. Busse (2001) and Goriaev et al. (2005) note that fund flows realized in the prior period influence the fund flows in the subsequent period. That is, there is a dependence to a timeline, which can only be from past to future. Nevertheless, spatial dimension of this flow-performance relation has infinite number of directions, which is not investigated in a cross sectional study. I model this location impact, which has not been studied in the literature before by addressing these spatial interactions. By doing so, I attempt to explain the conditions creating tournament like incentives better.

Despite its limited application to financial issues, spatial econometrics has been extensively used in many research areas, especially in regional science where the conventional geographical distance is taken as the spatial measure. Regional economic convergence (Rey & Montouri, 1999) or dependence of housing prices on their location (Holly, Pesaran, & Yamagata, 2010) are some issues that necessitate the usage of spatial techniques. Besides regional science, other areas are also open to spatial modeling. For instance, Tirtiroglu et al. (2011) employ spatio-temporal modeling in the measurement of performance for the US banks. They test the spatial clustering of bank performances by regressing them on the performances of other banks located in neighboring states and those situated on randomly chosen states. They also re-analyze this relation while controlling for the "proximity of the regulatory environment" of states by selecting the states that allow entry of banks regardless of their headquarters' location.

Different from the typical usage of spatial econometrics in the literature, in this dissertation, I attempt to model the fund flow-performance relation by using an abstract notion of space, i.e. the distance between fund performances on the analytical surface. In fact, the non-conventional concept of space and/or distance has been broadly discussed in the literature. Many studies state the necessity of spatial modeling and the need for abstract distance definitions especially in social sciences (Akerlof, 1997; Anselin, 1988; Dow, Burton, White, & Reitz, 1984). However, a limited number of papers consider space concepts other than Euclidian definitions. Language similarity (Dow et al., 1984), transportation costs (Conley, 1999), social networking (Conley & Topa, 2002), bilateral trade relations (Beck, Gleditsch, & Beardsley, 2006; Simmons & Elkins, 2004) are examples of non-geographical distance measures used in different studies. In my dissertation, on the other hand, the extension of the distance concept is through the analytical surface regarding the performance rankings of mutual funds. The funds are accepted as close if they have similar risk-performance structures.

In order to compute the locations of funds and the distances among them, I utilize the data envelopment analysis (DEA). In fact, DEA has previously been used in the literature to evaluate the performance of mutual funds (Basso & Funari, 2001; Choi & Murthi, 2001; Murthi, Choi, & Desai, 1997). These studies mostly focus on the application of the DEA which accounts for several criteria at the same time, on mutual fund industry as a performance evaluation tool. DEA, in this sense, provides a relative efficiency ranking for mutual funds which does not necessitate a definition of a benchmark (Murthi et al., 1997). Different from these studies, I use the information obtained from DEA performance evaluation as spatial weights in the spatial regressions which analyze the relation between fund flow and performance. Since DEA computes radial and Euclidian distances for the analyzed unit from an efficient frontier, the distance measure used in this dissertation is abstract in the sense of Anselin (1988); and it is a non-geographical, but still an Euclidian distance definition. I use a general spatial weight matrix obtained from the DEA. More precisely, the elements of the matrix are determined according to the inverse of efficiency measures for the funds. Two funds are considered as neighbors when a fund is in the "reference set" of the other. This reference set are attained through DEA based on the minimum radial distance among funds. Additionally, the relative measurement nature of DEA is also appropriate for our study concerning the importance of location in spatial econometrics.

In sum, the novelties of this dissertation are threefold: First, I attempt to understand the nature of flow-performance relation by using Turkish mutual fund data while accounting for spatial autocorrelation[1] and heterogeneity. Busse (2001) suggests that "*uncovering a potentially more complex behavior pattern should be a fruitful area for future research*". (pg. 73). For this aim, I utilize a new technique that may model the mentioned behavior more accurately. In addition, Ferreira et al. (2012b) note that convexity of the association between new cash flow and prior performance varies across countries based on their level of development. They show that the higher the level of development in a country, the less the amount

[1] Using the term "autocorrelation" in this sense may be confusing. The term "spatial autocorrelation" as first used by Anselin (1988) means "spatial dependence". Following spatial econometrics literature, this dissertation also uses spatial autocorrelation and spatial dependence terms interchangeably.

of the convexity that creates adverse incentives for mutual fund managers. In this vein, I expect to see higher convexity in Turkey. Second, by the aid of the Turkish dataset, I compute the actual net fund flow on a daily basis. Therefore, the fund flow-performance relation can be modeled without being subject to any estimation error. Last, I expand the "strict" sense of distance used in spatial econometrics to an abstract notion, and I model the distance between mutual funds as suggested in Anselin (1999). By doing so, I aim to contribute to both the literature analyzing the relation between mutual fund performance and fund flow, and the literature on the application of spatial econometrics by employing abstract distances.

The results of the analyses briefly indicate that investors of Turkish mutual funds allocate their money independently from other funds' positions, because no spatial interaction can be detected. The effect of neighborhood is only visible in the change in number of investors. It is found that if neighboring funds exhibit good performance, the number of individuals that invest in a given fund declines.

Furthermore, there is a constant outflow from all of the funds which may be attributed to the time period analyzed in this dissertation. During the sample period, domestic investors' holding period is very short and they tend to realize their profit as soon as they pass into the gain region (Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği (2006, 2007, 2008, 2009)). However, it seems that best performing funds experience a lower amount of outflow. Based on this finding, the risk changing incentives of Turkish mutual fund managers are investigated. Results confirm the expectations of this dissertation and show a significant impact of neighboring fund performances on the total risk changing decisions of managers. It is found that Turkish mutual fund managers decide the level of the fund's risk according to the prior performance of neighboring funds. They seem to increase the change in the total risk if neighboring funds exhibit good performance in the first interim of the year. Yet, their systematic risk change decision is unaffected from such an impact. Li and Tiwari (2006) suggest that managers are likely to change the unique risk when they want to close the performance gap between the peer group and the fund itself. Hence, changing the total risk based on the neighboring funds' performance, but keeping the systematic risk the same would be explained by such an attempt.

This dissertation continues with the presentation of the flow-performance relation in the literature. In addition, it explains why a spatial modeling techniques is need for analyzing this association while giving examples from other studies. Next chapter discusses the data and methodology. Chapter 4 displays the empirical findings, and the last chapter summarizes the conclusions drawn from empirical analyses.

CHAPTER 2

RELATED LITERATURE

In this chapter, first, a brief review of mutual fund cash flow-performance relation is provided. The asymmetric nature of this relation is discussed, and the existing evidence on the tournament behavior of fund managers is presented. Spatial econometrics, its difference from the traditional methods, and common usage areas are shortly illustrated in the second subsection.

2.1. The Asymmetry in the Cash Flow-Performance Relation

One would begin to examine the flow-performance literature by looking at the work of Ippolito (1992), in which the main aim is to investigate Akerlof's (1970) lemons problem in the mutual fund industry. He argues that in the absence of information about the true ability of fund managers, low quality funds can act like high quality ones. Investors evaluate a fund's quality by examining its recent performance. Therefore, in this model, funds with higher risk adjusted returns are considered as higher quality funds. By the aid of pooled and fixed effect regressions for the years from 1966 to 1984, Ippolito (1992) shows the association between fund growth and recent performance. However, the results indicate that the response of investors to the winner and loser subsets is not symmetric. Putting it differently, new cash inflow to the funds that display better than expected performance is much higher than the withdrawals from worse performing funds. Actually, the excess return definition that Ippolito (1992) adopts in his study coincides with the Jensen's alpha measure. Accordingly, he argues that the basic reason behind the serial correlation is the divergence across the investment abilities of fund managers, not the temporal association in the security prices. He notes that this correlation can be used in developing investment strategies in favor of the latest winner funds.

This disproportionate investor reaction to winner and loser funds is investigated from the point of view of portfolio managers in the paper by Brown et al (1996). They take the competitive nature of mutual funds as sports tournaments, since the winner fund is identified according to its performance relative to its rivals-the other funds. In other words, the managers have to compete with each other for higher cash inflow, because investors prefer better performance to the worse. Brown et al (1996) claim that the ranking system in the mutual fund industry creates a situation like "multi-period, multi game tournament". This study also notes that as long as the managers' compensation depends on the funds' total assets, managers are eager to increase the cash inflows to the fund. This increase in the cash inflows can only be possible when the fund's relative position is better in the second half of the year. As a result, this will create "a call option like pay off situation", since fund managers do not hesitate to increase the funds' volatility in hopes of receiving a better compensation. As a consequence of this tournament like or the "call option like pay off" situation, fund managers can modify their portfolio decisions based on their fund's relative performance prior to the end of the year.

For the first time in the literature, Brown et al (1996) put forth that this portfolio modification may not always serve the best interest of the investors, hence may create agency problem. In order to measure changes in the portfolio composition, they develop "risk adjustment ratio", and they compare the volatility of loser and winner portfolios in the first half of the year to that in the second half of the year by the aid of contingency tables. They analyze the performance of 334 growth funds over a period from 1976 to 1991; and empirically demonstrate that midyear worst performing funds alter the portfolio risk more than midyear winner portfolios in the second half of the year. This incentive to alter the portfolio risk is especially stronger for smaller, relatively new and less well-known funds, and more prevalent in the last 5 years of their sample period. In fact, this risk shifting behavior is a consequence of the convex reward-penalty system for mutual fund managers previously recognized in the study of Ippolito (1992). Brown et al. (1996) also examine how the managers skew the portfolio riskiness. They recognize two alternatives to increase the riskiness. First, the manager applies active portfolio management and revises the portfolio composition in favor of riskier securities, i.e. using derivatives. Second, the securities in the portfolio become riskier over time period, and the manager simply overlooks this new situation. To uncover the cause of increase in portfolio risk, Brown et al. (1996) create simulated control portfolios in which the securities are chosen randomly from the CRSP database. The cell frequencies indicate that increase in portfolio risk in the midyear is the result of active portfolio management.

Another distinction from the previous work is that Brown et al. (1996) allow for the fee differences and its impact on the tournament behavior. Two groups are constructed based on the existence of the front-end sales charges; and the contingency tables are compared to see whether there is a significant difference between these two groups. The basic logic behind the possible difference is that load funds benefit more from the brokerage system to be sold in the market, whereas no load funds generally use advertisements in the media. Therefore, for no load funds, performance rankings may become more prominent. Their results demonstrate that winners and losers in the no load funds group are significantly more eager to enhance the fund riskiness towards the end of the year. Before making a final conclusion, Brown et al. (1996) also checks the correlation between load structure and fund age. They indicate that load funds are well-established funds, while younger funds have usually no load structure. In other words, the load structure and fund age are highly correlated. Thus, Brown et al. (1996) note that the existence or absence of such a fee structure does not change their overall findings. They show that the tournament behavior is present among the fund managers as a consequence of competition for higher cash inflows, and hence, managers have incentives to modify portfolio riskiness as a result of this tournament behavior.

The asymmetric structure of fund flow-prior performance relation is studied in detail in the paper of Chevalier and Ellison (1997). Along the lines of Brown et al. (1996) they demonstrate that it is the convex flow-performance relation that creates the basis for incentives for the fund managers to alter the risk of their portfolio. However, the approach of Chevalier and Ellison (1997) to the asymmetry in this association differs from Brown et al. (1996). They investigate this convex nature as an example of an agency problem. They state that mutual fund managers may have information that is not observable by the outside investors; and they may use this information to boost the total assets of the fund, but not to maximize the benefits of fund investors. In fact, “not to serve the best interests of the investors” problem has been previously recognized by Brown et al. (1996), however, the focus of this paper is on the desire for winning the mutual fund tournament. Unlike Brown et al. (1996), the emphasis of Chevalier and Ellison (1997) is on the agency problem between managers and fund customers, which is created by the “implicit incentive contract”. This incentive contract is a result of compensations paid to the fund managers as a percentage of total assets under management. In other words, the fund managers attempt to have higher performance by boosting their private information in order to increase their own returns. Managers may not aim directly to win the tournament and become a part of the first ranked group. However, the corollary of this higher performance desire is to win the tournament as well. Yet, to increase their own returns may not always be in line with the expectations of fund investors. Then, the agency problem arises between the two sides of the fund industry.

Chevalier and Ellison (1997) analyze this problem and the risk altering incentives of fund managers for the data on 3000 growth and growth and income funds over a period from 1982 to 1992. Their findings show that funds that are below the market benchmark are more likely to increase their riskiness in order to "*catch-up*", while funds that are above this benchmark try to protect their relative position and not to gamble. On the extreme positions, however, the incentives are reversed. The losers may prefer to reduce their risk levels, whereas the winners are more likely to gamble. Another distinction from Brown et al (1996) paper is that, in the study of Chevalier and Ellison (1997), mutual fund managers shift the riskiness of their portfolios in the last quarter, but not in the mid-year. Once detecting the convex nature of risk-performance association, Chevalier and Ellison (1997) examine the conditions that strengthen the risk altering incentives to acquire higher performance. They note that, consistent with Brown et al (1996), newer funds are more susceptible to these incentives than older ones. The main conclusion drawn from Chevalier and Ellison (1997) is that the existence of performance fees as a percentage of total asset size and the convex nature of flow-performance structure creates incentives to take higher risks; and the managers respond to these incentives. The evidence showing the presence of such an incentive even in the absence of performance fees (Brown et al., 1996) can be considered as contradictory to the conclusion of Chevalier and Ellison (1997). Elton, Gruber, and Blake (2003) discuss this issue; and demonstrate that the asymmetry in the flow-performance relationship is sufficient to create incentives to alter the riskiness of the fund portfolio. They argue that the existence of performance based manager compensation discussed in Chevalier and Ellison (1997) is one reason that encourages risk shifting in the fund portfolios.

One should note that even if the fund managers fight for a better performance due to incentive based reasons as discussed in the study of Chevalier and Ellison (1997), still their relative position in the risk-performance space could be important. Studies by Brown et al (1996) and Chevalier and Ellison (1997) support the idea that the risk-performance choice of a fund manager is under the influence of the rivals' positions in a risk-performance space. Hence, spatial modeling of this issue may provide insights about the nature of fund flow-risk association.

Sirri and Tufano (1998) confirm the convex punishment and reward mechanism in the mutual fund industry by showing that new cash inflows depend on the prior performance. In line with Brown et al. (1996) and Chevalier and Ellison (1997), they suggest that this type of convexity may encourage the managers to raise the funds' riskiness. The primary focus of Sirri and Tufano (1998) is on the investors and how they make their mutual fund choices, however. Hence, their addition to the literature is to account for searching costs. The cash flow to a fund is modeled as a function of prior fund returns, risk level, expenses, fund size and growth in the fund category. In order to account for several nonlinearities, they study this association for more than 600 US equity funds between the years 1971 and 1990 by employing piecewise linear regressions.

The results show that fund flows react strongly and significantly to the past performance for the winners segment. In the worst performing funds' segment, however, the association between fund flows and past performance disappears. Sirri and Tufano (1998) also highlight the importance of this asymmetric reaction to the past performance in the creation of a call option like pay off system as indicated by Brown et al. (1996).

In the second part of their study, they compare the impact of fee changes on the fund flow-past performance relation. Interestingly, investors tend to react more to the fee decreases by increasing cash flows to these funds. However, fee increases do not have the opposite effect on cash flows. Next, the analysis is broadened by the inclusion of searching costs. The results demonstrate that the performance seeking behavior of investors is also affected from these costs. For funds with high searching costs, prior performance becomes less important. Sirri and Tufano (1998) state that higher searching costs mean reduced fund awareness, and therefore, may result in less desire to invest in these funds. Putting it differently, investors do not include the funds with higher searching costs in their "consideration set". At this point, media and large fund families play an important role on the prior performance cash inflow association, because they decrease the searching costs. A positive impact on prior performance and cash flow relation is detected if a fund is more visible in the media and if it is a part of a large fund family. More marketing activities by funds may result in higher fees; but these activities also reduce the searching costs. Less searching costs and more visibility results in more prominent prior performance-cash flow relation. To summarize briefly, Sirri and Tufano (1998) emphasize the non-linear association between fund flows and performance, and the impact of searching costs on this association. They point out that funds with higher fees attract more cash inflows relative to others, because these fund, most likely, have higher marketing activities, and hence, lower searching costs. Moreover, fund rankings and being part of a large fund family are important determinants of new cash inflows to funds.

The paper by Sirri and Tufano (1998) that investigates the impact of searching and investing costs on the fund flow-past performance relation is extended in the study of Huang, Wei, and Yan (2007). While the focus of the former study is on the participation costs of new investors, Huang et al. (2007) build a model which rationalizes at bottom the disproportionate flow-performance relation from the point of view of the individual investors. In fact, it investigates the role of these costs on the cash flows to funds with various performance levels. In other words, here, the emphasis is on the cross sectional differences among mutual funds. The basic assumptions of their model are as follows: First, investors have to bear participation costs as in Sirri and Tufano (1998). Next, investors are able to infer the managerial ability by examining the latest fund performance. Huang et al. (2007) indicate that this second assumption explains the past performance chasing behavior according to a Bayesian updating performance.

The participation costs that the investors have to incur are of two different types in this paper. First, the information cost is defined as the cost associated with seeking and evaluating the new information about a fund. This cost may be a result of an active searching or a passive accumulation. It is, in fact, the same searching cost definition used in Sirri and Tufano (1998), which has a negative impact on cash inflow-prior performance association. The second type of participation cost is the transaction cost which isincurred due to purchasing or selling decisions. Huang, et al. (2007) note three different effects of these costs on fund flows: *i. Participation effect*: As stated in Sirri and Tufano (1998), funds with higher searching costs are less likely to be taken into consideration sets by investors, since the costs would be higher than the utility gain obtained from investing in these funds. The past performance as a proxy for the utility gain should be high enough to beat the high costs. Hence, fund flows become gradually more responsive to the prior performance. *ii. Individual winner-picking effect:* Higher participation costs result in less intention to investigate a larger fund set. Instead, investors only consider the best performing ones. *iii. No trading effect:* Investors are willing to incur the transaction costs of selling the fund only if the performance is bad enough. The reverse is true for the buy decisions. Huang et al. (2007) indicate that due to the no trading effect, reduced sensitiveness in fund flows to prior performance is observed for funds with average performance. While the other two effects of participation costs have been shown before in the paper by Sirri and Tufano (1998), the "no trading effect" for average performance funds has been considered first by Huang, et al. (2007).

The model by Huang et al. (2007) first explains why the prior performance is a determinant of cash flows. They indicate that there are two types of investors: new and existing ones. Both investors have to make two decisions. First, they have to choose whether or not to incur the participation costs to obtain information about the funds that they have not already purchased. Second, for their existing fund portfolio or the funds that they bear the participation cost, they have to decide whether or not and how much to invest.

The model of Huang et al. (2007) begins with a discussion of a fund flow-prior performance relation under a benchmark scenario in which there is no borrowing constraints for investors to buy mutual fund shares. This model indicates that under this scenario, the purchasing decision is the same for new and existing investors, because they share the same information set once participation costs are incurred. That is, this decision is only associated with the information about the fund, but it does not depend on the features of other funds. Based on this modeling, Huang, et al. (2007) compute the certainty equivalent wealth gain only as a function of realized returns. Because the higher prior returns are indicators of higher posterior managerial ability in this scenario, calculation of the certainty equivalent wealth gain in this way is appropriate. Nevertheless, the managerial ability itself does not play a role in this calculation because investors do not know it before bearing the cost. As a result, the participation decision in a fund, that is the cash flow, only depends on prior performance of that fund.

In order to correctly analyze the cash flow to the fund, Huang et al. (2007) decompose the fund flow into two parts, namely flows from the existing investors and from new investors. Flow from both investors is under the influence of prior performance. This performance, however, has different impacts on flows from these two types of investors. If the fund has higher realized past return, the allocation amount of both type of investors increases, which reflects the learning effect. In addition, higher past return attracts more new investors, which is a result of participation effect. The model predicts that for the low levels of participation costs, the association between fund flow and past performance is convex and increasing for the low and average performing funds. Therefore, the sensitivity of cash flows to the past performance is very high. Even an average performance is enough for new investors to purchase a fund’s shares. In this case, participation effect is more pronounced among the average performing funds. For very high levels of fund performance, on the other hand, because all the potential new investors have already invested in the fund, the only driving force of the new cash flow is the learning effect. Based on their modeling, the association becomes linear for best performing funds.

When the participation costs are high, however, funds can attract cash flow only when their performances are good enough. On the other hand, funds with average or low performances can only attract cash flow from very limited number of investors, whose participation costs are low. Investors are less willing to invest in average performing funds when participation costs are high. Hence, the fund flow becomes less responsive to prior average performance for funds with higher costs relative to those with lower costs. As a result, the convexity of the flow-past performance relation decreases relative to low cost scenario.

Although this benchmark model with no portfolio constraints does not reflect the real world, its consequences are still important for this dissertation. Since it assumes no interaction among funds, the only performance that matters for the investors is the absolute one. It means that even in the absence of “ranking”, i.e. spatial dependence, the convex flow-performance relation is still valid. The level of convexity varies across funds, however; that is, the sensitivity of cash flows to the fund performance is stronger for the winner funds than their average and low performing peers.

Apart from the benchmark scenario, the possible portfolio constraints, such as minimum investment requirements are considered in the second part of their model. These constraints bring the relative fund performances into the picture. Now, the investment decision is based on past performance, participation cost levels as well as the ranking of funds. In this case, the model predicts that as the participation costs get higher, the investors begin to search for the winner funds in terms of past performance first. In other words, the individual winner picking effect is more pronounced when participation costs are high rather than low.

The last prediction to the model of Huang, et al. (2007) is on the effect of transaction costs, that is the costs created by buy or sell activities. Huang, et al. (2007) indicate that since the utility gain and cost comparison creates "no trade region" for the investors, higher transaction costs makes fund flows less sensitive to past performance for the funds with average performance.

After constructing the model, Huang, et al. (2007) examine these predictions empirically as well. They use quarterly data from 1981 to 2001 for the actively managed US mutual funds. The flow-performance association is analyzed by using cross sectional Fama-MacBeth type regressions, while fund age, total riskiness, fund size, aggregate flow and participation costs are included as control variables. They use marketing expenses, existence of a "star" fund, fund's affiliation with a large family, and number of categories in the fund family as proxies for the participation costs. Moreover, Huang, et al. (2007) investigate the changes in the flow-performance relation over time by analyzing each decade separately in their sample period. Following Sirri and Tufano (1998), they also employ piecewise linear regressions to allow for different sensitivity levels. Their results demonstrate that fund flow-performance relation is affected differently from these costs. For instance, if the investors cannot obtain information about funds easily, then a superior past performance is a prerequisite for investing in a fund. As a result, participation effect, which is about attracting new investors to a fund, is more prominent for winner funds. In a similar manner, for high levels of participation costs, the individual winner picking effect is stronger. However, for lower levels of these costs, flow to average performing funds will be more sensitive to past performance since investors are more willing to investigate these funds than their higher cost peers. Last, as the transaction costs increase, the trade and the flow sensitivity to performance is reduced for funds with average performance. Higher transaction costs make the no trading effect even more pronounced. The time varying analysis shows that in later decades of their sample period, the flow sensitivity to performance for funds with low and average performance has been enhanced relative to the 1980s because of lower participation costs. This increased sensitivity for average performing funds leads to a less convex relation between past performance and cash flow in the 1990s. These findings are consistent with the predictions of their model.

From a different angle, Koski and Pontiff (1999) hypothesize that the mentioned convex flow-performance relation is not due to risk altering behavior of managers, but instead it is a result of managers' slow response to cash inflows and outflows. That is, after a period of good performance, one may observe cash inflows to good performing funds. However, managers may prefer to react slowly to new cash inflow, because market conditions may not be appropriate to make new investments. This will automatically increase the cash on hand, and decrease the riskiness of their portfolio. Likewise, managers of poorly performing funds may be obliged to borrow, instead of liquidating assets in their portfolios, in order to gather necessary amount of cash to give back to investors who are redeeming their shares. This borrowing raises the total riskiness of their portfolio. Since derivative usage is an effective way to acquire the preferred risk level, Koski and Pontiff (1999) test this alternative explanation by examining the equity funds that can invest in derivatives. They hypothesize that these funds can reduce the undesired risk increases related to cash outflows by the aid of derivatives, thus, the convex relation will be less pronounced for these funds. Results of their pooled regressions, on the other hand, show evidence in favor of the tournament argument as suggested by Brown et al. (1996), Chevalier and Ellison (1997), and Sirri and Tufano (1998). They cannot find any significant difference between funds that use derivatives and their counterparts that do not employ derivatives. This study is also important to show evidence against the common belief that associates derivative usage with speculative purposes.

Although many papers confirm the convexity of flow-performance relation for open end mutual funds, there is contradictory evidence as well. First Busse (2001) argues that the tournament like incentive creating association reported in Brown et al. (1996), Chevalier and Ellison (1997), and Sirri and Tufano (1998) is in fact spurious. His criticisms are two-fold: He argues that daily returns on small cap and intermittently traded stocks are autocorrelated. Next, the securities in the portfolio generally react in the same direction to financial news, which produces cross correlation among security prices. Therefore, he questions the validity of the cross sectional independence assumption that the methods used in the previous studies have been built on for the data analyzed in these papers. To investigate the same research question raised by the aforementioned studies, Busse (2001) analyzes daily returns of US equity funds over a period from 1985 to 1995. He notes that autocorrelation and volatility measures are positively related; and hence, the monthly volatility measures calculated using monthly returns are biased upwards. He claims that one can acquire more accurate standard deviation estimates by directly employing daily than monthly returns. Here, the same methodology of Brown et al. (1996) is utilized to test their tournament hypothesis. In order to compare the volatility of winner and loser portfolios in the first and second halves of the year, Busse (2001) computes standard deviation ratios (SDR), while taking into account the autocorrelation and cross correlation in daily returns. Besides employing daily data, Busse (2001) compounds daily returns into monthly returns and analyzes them to provide results comparable with earlier studies which used monthly returns as well. He finds evidence against the tournament hypothesis with daily returns. However, his evidence with monthly return is consistent with the tournament hypothesis and hence the findings of the earlier studies. His replication demonstrates that standard deviations of monthly returns in the earlier studies, more specifically the ones in Brown et al. (1996), can be upward biased and can spuriously indicate managerial risk increasing behavior. In other words, once the daily data is used and the monthly data cleaned from the autocorrelation problem, the evidence for tournament like behavior disappears. The bias free data cannot reject the null hypothesis of no tournament like behavior among mutual fund managers. To avoid the cross sectional dependence in the p-values for the hypothesis testing, he uses bootstrapping methods in his simulations. Busse (2001) argues that it is the lower autocorrelation in the loser interim portfolios relative to winner portfolios that generates an apparent risk increase in winner portfolios towards the end of the year.

The argument of Busse (2001), which casts a shadow on the previous findings, is examined thoroughly by Goriaev et al. (2005). Goriaev et al. (2005) argue that since the precision of the daily data employed in Busse (2001) is higher than monthly observations, the potential of a smaller bias to affect the results in favor of tournament behavior is larger. Thus, the evidence would have supported the tournament hypothesis with daily data if there were such a behavior. No tournament behavior has been detected by Busse (2001), however. For this reason, Goriaev et al. (2005) address the contradictory evidence once more by investigating the effect of autocorrelation and cross correlation in the daily data on volatility computations and the validity of the independence assumption for mutual fund returns. Following Busse (2001), they only employ contingency table analysis for a period from 1976 to 2001. They confirm the findings of Busse (2001) indicating that monthly SDRs in terms of absolute values are more susceptible to biases caused by correlation in daily returns. Yet, they note that smaller biases in daily returns have a higher effect on distribution of statistics used for testing tournament hypothesis. In this respect, monthly observations may still be more reliable.

Goriaev et al. (2005) underline the importance of controlling for cross correlations in the tournament behavior estimations. They specifically argue that the direction of the biases in the monthly standard deviation estimations should be the same with those in the daily estimations. That is, autocorrelation produced by intermittent trading and small cap exposure as suggested by Busse (2001) should bias the daily return volatility estimations in the same direction as well. However, Busse (2001) found no tournament behavior when he employed daily returns; but the null hypothesis of tournament behavior could not be rejected with the monthly data. Based on this difference in the daily and monthly return results in Busse (2001); Goriaev et al. (2005) question the real source of this bias. They put forth that it is not the temporal dependence but the cross sectional dependence in the data that generates biases. They cannot find evidence in favor of tournament behavior once the cross correlation in the data is accounted for. Since the bias free monthly and daily returns produce the same results, they note that daily return usage is still more efficient. An important warning of Goriaev et al. (2005) is that their criticisms are only valid for the studies that use the return data directly from a source like CRSP Mutual Fund Database such as Brown et al. (1996) and Koski and Pontiff (1999), but not for the others that employ actual mutual fund holdings, such as Chevalier and Ellison (1997). Goriaev et al. (2005) indicate that this type of return data is affected from the correlation in the cross sections of mutual funds. The degree to which the latter dataset, and so the evidence about tournament behavior of fund managers, is open to such biases remains as a question mark. I attempt to provide new insights about the conditions generating tournament hypothesis in the mutual fund industry, because the spatial dependence that I account for can be an important factor affecting this behavior along with autocorrelation and cross correlation in the fund returns.

The existence of contrary evidence, however, does not impede the regulations in the mutual fund industry. Das and Sundaram (2002), and Elton et al. (2003) state that 1970 Amendment to the Investment Advisors Act only permits fulcrum fee, i.e. performance based fee for advisors, when the compensation fee is symmetric around a chosen benchmark. In other words, if managers perform better than a benchmark, they will get a reward-a fulcrum. On the other hand, there will be a penalty as well when managers underperform the benchmark. The main motivation driving this regulation is the "*option-like pay off structure*" as discussed in Brown et al. (1996), which may lead to excessive risk taking by fund managers. Incentive fees, nevertheless, can be asymmetric in nature, which is a base fee and an additional amount charged when the return is over and above a specific benchmark. This type of fee is usually the case for hedge funds and private partnerships (Elton et al., 2003). Das and Sundaram (2002) compare the effect of fulcrum fees and incentive fees on the investors' welfare. They conclude that when there is perfect competition among fund advisors, fulcrum fees serve the interest of investors better than incentive fees. On the other hand, if the evidence put forth by both Busse (2001) and Goriaev, et al. (2005) are valid, then there would be no reason to implement such a fee structure in order to prevent excessive risk taking by fund managers. As a result, it is worth investigating the evidence on flow-performance relation in the mutual fund industry once more.

Another study on this subject compares the incentive creating nature of flow-performance relation for mutual funds and pension funds (Del Guercio & Tkac, 2002). Again the asymmetric association between fund flows and past performance is confirmed for the mutual fund industry, but this relation is found to be linear for pension funds. In other words, poor past performance results in a loss of a considerable number of clients for pension funds, whereas it is not a pronounced risk for mutual fund managers. In line with Busse (2001) and Goriaev et al. (2005), they also show a high degree of autocorrelation in returns of mutual funds, which does not exist in pension fund returns. However, they employ annual mutual fund return data for the years from 1987 to 1994, and they do not mention a correction for the high degree of autocorrelation in their piecewise linear regressions. Given the findings of Busse (2001), and the more recent evidence of Goriaev et al. (2005), this autocorrelation and the return data usage cast doubt on the results of Del Guercio and Tkac (2002), and leaves this subject open to new investigations. Del Guercio and Tkac (2002) explain this high autocorrelation in returns of mutual funds by some funds drawing more cash inflows relative to the others now and in the future. They also note the "herding" behavior among fund managers. Findings of Del Guercio and Tkac (2002) and the other studies such as Brown et al. (1996), explicitly indicate the importance of position of other funds relative to the one whose performance is evaluated; yet, neither of them has accounted for the spatial dependence. By conducting a re-examination of flow-performance relation in the Turkish mutual fund industry while taking into account the spatial dependence, I attempt to fill this gap in the literature.

A different approach is presented in the paper of Kempf and Ruenzi (2008) for the incentive creating tournament behavior among fund managers. This study focuses on another type of tournament, namely family tournaments. Kempf and Ruenzi (2008) emphasize that besides the mutual fund industry ranking; there is another ranking inside fund families which determines the compensation and the promotion of managers. Hence, the relative position inside the family becomes important in the risk taking decision of fund managers. As a result, this study separates funds based on the size of the fund family. The findings indicate that managers in large fund families are more prone to increase risk if they are ranked among the losers. In the small fund families, on the other hand, the contrary behavior is detected: winner portfolios enhance their risk levels more than the losers do. The logic behind this different tendency between managers in small and large fund families is that the relative position will be important only if the number of peers is small. In other words, winning the tournament and leaving the others behind in the ranking turns out to be a key determinant of managers' compensation when the comparison group is small. Therefore, the managers of winner portfolios in small fund families are more likely to increase their risk in order to protect their relative position in the tournament. This finding is first order of importance for this dissertation as well. If one extends the results of small fund families set forth by Kempf and Ruenzi (2008) to developing countries, it would be logical to expect developing countries to have more prominent level of spatial dependence because most of them have smaller mutual fund markets than developed countries. Hence, the fund markets of developing countries might have a higher potential to produce biased results if the tournament behavior is in fact a product of the spatial dependence. The study of Kempf and Ruenzi (2008) shows that family tournaments are observed throughout the sample period, while the tournaments in the fund industry are only sample specific. In the first years of their sample period, i.e. from 1997 to 2001, the findings indicate that the ranking in the fund industry and risk increasing behavior is negatively related. In other words, loser portfolios increase their risk level in the second half of the year more than winner portfolios, which is in line with earlier papers ((Brown et al., 1996; Sirri & Tufano, 1998). In the last years of the sample, however, the tendency to alter the portfolio risk changes among the fund managers. The rankings inside the fund industry and the risk increasing behavior become positively related. The latter finding is, in fact, consistent with those papers such as Busse (2001) and Goriaev et al. (2005) which contradicts the previous tournament literature. Kempf and Ruenzi (2008) explain the contradictory evidence throughout their sample period by the employment concerns of managers. Specifically, they indicate that managers of loser portfolios increase the risk of their portfolio and involve in the fund industry tournament only if the unemployment risk is low. The unemployment concern is lower in the bullish markets. On the contrary, in bearish markets, managers of loser funds are reluctant to take more risks than winners, because this may only worsen the stability of their jobs.

According to Kempf and Ruenzi (2008), conflicting findings of earlier studies are not against the tournament behavior in the fund industry. These findings only show that tournament behavior is not stable over time, but it can be sample specific. Schwarz (2011), on the other hand, remark another point in the tournament behavior. Previous studies like Brown et al. (1996) and Busse (2001) have employed the risk levels in the first half of the year as the benchmark for the risk increasing behavior of fund managers. However, Schwarz (2011) notes that risk and return are interrelated concepts. According to Markowitz (1952), well diversified portfolios, for instance portfolios of mutual funds, should be on the risk-return efficient frontier. Hence, Schwarz (2011) argues that sorting only with respect to returns in the first half of the year as in the previous studies automatically creates a ranking based on the risk level as well. That is, in a bullish market, mutual funds with higher returns, i.e. winners, should also have higher risk levels than loser portfolios. In the second interim, the risk level of these winner funds will return to an average level. This mean reversion might create an illusion of a tournament like situation in the mutual fund market. Conversely, in a downward market in the first six months of the year, winner portfolios will have a lower risk profile. In the second part of the year, risk of these portfolios will increase due to mean reversion. In short, when there is mean reversion in funds' risk levels, the standard deviation ratios used by Brown et al. (1996) will produce spurious tournament behavior. Schwarz (2011) calls this tournament-generating bias as "sorting bias". He also argues that this bias explain the contradictory evidence in the tournament behavior literature.

Schwarz (2011) employs US mutual fund data from the beginning of 1990 to the end of 2006. First, the usual "risk adjustment ratios" and contingency tables as in Brown et al. (1996) are formed. Although the results vary from year to year, the evidence at this stage is generally consistent with the tournament hypothesis. Next, in order to show the "sorting bias", he picks two years, namely 1991 and 2001, in which the tournament behavior is the most pronounced. In 1991, there is a bullish market in the US; hence the funds' risk and return are positively related. In contrast, the bearish market in 2001 produces negative correlation between funds' risk and return. These findings are completely in line with the study of Kempf and Ruenzi (2008) in which the conflicting evidence is explained by career concerns of managers. Schwarz (2011), however, argues that the mean reversion in the fund risk creates a spurious tournament behavior in the market, since the first half standard deviations used as benchmarks suffer from the sorting bias. To prove his point, he uses three methods. First, he computes the frequency difference as an alternative tournament behavior measure. This frequency difference is the gap between high risk and low risk cells for low return funds. Second, a "before ratio", that is the ratio of median standard deviation of winner funds to median standard deviation of loser funds, is defined. A "before ratio" greater than one indicates that winner portfolios have significantly higher risk in the first half than the loser portfolios. The last method is to regress second and first half standard deviations against first half fund performance rankings. His findings are consistent with Brown et al. (1996). To support his argument, he also employs a simulation analysis. He creates a dataset that does not include any tournament behavior among fund managers. Interestingly, the results from analysis of this data are again consistent with tournament behavior even though its absence is known with certainty.

Schwarz (2011) suggests using actual fund holdings in order not to have sorting bias. If there is a tournament behavior, then winner fund managers would sell the highest risk holdings first to decrease the overall riskiness of their portfolio and vice versa. Therefore, the benchmark risk level and the second half risk position of a fund could be correctly identified. However, different from the previously documented bias by Goriaev, et al. (2005) in the mutual fund tournament literature, Schwarz (2011) notes that the sorting bias may also affect the studies that worked with actual portfolio holdings like Chevalier and Ellison (1997). The driving force in this case is not the mean reversion caused by risk motivated trading of portfolio securities but the "*non-risk-motivated trading*". As a result, Schwarz (2011) uses a bootstrapping method and simulates the non-risk-motivated trading pattern so that he obtains a bias free benchmark risk level. Results based on this dataset are still supportive of tournament behavior. Nevertheless, evidence based on this bias free data is mostly insignificant and weaker than that based on the “sorting biased” data. In sum, for the period covered in this study, Schwarz (2011)’s results are in line with Brown et al. (1996); that is in the second part of the year loser funds show an increase in the portfolio risk level. However, the evidence is not as strong as the one from a biased data.

Chen and Pennacchi (2009) discuss the disproportionate nature of flow and performance relation while paying special attention to tracking error. In fact, Del Guercio and Tkac (2002) consider the tracking error issue and show that although low tracking error is desirable for pension funds, it is not a major concern for mutual funds. Chen and Pennacchi (2009), on the other hand, underline the fact that although a fund manager decreases the standard deviation of total portfolio returns, she may increase the deviation of portfolio returns from a benchmark at the same time. The basic motivation behind using the tracking error as a risk measure can be explained as follows, If the manager’s compensation never declines to zero due to the convex fund flow-performance relation, then loser portfolios depart more from the optimal/benchmark portfolio. This departure may not always be observed from the risk measure based on total portfolio return but be evident from the tracking error. Therefore, one should consider the deviation from a benchmark portfolio as a risk proxy in addition to the other risk measures. After constructing a theoretical model arguing that standard deviation of the tracking error is a more appropriate risk measure, Chen and Pennacchi (2009) demonstrate that the loser fund portfolios exhibit more tracking error from a benchmark compared to the winner portfolios. As a result, previous findings documenting no tournament behavior may not be justifiable according to this study, because the risk measures based on total returns are not suitable to account for the risk shifting behavior of loser fund managers. In order to test the theoretical implications of their model empirically, Chen and Pennacchi (2009) compare the total return SDRs, first defined by Brown et al. (1996), and Busse (2001), with tracking error SDRs while controlling for autocorrelation and cross correlation in returns. Beside the nonparametric SDR tests, they also employ a parametric test, a time series method, derived from the empirical model in their paper. Monthly data for the years 1962 to 2006 is used in their analyses. From the total return based SDR tests, Chen and Pennacchi (2009) cannot provide evidence supporting the well documented poor performance-risk altering behavior. This finding is consistent with Busse (2001) and Goriaev et al. (2005). The SDRs for the tracking error measurement, on the other hand, indicate that fund performance and standard deviation of tracking errors are negatively associated. In other words, the loser funds, including the well-established and larger ones, have higher tracking error based standard deviations. This latter conclusion is consistent with the predictions of their model. Second, they reveal from the parametric tests that the most influential factor determining the risk altering behavior is the tenure duration of the manager. In other words, managers with longer tenures are more prone to engage in a tournament behavior after a poor performance than the managers with shorter tenures.

The study of Huang, Sialm, and Zhang (2011) oppose the general view of negative performance consequences of the risk altering behavior. In particular, their paper discusses whether this tournament behavior is beneficial or not for the investors. They note that the risk altering behavior will be harmful for the investors when there is agency problem. In such a situation, in addition to not observing a positive performance impact of risk shifting, trading costs also deteriorates the fund’s position. On the contrary, Huang et al. (2011) argue first that if the mutual fund industry has comparable costs and performance levels, the competition in the market is not influenced, to a large extent, by this risk altering behavior of the managers. Because the funds' performances and costs are similar in the fund industry, new cash flows, that is investors, would be indifferent between different fund types. As a result, fund managers could create any portfolio allocations depending on the expected return and risk levels. Their second argument points out that risk altering behavior can be a result of active management, which reflects the skill of the manager, but not necessarily an outcome of the gambling behavior. Then, fund investors would not be hurt, but benefit, from changes in the risk level in the mutual funds' portfolios, because the performance of the funds will also increase. To assess the risk altering behavior of the managers, and the possible performance consequences, Huang et al. (2011) generate a holdings-based risk shifting measure. Here, they compare the difference between the standard deviations of most recently disclosed fund positions and the fund's realized returns. More specifically, they construct a hypothetical portfolio that contains actual security holdings in the fund's portfolio for the past 36 months. Then they calculate the return and standard deviation of return on this hypothetical portfolio. This measure shows the variation only due to the portfolio changes, but not due to market changes. They put this variation measure side by side with past realized volatility that is found from the actual fund returns over the same 36 months time period. This latter measure provides the total risk of the portfolio. These two standard deviations should be the same unless the portfolio weights are altered in a given period. If the difference between these two measures is positive for a fund, one can conclude a risk shifting behavior for the manager. Huang et al. (2011) indicate that using overlapping periods help to separate the portfolio specific risk alterations from those imposed by the market conditions. The period from 1980 to 2009 is selected for their analyses. Consistent with the arguments of the agency theory literature, Huang et al. (2011) document that risk increasing funds experience poor performance relative to the funds that do not change their risk exposure. Likewise, underperformance after a risk altering behavior triggers more risk shifting in the later periods. Evaluating the managerial skill component reveals that risk shifting is a costly activity, and it indicates either a lack of skill or an existence of agency problem in the mutual fund industry rather than superior management. Overall, the findings of this paper show that risk increasing behavior of fund managers is a product of opportunistic trading and it causes agency problem. Therefore, it hurts investors instead of benefiting them.

The international evidence on the area of flow-performance association comes from the study of Ferreira et al. (2012b). They explicitly indicate that this association can vary based on differences in the economic and financial development level of countries analyzed in the study. The source of this difference is a mixture of differences in investor sophistication levels and participation costs across countries. The investor sophistication is defined in the study as the correct interpretation of new information. Ferreira et al. (2012b) argue that chasing past performance is a result of behavioral biases. That is, investors invest in winner funds more than they do in loser funds, because they tend to pay more attention to the latest information, and mutual funds are more likely to advertise their performances when they are good. As a result, Ferreira et al. (2012b) expect to see less chasing of past performance behavior as the investor sophistication increases. Investors in developed countries have well-functioning financial markets. Therefore, investors in these markets are assumed to be better at interpreting new information. Hence, Ferreira et al. (2012b) expect to see a less convex relation between flow and performance in developed countries. Huang, et al. (2007) have previously documented that funds with higher participation costs provide higher previous returns in order to compensate investors for these costs. Based on this finding, Ferreira et al. (2012b) anticipate to observe a more convex flow-performance structure in countries where participation costs are higher. They note that participation costs are expected to be lower in developed countries as well, since obtaining and evaluating new information are easier in these markets. These hypotheses are tested for 28 developed and developing countries with quarterly data between the years 2001 and 2007. Nevertheless, their sample does not include Turkish mutual fund industry. The selected proxies for the level of investor sophistication and participation costs are economical and financial development indicators, such as GDP per capita, as well as the mutual fund sector development indicators, like age, size and transaction costs. Their results indicate that countries show different levels of convexity. Most of the convexity levels are higher than that is observed in the US mutual fund market. In addition, more sophisticated investors in developed countries penalize loser portfolios as much as they reward winner portfolios. Therefore, they observe a reduced amount of convexity in these countries as hypothesized before. Participation costs proxied by transaction costs also provide the expected result, when the economical, financial and mutual fund industry development of the countries is controlled for. The relation is found to be less convex in developed countries where the participation costs are smaller. The basic conclusion drawn from this study is that incentive creating flow-performance structure is more pronounced in developing countries which may necessitate extra regulations.

The study by Ferreira et al. (2012b) put document interesting findings. First of all, they indicate that the US mutual fund market is not a representative of the world markets. Many mutual fund industries have differences in their cash flow-prior performance relation. Second, they demonstrate that developing countries has a higher level of convexity than their developed counterparts. In the US mutual fund market, as a developed country, investors penalize the loser portfolios more than the investors in developing countries. This finding may seem to be in conflict with earlier results at first, but it is, in fact, in line with findings of some of the earlier US fund market studies, namely Huang et al (2007) and Kempf and Ruenzi (2008). Huang et al. 2007 show that as the participation costs for the mutual fund investments has declined over time, the convexity has become less pronounced. The study of Ferreira et al. (2012b) covers a period from 2001 to 2008. Therefore this less pronounced convexity for the sample period analyzed in this paper can be explained by lower participation costs during that periodKempf and Ruenzi (2008) indicate that fund managers are more likely to participate in a risk increasing behavior when they feel that their positions as managers are not in danger. In the sample period chosen by Ferreira et al. (2012b), there is a downward market in the US. As a result, fund managers may not prefer to engage in a risk shifting behavior in order to not to lose their jobs in case of huge losses.

Together with the family tournament findings of Kempf and Ruenzi (2008), one may claim that another reason for the difference between findings for developed and developing countries can be the relatively smaller size of mutual fund markets in the developing nations. Kempf and Ruenzi (2008) show that in smaller fund families, the relative position of a fund inside the family becomes more important than that in larger fund families. This finding might be taken as an indication of a higher spatial dependence in smaller fund families. Broadening these conclusions to the mutual fund markets may mean that different mutual fund markets may show different levels of spatial dependence based on their size. Given earlier evidence in the literature, it is conceivable to conjecture that not taking into account this spatial dependence among mutual funds may result in spurious relations between fund flows and performance. Based on the evidence in Ferreira et al. (2012b), this danger of false inferences about the behavior of fund managers may be even stronger in the developing countries where the mutual fund industries are smaller. This may be another explanation for the different convexity levels observed in different countries. A smaller mutual fund market may exacerbate the tournament creating incentives as well as the spatial dependence among fund managers. This would result in either higher biases in the computations, or, if the tournament behavior is not a consequence of spurious findings, higher level of flow-performance convexity in developing countries. In my dissertation, by controlling for these spatial interactions, I attempt to add to the clarification of this ambiguity.

A recent study on the tournament behavior in the Turkish mutual fund industry belongs to Öztürkkal and Erdem (2012). They begin their discussion by stating the importance of mutual fund prior performance from the point of view of investors and fund managers. They note the linkage between behavioral finance – specifically the gambling behavior – and managerial risk incentives by referring to the well-known prospect theory of Kahneman and Tversky (1979) as well. However, Öztürkkal and Erdem (2012) continue their examination on the basis of Brown et al. (1996), and they do not analyze the behavioral finance linkage. In fact, the study of Öztürkkal and Erdem (2012) is a replication of the paper by Brown et al. (1996). Specifically, they investigate the existence of tournament behavior in Turkey, as a developing country, by using monthly data for all type-A funds for the period from 2002 to 2007. Following the methodology of Brown et al. (1996), they compute the return data, then they compare the volatility of the winner group – above median funds – to that of the loser group – below median funds – using risk adjustment ratios. The findings for Turkey are in line with the tournament hypothesis. That is, in months of June and July, fund managers with loser portfolios increase the riskiness of their portfolio relative to the first part of the year, whereas winner funds decrease the risk in the second part of the year. Öztürkkal and Erdem (2012) also compare the ratios of portfolios that shift the portfolio risk, and demonstrate that risk altering is a common case among the loser funds. In line with the previous argument, they explain risk altering behavior of managers in the second half of the year by the fund evaluation process realized at the end of the year. Brown et al. (1996) argue that the risk shifting behavior is a consequence of managers' gambling incentives caused by the low level of penalty in terms of cash flows. Öztürkkal and Erdem (2012), however, point out that tournament behavior cannot only be attributed to these incentives of managers. They indicate that in Turkey, a developing country, fund managers may not be the sole decision makers because the turnover rates for fund managers are very high. Moreover, most of the mutual fund companies are subsidiaries of other financial intermediaries or banking companies. As a result, attributing the risk shifting behavior solely to the managerial risk appetite may not be a correct inference. Bank parents may encourage excess risk shifting by their mutual fund subsidiaries in the second half of the year to attract new investors. According to Öztürkkal and Erdem (2012), the risk shifting tendency for the portfolio management companies in the second half shows the pressure of attracting new cash flows to the fund.

The study of Öztürkkal and Erdem (2012) has importance for my dissertation as well. They are the first to check the tournament behavior among Turkish mutual funds. By analyzing a data that is not publicly available in an emerging country, they have definitely added to this literature where most studies are based on the data from the US market or developed markets. However, this study has its own drawbacks.

First, due to the data limitations, Öztürkkal and Erdem (2012) only use the equity portion of the mutual fund portfolios, and relate the results with the new cash inflow. This would be an accurate analysis, if the only way to change the risk of a portfolio is to alter the security structure. However, a fund can disinvest its holdings in bond market and increase its equity investments in the portfolio and increase the risk of the portfolio. To decrease the portfolio risk, a fund may increase its investment in bond markets or hold cash. Putting it differently, one cannot be sure whether the new money that is invested in equity securities comes from the new investors or from liquidation of the other investment alternatives unless all the portfolio holdings are known. A better approach to analyze the risk shifting would be to apply Schwarz (2011)'s proposition. That is, to decrease (increase) the risk of the portfolio, fund manager would sell first the highest (lowest) risk holdings, and replace them with a lower (higher) risk security. Analyzing only the equity portion with the risk adjustment ratio method would not allow such an analysis.

Second criticism towards the study by Öztürkkal and Erdem (2012) may be directed to their sample. Their analysis is based on all type-A funds. However, type-A funds can also be classified into different classes according to their holdings. Capital Markets Board of Turkey reports in 2010 that there are 17 different classifications for mutual fund industry in Turkey (SPK Yatırımcı Bilgilendirme Kitapçıkları, 2010). According to Turkish Intuitional Investment

Managers' Association, apart from the "money market" funds, "notes and bonds" funds and "foreign securities" funds, all the other funds can be type-A or type-B (Türkiye Kurumsal Yatırımcılar Derneği, n.d.). As a result, the study of Öztürkkal and Erdem (2012) puts several type-A funds, ranging from the equity funds to index and sector funds into one basket and analyze all of them together. The previous literature, on the other hand, mostly employs growth oriented equity funds in their analysis. In particular, the existence of index and commodity funds in the sample of Öztürkkal and Erdem (2012) may have a potential to bias their results.

Furthermore, although Öztürkkal and Erdem (2012) have noted that the survivorship bias is not a major concern for their study, they have not considered the criticisms set forth by Busse (2001) and Goriaev et al. (2005). Since Öztürkkal and Erdem (2012) employ monthly return data, these criticisms are valid for their study as well. In other words, it is likely that their findings suffer from the biases that are caused by autocorrelation and cross correlation in the data. Last, Öztürkkal and Erdem (2012) have only employed the "risk adjustment ratio" defined by Brown et al. (1996), but they have not considered any regression framework. This methodological shortfall has been criticized in Busse (2001) and Goriaev et al. (2005) as well. In this dissertation, I, however, aim to examine the Turkish mutual fund industry by spatial regressions. These spatial regressions take into account spatial dependence, which is very likely to affect risk shifting behavior of fund managers. Hereby, I plan to add to the tournament behavior explanations in the mutual fund industry as well as to the spatial econometrics literature by extending the distance concept to a new area. In addition, unlike developed countries, emerging markets may experience a higher degree of convexity in the prior performance-cash flow relation. This relation has only been considered in the paper by Ferreira et al. (2012b). By conducting a detailed study in Turkish mutual fund industry, I also attempt to contribute to the convexity and risk alteration incentive issues.

The literature on relation between prior performance and cash flow shows clearly the significance of the issue for the mutual fund industry and its investors especially for developing countries. In this dissertation, I attempt to improve the models analyzing the mentioned association and the tournament like behavior among fund managers with the aid of spatial techniques. The tournament behavior literature suggests a nonlinear response of cash flows to the relative position of funds and this nonlinear response might create a spatial dependence among mutual funds. Although the importance of autocorrelation and cross correlation has been realized in several papers, to my knowledge, spatial dependence caused by fund rankings in the mutual fund industry has been left uninvestigated so far. The methods I use in this dissertation allow me to characterize the nature of the relationship between flow and performance better and to identify the conditions that determine the extra risk taking behavior of managers shown in many papers. Therefore, analyses carried out in this dissertation add to the tournament behavior explanations in the mutual fund industry as well as to the spatial econometrics literature by abstract distance measure.

2.2 A Modeling Proposal: Spatial Econometrics

Traditional econometric techniques usually rely on Gauss-Markov theorem which assumes that observations are independent, and their variation is constant. These two assumptions are often violated when one includes location as a component. The violations may cause incorrect inferences in terms of coefficients, significance levels and goodness of fit tests, and result in inappropriate model specifications (LeSage, 1997). Spatial econometrics, which accounts for this location component, can be considered as a sub-field of traditional econometrics (Anselin, Gallo, & Jayet, 2008). Anselin (1988) defines spatial econometrics as the modeling techniques that account for the *peculiarities* caused by the space component. These peculiarities, namely spatial dependence and spatial heterogeneity, are called spatial effects.

Spatial dependence may be best described by the words of Tobler (1970): "*Everything is related to everything else, but near things are more related than distant things*" (pg. 236). From a geographical perspective, he explains this association as such: the growth of population in one location is a result of its own characteristics, but it also depends on the population of other locations. Anselin (2010), on the other hand, more formally defines spatial dependence or spatial autocorrelation as "a type of cross correlation impacted from the relative position of the observations in geographic/network space which cannot be solved by employing standard techniques". Here, the *structure* of the relation represented by correlation among observations is obtained from a specific ordering according to their relative positions in the space (Anselin, 2006).

The similarity and the difference between spatial dependence and *statistical* dependence is noted in Anselin (1988). The observations in a time series model show dependence to the prior observations in the dataset, which reflects one-dimensional dependence. Spatial dependence, however, represents that observation at location *i* varies according to another observation at location *j*. That is, in an error variance-covariance matrix, the off diagonals being not equal to zero is in line with a "spatial ordering" (Anselin, 2003). Here, the one-dimensional dependence in time series models becomes multi-dimensional in the case of spatial econometrics. This multi-dimensional dependence impedes a solution obtained by employing traditional methods. In order to include the neighborhood concept, so the spatial autocorrelation into the model, spatial weight matrices are used. These matrices can be binary or general spatial weight matrices (Anselin, 1988).

LeSage and Pace (2009) explain the inadequacy of standard econometric techniques to account for spatial dependence as such: in a linear regression model, the disturbance term (ε_i) is assumed to be distributed normally, with zero mean and a standard deviation (σ^2). For two observations that are statistically independent, the following condition must be satisfied: $E(\varepsilon_i \varepsilon_j) = E(\varepsilon_i)E(\varepsilon_j) = 0$. This equation, on the other hand, does not describe the spatial dependence where the observation i at one region changes accordingly to the observation j from the neighboring location. LeSage and Pace (2009) explain the effect of neighboring in the data generating process as follows. Let the neighboring observations $i = 1$ and j = 2, and the values of i depend on j. The data generating process may be formulated as shown below (LeSage & Pace, 2009):

$$
\begin{aligned}
y_i &= \alpha_i y_j + X_i \beta + \varepsilon_i \\
y_j &= \alpha_j y_i + X_j \beta + \varepsilon_j \\
\varepsilon_i &\sim \mathrm{N}(0, \sigma^2) \quad i = 1 \\
\varepsilon_j &\sim \mathrm{N}(0, \sigma^2) \quad j = 2
\end{aligned}
$$

However, as many researchers correctly indicate, this simultaneous data generating process would cause a degrees of freedom problem, since there would be potentially $n^2 - n$ parameters to estimate (Anselin, 2006; LeSage & Pace, 2009). This problem is solved by using a spatial weight matrix in spatial autoregressive data generating process. The general first order model can be shown as follows (Anselin, 1988):

$y = \rho W y + \varepsilon$, where W represents $n \, x \, n$ spatial weight matrix; y is the dependent variable, ρ is the scalar parameter that demonstrates the strength of the spatial dependence, and ε is the disturbance term that has a multivariate normal distribution with a zero mean and constant variance-covariance matrix. Spatial weighting is not limited to the dependent term, but also the exogenous variables and the error term can be scaled by this weight matrix.

There are basically two reasons that create spatial dependence as stated in LeSage (1999). First, some data collection process may show dependence to space units such as addresses, zip codes or mobile labor force. Not to take into account these spatial effects may cause measurement problems. Second, as in the standard econometrics, omitting an important variable that has an effect on the dependent variable may result in autocorrelation as a modeling problem. Here, neglecting the spatial dimension of economic, socio-demographic, geographical data may generate spatial autocorrelation. Anselin (1988) explicitly emphasizes that the simple extension of time series techniques is not sufficient to tackle the different nature of spatial dependence.

Spatial heterogeneity, on the other hand, means having unstable parameters and varying functional forms in the dataset due to their locations in the space (Anselin, 1988). Most basically, the diagonal elements of error variance-covariance matrix vary. This can be a result of initial data set, or fluctuating number of neighbors for each location. In the second case, heteroskedasticity occurs although the initial process does not suffer from such a problem (Anselin, 2003). For instance, this is likely to be the case when one works with a cross sectional data with distinct spatial units such as rich and poor regions, because the borders are specified arbitrarily. In such a case, heterogeneity in the data can be straightforwardly linked to the location of the observations (Anselin, 1988). Contrary to the requirement of new techniques for spatial dependence, spatial heterogeneity does not necessitate the development of new methods to account for it. Instead, the well-known statistical methods dealing with simple heterogeneity are adequate to solve the problems associated with spatial heterogeneity. This is why Florax and Van Der Vlist (2003) note that spatial dependence is more discussed in the literature compared to spatial heterogeneity problem. Nevertheless, spatial econometrics usually provides more efficient procedures relative to standard techniques in addressing spatial heterogeneity. Most of the time, spatial heterogeneity is inseparable from the spatial dependence. Anselin (2010) defines this issue as the "inverse problem". Spatial heterogeneity may also include additional information like spatially varying coefficients or spatial structural changes (Anselin, 2006).

As a solution for spatial heteroskedasticity, if the variance-covariance matrix is known a priori, one may use ordinary least squares or maximum likelihood method. On the other hand, when this matrix is unknown, the "*heteroskedasticity-consistent covariance matrix estimator*" can be used as an estimator (Arbia, 2006).

Spatial modeling has become a widely used technique in different empirical studies, particularly in regional science. This is actually a natural area for spatial studies owing to its distance-based nature. On the other hand, Manski (1993) notes the importance of so-called "social norms", "peer influences", " social interactions" or "herding behavior" on the decision making process of individuals. He explains such an effect in three ways: i) *Endogenous effects:* Individual's tendency to behave in a certain way that changes accordingly to the group behavior; ii) *Exogenous effects:* Individual's tendency to behave in a certain way that changes accordingly to the exogenous characteristics of the group; iii) *Correlated effects:* Individuals in the same group are more likely to act in a similar way since their characteristics or their environments are alike. Based on these three influences on human behavior, one may conclude that areas other than regional science also require spatial modeling. Furthermore, besides "geographical distance", analyzing these issues requires definition of new distance metrics.

This dissertation can only provide a very brief set of examples from this line of research. The examples will be presented into two groups. In the first group, the papers are chosen from different areas to show the ample usage of spatial econometrics. The common point of these studies is using "geographical distance" as their spatial weight matrix. The second group, on the other hand, consists of studies with "non-Euclidian" based distance measures from various literatures.

Rey and Montouri (1999) provide one of the seminal works in the regional science. They indicate that regional economic convergence is an area that must be considered with the location impact, since the determinants of the convergence such as factor mobility or technology transmission are highly impacted from the geographical position. In fact, this is one of the examples that Anselin (1986) mentions in his study. He notes that the papers investigating poor and rich regions may suffer from the biases caused by spatial interactions unless they are explicitly accounted for. From this reasoning, Rey and Montouri (1999) criticize the earlier studies on regional convergence on the grounds taking the regions as independent units, and ignoring the inter-regional interactions. Therefore, they re-examine the income growth among different regions in the United States while benefiting from exploratory spatial econometrics for the years from 1929 to 1994. They estimate both cross sectional variation of income per capita (σ-convergence) and the differences in growth among poor and rich regions (β-convergence) while adopting a binary spatial weight matrix in which the common border is represented with 1. The spatial autocorrelation is computed by the aid of Moran's *I* statistics. The beta convergence is examined through three types of spatial regressions: i) Spatial error model, where the spatial effects are considered in the error term; ii) spatial autoregressive model, in which a spatial lag is included into the model, iii) spatial cross sectional model, in which only an exogenous variable is scaled through the spatial weight matrix. In terms of Manski (1993)'s classification, the spatial error model reflects the correlated effects while spatial autoregressive model accounts for endogenous effects. The last model of this paper takes into account the exogenous effects. As stated in Anselin (2003), the spatial autoregressive model brings into picture the "spatial multiplier concept". That is, an enhancement in the income level of the neighbors affects the income growth of the country in the analysis. However, this change in the income growth also impacts the neighbors until equilibrium is reached. The other two models do not have such a multiplier impact (Manski, 1993).

The findings of the paper by Rey and Montouri (1999) point out that spatial autocorrelation highly exists. Moreover, they find that there is convergence among the states in terms of relative income, but this convergence of income depends strongly to the neighboring states. That is, regions have tendency to be clustered according to their income levels. High income states are near to each other, while low income ones form another cluster. As a result, Rey and Montouri (1999) show that conventional models applied in the regional convergence literature can suffer from misspecifications when spatial dependence is not considered.

Income inequalities and growth convergence highly require the addition of spatial effects. Among many others, Yıldırım, Öcal, and Özyıldırım (2009) also examine the regional convergence and income inequality issues for Turkey for the years 1987-2001. The novelty of their study is to take into account these spatial interactions while analyzing interregional inequalities in an emerging country. They also note that previous studies on the regional convergence cluster the countries into mutually exclusive groups that assume total independency. As in the study by Rey and Montouri (1999), Yıldırım et al (2009) model beta convergence by separately scaling the error term, dependent variable and exogenous variable by the spatial weight matrix. This matrix consists of binary terms, representing the physically adjacent provinces. Different from the prior regional inequality studies, Yıldırım et al (2009) also employ geographically weighted regressions as an alternative to account for spatial effects. Geographically weighted regressions are an extension of OLS model. Here, in the parameter estimation process, the observations are directly weighted with a function which reflects the distance between the region i and all other regions. Therefore, the estimated parameters are region specific. This technique is beneficial in terms of dealing directly with the spatial heterogeneity. The overall findings show the existence of income convergence across provinces in Turkey. In other words, poor provinces converge to rich ones in terms of income growth rates. However, the linear association between per capita income growth and independent variables differ based on the location of the provinces. Hence, as Yıldırım et al (2009) specify, spatial models provide a better fit than the OLS model. This comparison between models shows that the high deviation in the convergence among provinces cannot be represented in the conventional beta methods.

Regional science is also helpful while examining the factors of house prices. Although the main driver behind the rise in the house prices is real income, Holly, Pesaran, and Yamagata (2010) indicate that regional differences must be taken into account. Location becomes an important component in this model, because expensive housing in metropolitan areas may force households to choose houses in neighboring states. Labor mobility is another reason which directs house investors to migrate to neighboring states. The study of Holly et al. (2010) define a binary spatial weight matrix having a value of 1 if two states share a common border or vertex and zero otherwise. Holly et al (2010) analyze annual state level data for the years between 1975 and 2003. To observe the spatial autocorrelation, first, they decompose the error term into idiosyncratic component. Then, they run a regression of error terms while employing a spatial lag. This second part of the analysis is to show the degree of spatial dependence. The results indicate the presence of spatial dependence among the neighboring states in the US. Hence, the study by Holly et al. (2010) emphasizes the significance of spatial dependence along with other fundamental determinants in modeling the house prices across regions.

Spatial econometrics modeling is also used in microeconomics. Pinkse, Slade, and Brett (2002) investigate the competition and price formation in monopolistic competition markets, where products are not identical but substitutes. They aim to develop an empirical technique that separates price competition as global and local. In the microeconomics literature, local competition refers to a rivalry on a one dimensional spatial surface in which the firm competes with the two other firms neighboring from either sides. That is, the impact of neighborhood decays as the distance increases. Remote competitors have no or very little impact. In the global competition model, all firms compete with each other. They argue that in the classical monopolistic competition view, the competition is taken as symmetric. The spatial modeling of Pinkse et al. (2002), however, is based on the notion that prices are formed according to the price fluctuations in the neighborhood. In other words, the local competition does not need to be considered in a one-dimensional space, while the global competition can be asymmetric as well. Pinkse et al. (2002) select the US oil terminals of October 1993 to proxy the competition in the refined oil market. They employ several measures of distance, namely "*gasoline terminals that are nearest neighbors, that share a market boundary, that share a market boundary with a third competitor, and the Euclidian distance between terminals*". Putting it differently, the distance measures are defined as being a nearby neighbor, sharing a common border, and having a Euclidian distance that is smaller than a threshold value. Pinkse et al. (2002) develop a semi parametric approach to model the non-linear relation in the price formation process while accounting for the spatial effects. Their results indicate that only the first measure of distance is a spatial determinant of the competition among oil terminals. In addition, they show the price formation is more local than previously thought when the spatial interactions are considered. Their procedure which permits the ordering of different distance measures according to their importance and their interactions, adds to the spatial econometrics.

Last but not least, beside the frequent usage of spatial econometrics in regional science, spatio-temporal modeling is a newly used technique in evaluating the performance of banks. Tirtiroglu et al. (2011) investigate the role of distance on the performance of the US banks. Taking the spillover discussions as the underlying literature, they examine the effect of neighborhood on the total productivity factor growth of the US banks. Specifically, they investigate whether bank performance in adjacent states is related; if so, how far this spatial diffusion reaches, and what the real motivation behind the diffusion is, i.e. neighborhood or regularity similarities. To examine these questions, Tirtiroglu et al.

(2011) benefit from both panel and the lagged spatial regressions utilizing annual data for the years from 1971 to 1995. First, to observe the impact of neighborhood on panel specification, they run the regressions with neighboring states and randomly chosen states. Their findings indicate that the performance of banks, proxied by total factor productivity growth, is clearly related to their location. To clarify whether this relation between location and performance is caused by similarity in regulatory environments of states rather than their physical distance, Tirtiroglu et al. (2011) re-analyze this association for states that allow entry of banks regardless of where their headquarters are located. The overall results demonstrate that physical distance based proximity is a stronger determinant than regulatory proximity. Tirtiroglu et al. (2011) note that ignoring spatial effects when modeling banking performance may suffer from a severe omitted variable problem.

Above and beyond the ample usage of spatial methods in regional science, these interactions also draw attention in the social science literature. Many studies report that individuals, groups, families, voters are under the influence of others in their decision making process (Akerlof, 1997; Anselin, 1988; Dow et al., 1984; Ward & Gleditsch, 2007). Usage of spatial methods is motivated by this feature of social sciences. For instance, the lack of independence between sample units in the cross-cultural studies and its spatial consequences are noted in Dow et al. (1984). They indicate that dependent samples may cause artificially high or low correlation estimationswhich is known as Galton's problem in the anthropology literature (Dow et al., 1984). The importance of spatial weight matrix is highlighted once more in incorporating the spatial dependence into the model. They also indicate that the spatial distance can be a social distance concept such as language similarity or physical distance as mostly used in the regional science. Indeed, Anselin (1988) argue that the notion of space is not limited with the Euclidian definition of distance; instead "*policy space, inter-personal distance or social networks*" can be modeled with spatial econometrics (pg. 8). Although a non-geographical or non-Euclidian distance measurement is attractive as in the study of Dow et al. (1984), its construction could be problematic. There could be false inferences unless the distance matrix reflects the real process correctly. Furthermore, Dow et al. (1984) sets forth that the estimation procedure of the autocorrelation parameter has major importance. In order to find the best estimation procedure regarding the efficiency and unbiasedness of spatial regression models, they compare the OLS estimations to maximum likelihood, iterative generalized least squares and iterative residual regressions through simulations. This evaluation is made based on linguistic similarity distance matrix as an example of the non-Euclidian distance matrix. Dow et al. (1984) suggest that the proximity between two languages is defined according to the nodes along the path in the linguistic genetic tree. In fact, their distance measurement is an extension of previously proposed matrix in the anthropological spatial distance study of White, Burton, and Dow (1981). The results of Dow et al. (1984) show that OLS is no longer the most efficient estimator, although it remains unbiased. In addition, it has variance underestimation problem which results in more significant coefficient estimates. However, the remaining procedures cannot dominate one another, and they can be equally used in the spatial regression models estimations. Since Dow et al. (1984) attempt to compare various estimation procedures in the spatial regressions, they do not focus on the comparison of two types of distance matrices. Yet, it would be interesting to investigate the impact of different "space" definitions in such a study.

Akerlof (1997) provides one of the earliest studies that discuss the importance of social distance. He argues that the "representative agent" models that define the utility of individuals so far are insufficient in accounting for personal or sub group differences. In these models, the main aim is to maximize the utility function, so there is no need to behave in a different way for any individual. Akerlof (1997) underlines the importance of rules and values in distinct sub groups, and indicates that each individual should be characterized according to their location in the space. The social interactions are affected from the distance among these individuals. Putting it differently, the closer the individuals are in the space in terms of group norms, the more social interaction will be observed. This proximity is a more general concept than the one defined in the Euclidian sense. Unfortunately, the paper of Akerlof (1997) is a theoretical one. While its addition to the literature is to highlight the role of spatial interactions for social sciences, it does not suggest a proxy for inter-personal distance measurement. This criticism is in fact valid for the work by Anselin (1988) as well. There is no proxy suggested in Anselin (1988) for these non-Euclidian distance measures.

Examples of non-Euclidian distance proxy while using spatial modeling in social sciences is provided by several studies, including Dow et al. (1984) and Conley (1999). The concept of economic distance, i.e. the interdependence among individuals, is first proposed by Conley (1999). The main aim of his study is to create a consistent generalized method of moments estimator with a nonparametric modeling of dependence, when the distance is measured with an error. This is the major difference of this paper from the work of Dow et al. (1984). Dow et al. (1984) do not accounte for the possible errors in the measurement of the distance matrix and its consequences. Conley (1999) compares parametric and nonparametric estimation techniques for generalized method of moments. He indicates that in the parametric modeling approaches, the measurement of distance usually generates problems, because classical theory assumes a normal distribution of the data with a covariance matrix expressed as explicit distances. In this study, the location is defined as the random field of each observation. The distance between two observations, *i* and *j*, is the difference between their locations, s_i and s_j. The smaller this distance becomes, the higher the correlation between random variables X_{si} and X_{sj} is. In other words, the economic distance between observations shapes the dependence between their random fields, which results in spatial dependence. In fact, Conley (1999) argues that this is an approach which makes the modeling of dependence between observations straightforward. As an economic but imperfect distance measure, he points out trades volumes or transportation costs of human or physical capital as candidates. Accordingly, the transportation cost between two countries, such as the US and Mexico; the US and Japan, etc. is chosen as the empirical examples in his modeling. In line with Dow et al. (1984) and Akerlof (1997), Conley (1999) also highlights the lack of independence among observations in the economic theory, so the inconvenience of traditional models based on Gauss-Markov theorem.

The application of spatial econometrics to social sciences by the aid of non-geographic distance metrics can be seen in Conley and Topa (2002). They examine the spatial interactions in the determination of unemployment while considering the role of social networking among individuals proxied by different economic distance measures. Their paper emphasizes that social networking helps to find new job areas. This type of social networking can be directly associated to physical distance, that is, individuals have a relation with those who are nearby. It may also have dimensions reflecting common points, namely ethnicity, religion, nationality, education etc alongside the geographical characteristic. In other words, besides the impact of physical proximity in finding jobs, non-geographical determinants also generate clusters-spatial dependence-in the data. Conley and Topa (2002) benefit from Chicago Census tracts for different distance measures, that is physical proximity between centroids of two tracts, public transportation travel time, the Euclidian distance between two vectors representing the percentage of different races and ethnicities of Chicago, an Euclidian distance measure based on the distribution of occupations within a tract. They apply the method proposed in the paper by Conley (1999) in order to account for the problems caused by imperfect distance metrics. Although their results are mixed, and they suggest further research in this area, in general, they find evidence of spatial dependence on the determinants of unemployment. The significance of this spatial dependence decreases as the distance in terms of different measures increases.

Conley and Dupor (2003) argue that economic fluctuations should be modeled by taking into account sector interactions if one does not want to ignore valuable disaggregate information hidden in cross-sector correlations. The purpose of their paper is to assess the productivity relation among different US sectors while accounting for spatial effects. The distance between two sectors in this model is defined as the similarity in their input-output structure. According to the output structure, the economic distance is denoted as small if two sectors provide goods for similar industries. The second measure is based on the input similarity of sectors and two sectors are considered as alike if they use similar technologies. The input-output data used in the analysis is provided by the Bureau of Economic Analysis quinquennially, including the years from 1972 to 1987. The results show strong co-movement between total productivity growths of the US manufacturing industries, even after the impact of business cycle is removed. The productivity growth rates indicate high correlation in the sectors in which the input distance is smaller. The productivity of these sectors tends to move together, and hence adds significantly to the aggregate productivity fluctuations.

Economic distance measure examples are not limited to these papers. In fact, several social science studies benefit from the spatial econometrics literature from time to time. Another example in this area belongs to Pinkse and Slade (2004) that investigate the beverage industry mergers in the UK for the time period of August/September and October/November 1995. They note that unless the consumers decide among discrete alternatives, and buy only one unit of a product, for example automobile, they have to make a choice in a product-characteristic space, where all the dimensions reflect distinct brands and amounts. Following on their previous work (Pinkse et al., 2002), Pinkse and Slade (2004) semi parametrically compute the cross-price elasticities, and employ them as the distance matrix. More clearly, the beer brands are considered to be "close" if they have the same product type, they are produced by the same brewer, and their alcohol amount is comparable. The results show that all of these distance measures affect the competition in the beer market albeit differently.

In an interesting study in the economic policy area, Simmons and Elkins (2004) note that liberalization policies applied by different governments show similarities both regionally/spatially and throughout time. They investigate the choice of foreign economic policy decisions, and the role of other countries in this process. They argue that the effect of distance/closeness in the economic policy making is spurious, and may be explained by other associations. As a result, they raise the following questions: (1) Does the policy choice of elsewhere change the payoffs of an application of a particular policy? (2) Is the policy choice effective on the information set that the government uses for its own policy making process? In this paper, Simmons and Elkins (2004) point out that the spatial similarities, formally spatial dependence, does not only have the capability to bias the parameters by impacting error terms, but also constitutes the core of the study. Hence, they add a spatial lag to their model to deal with this spatial dependence. As the authors highlight, the focus of the methodology is to determine the spatial distance matrix. Various forms of non-geographical distance definitions are utilized. First of all, since the payoff of a liberal economic policy depends on the competition in the foreign markets, hence other countries' policy decisions, Simmons and Elkins (2004) generate a "competitive distance" measure based on the bilateral relations between two countries. This competitive distance metric aims to measure if these two countries compete for a share in a third market. They constitute a correlation matrix using the ratio of total export of each country to the others in the sample. This correlation matrix indicates the extent of the bilateral trade association countries have with each other. In other words, this measure aims to assess the competition degree of countries in a third market. Simmons and Elkins (2004) are also interested in the export distribution of each country across different industries. Again they construct a correlation matrix that shows the export data of each country in 9 sectors. Both correlation matrices are utilized to designate the most competitive 10 countries in the two categories. The mean values of each country for these two categories represent the spatial lag variables in their models. Likewise, Simmons and Elkins (2004) note that countries that are similar in terms of educational and technological background compete for the market share in the same industries of foreign markets. They develop another distance measure, and a spatial lag, based on the most similar 10 countries' mean value obtained by the aid of this new correlation matrix. This new distance measures is constructed to show the informational impact of neighbors' policy decisions. Here, Simmons and Elkins (2004) control for the effect of Euclidian distance on the policy diffusion between countries by adding two "true" geographical distance variables: the log distance between capitals of two country and sharing a common border. They examine 182 countries that are members of IMF between the years 1967 and 1996. They use a semi-Markov model and a hazard model with spatial lags that are determined by the aid of distance measures discussed above, and included in the models to account for the "neighborhood effect" which may cause omitted variable problem if ignored. Both are spatial autoregressive models. Their findings point out that countries that are close to each other in terms of policy distance measures, apply similar policy liberalizations as well.

Policy formation literature and the effect of neighborhood on this process can be expanded through the study of Beck, Gleditsch, and Beardsley (2006). Referring to Galton's problem (Dow et al., 1984) and in line with Tobler (1970); Beck et al. (2006) emphasize the inadequacy of independence assumption employed in the traditional statistical methods that are used in the political economy papers. First of all, they discuss the appropriateness of two spatial methods, the spatially lagged error, and the spatial autoregressive models, for the economic policy formation research. They note that spatial error models deal with the spatial dependence in the error term, which assumes that the explanatory variables are free from this space effect. This assumption becomes particularly hard to defend when a new explanatory variable is added to the model, and this is more likely to be the case in the economic policy implementations. In other words, policy formation has a social multiplier effect that is represented by a spatial lag of dependent variable into the models. This spatial lag of dependent variable reflects endogenous effects in the terms of Manski (1993)'s classification. This is why Beck et al. (2006) find the spatial autoregressive models more adequate than spatial error models. Along the lines of many others (i.e. (Akerlof, 1997; Anselin, 1988; Conley, 1999; Dow et al., 1984), Beck et al. (2006) also underline the need for defining new distance measures other than geographically based ones. They hypothesize that the democracy level is likely to be impacted from the level of democracy elsewhere. Although there is a vast literature discussing the spatial effects in the diffusion of democracy[2], Beck et al. (2006) criticize these studies for taking only the geographical distance while defining the proximity between observations. However, they claim that geographically remote units may be close to each other in terms of other "non-geographical" distance definitions. By utilizing Polity IV data as democracy level proxy, they define two measures of democracy diffusion-connectivity: First, following the tradition, Beck et al. (2006) accept countries as connected if the distance between them is less than a threshold, 500 km, which results in a binary matrix. Second, the proximity or distance is determined according to the trade volumes among the states. The partners with highest trading volume have the largest impact on each other. The basic difference between the first and the second measures is the weighting schemes used. In the former one, all neighbor countries have the same weight; in contrast, two neighboring countries can have different weights depending on their trading volume in the latter one. Following previous estimation procedure comparisons (Dow et al., 1984), Beck et al. (2006) employ the maximum likelihood estimators for the spatially autoregressive model. The lagged terms are provided according to the two types of

[2] For instance, see O'Loughlin (1986) for a geographical based evaluation; and O'Loughlin et al. (1998) in which a contiguity matrix for changing borders during the sample period is employed.

distance matrices. The findings show that although trading volume drops as the geographical distance increases, trading based distance measure still has unique information that is not contained in geographic distance measure. Specifically, trade relations with more democratic countries enhance the partner's democracy level as well. The effect of income, however, is reduced by half when the spatial interactions are included in the model.

The last paper that is covered in the literature review chapter of this dissertation sets forth that national identity formation, similar to the fashion formation, is also under the influence of "neighborhood" (Lin, Wu, & Lee, 2006). Lin et al (2006) argue that in a multi-ethnicity society, the formation or collective choice of a national identity is closely related to the proximity in terms of township and occupation. By the aid of a survey data obtained from the post presidential election surveys for the years 1996 and 2000, they discuss three collective choice models; and they empirically compare spatial regressions to hierarchical linear regressions and regressions with dummy variables. To do so, a sample of Taiwanese people, from 3 minor ethnic groups besides the dominant group "Han"s, are chosen as the subjects of their study. In order to incorporate the neighborhood impact into the model, Lin et al (2006) utilize spatial autoregressive model, which includes a spatial lag along with other explanatory variables. Although it is stated that a binary spatial weight/distance matrix, in which 1 designates the neighborhood, is constructed, one needs to define the neighborhood or the proximity concept clearly. An element of this weight matrix becomes 1 if the two individuals share the same town or the same occupation. In this sense, one may consider the first distance concept as geographical, and the second as non-Euclidian. The empirical results demonstrate that neighborhood in terms of both township and occupation has influence on the identity formation.

From this point of view, Lin et al (2006) make an analogy between identity formation and fashion adoption, and indicate that collective choice of identity may spread among the individuals like fashion adoption. The more the individuals get closer to the others occupationally or geographically, the more likely they chose the same national-identity with others. Although Lin et al (2006) essentially employs spatial modeling, they discuss the appropriateness of linear regression with dummy variables and hierarchical linear regressions for their study. First, they note that the binary weight matrix they use in the spatial models may be seen as similar to dummy variables in the regression analysis. However, as Lin et al (2006) also state, there is a core difference between them. Even tough the dummy variable approach assumes a perfect and identical relation among the units, the spatial weights – even binary matrices – can assign a degree of relation. In this sense, dummy variables can reflect only the perfect and the unique interrelations in a spatial distance matrix. The comparison of hierarchical linear regressions to spatial modeling reveals that the former method is not appropriate due to the lack of interrelation coefficient in these regressions, dynamic nature of modeling and the endogeneity problem.

From the above mentioned studies, non-geographical distance based spatial econometrics can be considered as a burgeoning line of research. This dissertation, actually, aims to provide a new economic distance measure in the finance area. In addition, as Goriaev et al. (2005) explicitly note, tournament behavior literature implicitly assumes a total independence in the error terms across funds. However, since several studies in the mutual fund literature puts forth that fund managers are affected from the other managers in the neighborhood, this assumption is hard to defend. The feature of spatial modeling that considers not only the incentives created by individual factors, but also the interactions between fund managers makes this modeling well suited for the nature of the analysis that is conducted in this dissertation. Hence, taking the spatial dependence into account may add to the explanation of the tournament behavior.

CHAPTER 3

DATA AND METHODOLOGY

This chapter explains the data used, and the models employed throughout this doctoral dissertation.

3.1. Sample Description

Turkish mutual funds can be categorized into different groups on the basis of type of assets that they invest in, such as sector funds, variable funds, equity funds etc. In fact before 2013, mutual funds were classified into two as type-A and type-B depending on whether a fund is subject to a minimum equity investment restriction or not. Any mutual fund can be organized as a type-A or type-B, except the “money market funds”, which should be a type–B fund. In practice, on the other hand, “notes and bonds”, and “foreign securities” funds are organized as type–B funds, while “variable funds” and “balanced/mixed funds” can either be a type-A or type-B fund. Other funds, such as sector funds or index funds, are established as type–A funds (Türkiye Kurumsal Yatırımcılar Derneği, n.d.). The only criterion for classifying a fund as type-A mutual fund was the investment of at least 25% of their overall assets in equities issued by Turkish companies at all times. This classification was abandoned in the beginning of 2013 by the new CMB communiqué (*Yatırım Fonlarına İlişkin Esaslar Tebliği Seri: III No.52.1*, 2013). Now, each fund category has its own investment criteria to follow.

Literature, such as Chevalier and Ellison, (1997), Ferreira et al., (2012b), and Sirri and Tufano (1998), mainly focuses on equity funds to investigate the possible fund flow–past performance relation. Del Guercio and Tkac (2002), for instance, examine the same relation for pension funds and show a linear instead of a convex association between fund flow and past performance. Following the literature, a study trying to model the possible fund flow-performance relation would only use data from equity funds which are type-A funds in Turkey. However, due to the small number of equity funds available in the Turkish mutual fund industry, I also include type-A variable and mixed funds which also invest heavily in equity. Type-A sector funds are excluded from the sample because they have restrictions on sectors that they can invest in. Furthermore, type-A index funds are excluded from the sample because their goal is to match the performance of an index not to beat it therefore they may not be subject to the tournament behavior. According to the monthly report of Capital Markets Board of Turkey (CMB) on August, 2014, there are 25 equity funds, 15 mixed funds and 40 variable funds in Turkey. To overcome the data limitations of this study, analyses carried out in this dissertation may be repeated with data from other fund markets. In particular, using the US mutual fund data would provide comparability with previous fund flow literature as well.

For the analyses of this dissertation, I use daily data of these mutual funds including the dates from January 02, 2002 to December 31, 2011. The dataset contains a total of 70 funds. Specifically, there are 13 mixed funds, 18 equity funds and 39 variable funds in the sample. Following Busse (2001) and Goriaev, et al. (2005), one may argue that daily data will provide better precision. The dataset obtained from CMB begins at the end of the June 2001; hence the sample is started from the beginning of 2002. The dataset includes following items for each fund on each day: the fund's name and ticker symbol, total net asset values (TNA), TNA per share, number of shares, number of investors, and the portions of fund's portfolio invested in broad asset classes such as equity, treasury bills and bonds, reverse repo, money market, foreign markets, and other investment options. The reason for terminating the sample at the end of December, 2011 is the regulatory changes in the definition of equity funds by the Capital Markets Law that came into effect on January 2012. According to this law, the requirement to invest only in equities listed on the Borsa Istanbul (BIST) is abolished. Instead, currently, equity funds can invest in both domestic and foreign company shares. The ability to invest in foreign shares brings into picture the exchange rate risk. Therefore, without knowing their exact portfolio allocations, it is not possible to analyze the risk characteristics of these funds. Furthermore, minimum required investment in equities is increased from 75% to 80% for these types of mutual funds. The second reason to analyze data up to December 2011 is another regulation change in the definitions and investment criteria of Turkish mutual funds. As mentioned before, the distinction between funds as type-A and type-B is abandoned in 2013. To provide consistency in the sample, this dissertation only uses data for type-A mixed, variable and equity funds for the years between 2002 and 2011.

This restriction in the sample period would constitute another limitation of this dissertation. This study could be repeated and, the results could be verified if one could access the exact portfolio holdings of funds after 2011. However, since this data is not available right now, the dissertation can only use the data up to December 2011. The complete list of funds that are included in the sample of this study can be found in the appendix A.

Furthermore, as it will be explained in the next chapters, the data from January 2002 to December 2004 is used to compute Jensen's alphas and Four Factor alphas, which will be employed as performance proxies. Therefore, the models of this dissertation is estimated by using data for the period from January 2005 to December 2011.

The new money growth rate, as a proxy for new cash flow into the fund, is estimated in the literature as follows (see for instance, Sirri and Tufano (1998); Ferreira et al. (2012b); Chevalier and Ellison (1997)) :

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t})}{TNA_{i,t-1}} \tag{1}$$

Here $TNA_{i,t}$ represents the total net asset value of fund *i* for the end of the period *t*, while $R_{i,t}$ is the fund's return in the current period, depending on the data frequency employed in the study. Because of the nature of the data provided by Turkish funds, it is possible to calculate the actual flow of funds to a Turkish mutual fund directly. The mutual fund participation certificate account reported in the balance sheets of mutual funds shows the number of shares of a mutual fund held by investors as of the end of a calendar year. Since these financial statements are prepared in comparison to the previous year, the change in the balance of this account from one year to the other provides the actual cash flow to the fund created in the latter year. However, these audited financial statements are only publicly available on an annual basis. This study needs more frequent data to observe the potential changes in the flow-performance association during the year. This problem can be overcome by using the number of shares and TNA per share data from daily portfolio reports of Turkish mutual funds to the CMB. Using this data, the cash flow generated during the day can be calculated as follows:

$$Flow_{i,t} = \Delta NOS_{i,t} \times TNAP_{i,t-1} \tag{2}$$

In this equation, similar to the first one, flow denotes the cash flow to a fund *i* in period *t*. The CMB communiqué that regulates the redemptions and purchases of mutual fund participation certificates requires a two business day waiting period to complete the whole process of buy and sell orders for type-A mutual funds. Therefore, the flow to a fund *i* at time *t* is due to buy and sell orders submitted to this fund at time *t-2*. The fund adjusts its number of participation certificates outstanding at time *t* to reflect the completed orders from time *t-2*. Thus, to calculate the flow at time *t,* the change in the number of participation certificates (Δ *NOS)* of fund *i* from time *t-1* to *t* is needed. Furthermore, an order submitted at time *t-2* is executed at the *TNA* per share ($TNAP_{i,t-1}$) on *t-1*. This amount of flow is shown in fund's accounts on day *t.*

Prior literature makes two fundamental assumptions in the estimation of fund flows. First, cash inflows are realized at the end of the period; and second, all the capital gains and distributed dividends are reinvested (Del Guercio & Tkac, 2002; Ferreira et al., 2012b; Sirri & Tufano, 1998; Zheng, 2008). Sirri and Tufano (1998) check the validity of the first assumption, and could not find any effect of this assumption on their findings. I, on the other hand, have access to the actual cash flow to funds on a daily basis, from which I can calculate cash flows to funds with any frequency I need. Therefore, I do not need to make assumptions about timing of cash flows to funds in this dissertation. This assumption free actual data usage constitutes one of the strongest points of this dissertation. In addition Del Guercio and Tkac (2002) suggests the usage of percentage change in number of investors as another measure for cash inflows, which is also available on a daily basis on the web page of the CMB for Turkish mutual funds. I use this flow measure as the second flow definition alongside the flow obtained by using equation (2).

3.2. Models

There are various approaches used to calculate the changes in a fund's risk depending on the cash flow structure. In their seminal work, Brown et al. (1996) use the risk adjustment ratio to compare the volatility of loser and winner portfolios by the aid of contingency tables. Chevalier and Ellison (1997) employ a semi–parametric approach in which they estimate both the relation between cash flows and alterations in risk and the functional form of the relation. On the other hand, Sirri and Tufano (1998) and Ferreira et al. (2012b) use piecewise linear regressions in order to account for the nonlinearities in the mentioned association. Busse (2001) compares the usefulness of standard deviation ratios defined in the Brown et al (1996) with the regression specifications, and note that one should also benefit from regression while examining the presence of tournament behavior in order to avoid several biases.

Along the lines of previous studies, this dissertation will benefit from regression specification as well. However, since I argue that the location component should be added to the analysis, I will use spatial regressions. In these types of regressions, neighboring relation has a direct impact on the dependent variable. Anselin (2006) classifies the basic spatial interactions of this type into two as: *i.* Spillover which is the direct impact that the neighbor's decisions have on the agent's decision variables through the effect of a neighbor's choice on the utility function of the decision maker. *ii.* Resource flow which demonstrates the indirect effect that neighbors have on the agent's decision through the consumption of an available resource.

Spatial regressions are generally categorized into two types (Anselin, 1988, 2006) as spatial lag or spatial autoregressive models and spatial error models. Spatial lag models depend on a theoretical basis; that is, the spatial dependence, which is the essence of the relation, is rooted from the underlying theory of the research question (Ward & Gleditsch, 2007). According to Manski (1993)'s classification, spatial lag models include the endogenous effect, which notes that individuals in a group are alike, because they tend to behave in accordance with the group rules. Since individuals and the group behaviors affect each other, this type of modeling reflects a social or spatial multiplier (Anselin, 2003; Manski, 1993). The examples of spatial lag models can be seen in Rey and Montouri (1999); Beck et al. (2006), and Ward and Gleditsch (2007).

Unlike the spatial lag models, the spatial error specification does not require a "spatial" characteristic in the model; instead, the cross sectional data may generate correlation issues as well (Anselin, 2006). In other words, the spatial error models handle the spatial dependence as a nuisance (Ward & Gleditsch, 2007). This type of modeling accounts for the *correlated effects* (Manski, 1993) on decision makers/individuals due to being a member of the same group and facing the same environmental conditions. Because it has the capacity to deal with both spatial and non-spatial dependence, spatial error specification is considered as a more general model (Anselin, 1988).

In both specifications, the spatial feature of the model causes the OLS estimator to lose its "BLUE" properties. Since OLS estimator becomes inefficient and biased, the maximum likelihood estimation is offered as an alternative method (Anselin & Griffith, 1988; Anselin, 1988; LeSage & Pace, 2009).

Apart from these types of spatial regressions, spatial Durbin model is also discussed in some of the studies (Anselin, 1988; LeSage & Pace, 2009; Rey & Montouri, 1999; Viton, 2010). In this type of model, Anselin (1988) and LeSage and Pace (2009) show the usage of exogenous variables scaled by the weight matrix to represent the contiguity alongside the lag dependent variable. In this sense, this type of spatial Durbin model becomes a nested model of spatial error models. However, it has the capacity to combine endogenous effects with the exogenous ones according to the classification of Manski (1993). This type of modeling permits taking spatial dependence into account on the right hand side of the regression equation. If this spatial dependence is not taken into account, it has a potential to bias the estimations. In addition, it accounts for the spatial dependence in the error terms, which causes loss of efficiency if ignored (Elhorst, 2010). This type of modeling is also useful when the endogenous and exogenous effects are not separable (Elhorst, 2010; Manski, 1993).

On the other hand, LeSage and Pace (2009), Rey and Montouri (1999) and Viton (2010) discuss the usage of the scaled exogenous variables alone without adding a spatial lag into the model. This type of modeling is called "spatial lag of X model" by LeSage and Pace (2009). They note that in such models, since the exogenous variables keep their non-stochastic property, OLS produces efficient and unbiased estimates. Although these models seem more familiar than other spatial models, Rey and Montouri (1999) point out that omission of spatially scaled independent variables may cause spatially autocorrelated error terms.

This dissertation examines the impact of cash flows to the neighboring mutual funds and performance of these funds on flows to a fund and the decision of this mutual fund to change the risk structure of its portfolio. In the seminal work of Manski (2000), the interactions between the decision makers are classified into three types: Constraints, expectations and preferences. For the preference interactions, he notes that a decision maker chooses among the alternatives depending on the choices of others. That is, consumption or investment choices of decision makers are not independent from one another. In this sense, cash flows to a fund may be modeled as a function of cash flows to other funds, since they reflect the investment choice of individuals. Previous studies, like Del Guercio and Tkac (2002) and Ferreira et al. (2012b), have shown very high autocorrelation among mutual fund cash flows. Del Guercio and Tkac (2002) offer the "*herding behavior towards specific managers*" as a possible explanation for this autocorrelation. Ferreira et al. (2012b) add one period lagged flows to their flow-performance model in order to control for this autocorrelation. From the point of view of this dissertation, this dependence among the fund flows may be resolved through the consideration of neighborhood effects. In a similar manner, Zheng (2008) notes, in his review, a spillover effect for fund flows among the winner funds, which is not observed in the loser group. A better modeling for this spillover impact may be provided through the inclusion of neighborhood concept. Moreover, Anselin (1988) explicitly indicates that examining poor and rich regions may be subject to spatial interactions, because the boundaries of these regions are arbitrarily specified. Similarly, in the cash flow-fund performance relation, the boundaries of high and low cash flow attracting fund sets are designated in a non-uniform way. Therefore, the cash flows to a fund may be modeled as a function of the cash flows to its neighbors as suggested in Anselin (2006). Since the neighboring impact on fund flows has a potential to create a social multiplier by the aid of a feedback mechanism, spatial lag models are better for the purposes of this research.

As noted before, spatial lag models are powerful to capture the impact of neighboring dependent variables. In this dissertation, the impact of cash flows to the neighboring funds will be observed by the aid of these models. However, the performance of neighboring funds may also be influential on the cash flows. Hence, besides the spatial lag models spatial Durbin models will also be employed in order to observe the impact of neighboring funds' performance on cash flows to a fund and that fund's risk change decisions. Each model has a different interpretation in terms of interaction effects defined by Manski (1993, 2000); hence running these models separately will provide valuable information on the nature of cash flow-past performance association.

Following the flow-performance literature, the cash flow to a fund *i* will be modeled first as a function of prior performance, age, size, risk, lagged flow and expense ratio. This classical regression will serve as a benchmark for the spatial regressions as well.

As correctly indicated by Del Guercio and Tkac (2002), larger funds have a higher potential to attract more cash flows apart from the previous performance. To control for this effect, cash flow obtained from daily reports to the CMB is used in the model as a percentage, thus, it is scaled by $TNA_{i,t-1}$, and becomes $Flow_{i,t}/TNA_{i,t-1}$. The second flow proxy, namely the change in number of investors, is also scaled by the number of investors of fund *i* in the previous period, and becomes (Δ number of investors$_{i,t}$/number of investors$_{i,t-1}$). Finally, the conventional model frequently used in the literature can be seen below:

$$\begin{aligned} Flow_{i,t} = {} & \gamma_0 + \gamma_1 Perf_{i,t-1} + \gamma_2 Age_{i,t-1} + \gamma_3 Size_{i,t-1} + \gamma_4 Risk_{i,t-1} + \gamma_5 Expense_{i,t} \\ & + \gamma_6 Flow_{i,t-1} + \gamma_7 Semiannual\_Dummy + \gamma_8 Best\_Worst_{t-1} \\ & + \gamma_9 Best\_WorstxPerformanc\ e + \varepsilon_{i,t} \end{aligned} \quad (1)$$

Where $\varepsilon_{i,t}$ follows an independent and identical distribution.

Apart from the fund characteristic variables, three additional variables are included to the model. First one of these is the *Semiannual Dummy*, which takes the value of *1* if the data is from the second half of the year and zero otherwise. The *Best-Worst* is a dummy variable representing the fund's performance according to the median fund performance in a given year. It takes a value of *1*, when the performance of fund *i* is higher than the median fund performance in that year and *0* otherwise. The last variable is an interaction term, *Best-Worst x Performance*, which shows the incremental effect of performance for best performing funds. This variable is added to the model in order to account for changes in the strength of the relationship for best and worst performing funds.

The hypothesis tested by this equation is that there is a relation between prior performance of mutual funds and their current cash flows. In other words, basic research question of this dissertation is examined by equation 1: “Do the Turkish mutual fund investors chase past performance?”

Based on the results of studies conducted in different countries (Chevalier & Ellison, 1997; Del Guercio & Tkac, 2002; Huang et al., 2007; Sirri & Tufano, 1998), I can expect a positive but convex relation between fund flows and past fund performance in Turkey as well. In particular, the expected behavior for Turkish mutual fund investors is to buy past winners and to sell past losers in a nonlinear fashion. Ferreira et al. (2012b) have shown a more convex relation for developing countries than developed countries in their world-wide sample. Together with the findings of Kempf and Ruenzi (2008) for the mutual fund families, I can expect to observe a strong tournament behavior in the Turkish mutual fund industry because of its small mutual fund universe and developing country characteristics.

Expectations for the control variables may differ, on the other hand. *Age* is one of the nonperformance related variables in the relationship between fund flow and past performance. Literature has mostly defined age variable as the logarithm of the fund’s age (Ferreira et al., 2012b) or logarithm of (1+age) (Huang et al., 2011). Ferreira et al. (2012b) finds a negative relation between fund flows and age. Specifically, they note that larger and older funds attract less flow. Kempf and Ruenzi (2008), on the other hand, investigate the drivers of family tournaments in the mutual fund industry. They point out that fund age is not a determinant of this type of tournaments. Based on these findings I expect to see a negative or insignificant coefficient for the age variable in the flow regression.

The next control variable in the model is *Size*, which is modeled by logarithm of TNA in the previous period. Chevalier and Ellison (1997) remove the very small sized funds in order to prevent the possible biases these funds may create. However, they find that larger funds show a slower growth in terms of new cash flow. In both young and old sub samples, the coefficient of size is negative and statistically significant. Sirri and Tufano (1998) note that the same dollar cash flow has a greater impact on smaller funds than larger funds, so it has to be controlled for in flow – performance analyses. In line with the Chevalier and Ellison (1997) study, they also find negative coefficients for fund size across alternative performance definitions. Del Guercio and Tkac (2002) report very weak or insignificant impact of fund size on fund flows. Even though first impression is that larger funds draw more cash flows to the fund (as indicated by Ferreira, Keswani, Miguel and Ramos (2012)), given the prior evidence, one can expect to observe a negative coefficient for this control variable. On the contrary, a positive coefficient would indicate that larger funds grow faster than the smaller ones in terms of new cash flow. This could be the case in Turkish mutual fund market because larger funds are usually managed by banks. There are findings showing that banks play significant roles in financial markets and they are different from other financial intermediaries (i.e. James 1987). In addition, Sirri and Tufano (1998) indicate that investors tend to choose the funds that are "*easier for them to identify*". It is possible that investors know bank related funds better relative to nonbank owned ones and this may create a tendency to herd towards these funds. As a result, the coefficient of the size variable for the Turkish mutual fund industry may be different from the one in the existing literature.

Risk is another explanatory variable in the regressions that explain the relation between fund flow and performance. A negative coefficient for the risk variable will indicate risk averse behavior of investors. First, Sirri and Tufano (1998) add risk computed as the standard deviation of monthly fund returns to the fund flow-prior performance regressions. Their evidence for risk aversion is weak and mostly insignificant. Del Guercio and Tkac (2002) examine intensively the determinants of flow to mutual funds and pension funds. They define the risk variable as the tracking error from a specific benchmark. They demonstrate that in contrast to pension funds, mutual fund investors do not consider this risk variable while distributing their investments among mutual funds. Huang et al. (2007) use the standard deviation of returns as the risk variable, and find negative and mostly significant coefficients. As a result, the expectation for the coefficient of this variable is negative.

As previously noted, Del Guercio and Tkac (2002) and Ferreira et al. (2012b) include $Flow_{t-1}$, one period lagged flow, in their models to control for the autocorrelation in mutual fund flows. Del Guercio and Tkac (2002) state that this autocorrelation only present in the mutual fund cash flows, but not observed in the flows of pension funds. Hence, this dissertation includes one period lagged flow among the explanatory variables of individual fund flows. A positive coefficient for this variable will indicate that funds that have high cash flow last period will continue to attract new flows from investors in the future as well.

Total fees are shown to be an important variable affecting flows to the funds. Sirri and Tufano (1998) demonstrate that investors mostly prefer lower fees, so the coefficient of this variable is negative. The growth in funds with higher expenses is inversely associated with the fee alterations. This negative impact of total fees on the fund flows is verified by Huang et al. (2007) as well. However, Ferreira et al. (2012b) cannot demonstrate a statistically significant effect of total fees on fund flows, although the sign of the coefficient is negative. Based on this evidence, one may expect a negative coefficient for the *Expense* variable proxying for the total fees in the regressions. Expense ratios used in the analysis of this dissertation are obtained directly from the web site of CMB on a yearly basis.

In addition to these variables, one might expect an investor to take into account the investment choices of other investors when deciding to invest in a specific fund. This influence might be through the changes in the preferences of investors. In other words, individuals may change the funds in their "consideration set" under the influence of choices of other investors, which would eventually cause a "*herding behavior towards specific managers*" (Del Guercio & Tkac, 2002). To capture this possible influence, next model considers the impact of flows to other funds on the flows to fund *i* through a spatial lag of the dependent variable. More precisely;

$$\begin{aligned} Flow_{i,t} = {} & \varphi_0 + \rho\sum_{j=1}^{n} W_{ij}Flow_{i,t} + \varphi_1 Perf_{i,t-1} + \varphi_2 Age_{i,t-1} + \varphi_3 Size_{i,t-1} + \varphi_4 Risk_{i,t-1} \\ & + \varphi_5 Expense_{i,t} + \varphi_6 Semiannual\_Dummy + \varphi_7 Best\_Worst_{t-1} \\ & + \varphi_8 Best\_WorstxPerformance + \xi_{i,t} \end{aligned} \tag{2}$$

Where $\xi_{i,t}$ follows a multivariate normal distribution with a constant variance-covariance matrix.

The coefficient for the spatially lagged flow variable shows the impact of others' choice on individual's investment decision to a fund. If the herding behavior towards specific managers discussed in the prior literature is a result of spatial grouping, then investors tend to choose particular set of funds. In that case, funds outside of this particular set are likely to be less preferred. Hence, the expected sign for ρ is negative. While no change is expected in the signs of nonperformance related variables, this may not be the case for the performance variable. Literature suggests a convex past performance-fund flow relation particularly for developing countries. Although many studies explicitly emphasize the role of ranking in the mutual fund industry (such as Brown, et al. 1996; Del Guercio and Tkac 2002; Kempf and Ruenzi 2008), they do not consider the possible spatial consequences of such a ranking in their analyses. After controlling for the spatial interactions in the fund flow-past performance relation as intended in this dissertation, the previously found convexity may decrease or totally vanish. Therefore, the expected sign of performance variable is unknown in equation (2).

The herding behavior among mutual fund investors may be a result of past performance as well. Investors are likely to use past performance of mutual funds when allocating their investments across mutual funds. Then, the spatial interactions due to the groupings in the fund industry may be resolved by adding a spatial past performance variable. In other words, to observe the impact of neighbors' past performance on the relation analyzed in equation (2), a spatially scaled past performance variable is inserted as an additional explanatory variable to that equation. In the terms of LeSage and Pace (2009), this new model, presented below, is a spatial lag of X model:

$$\begin{aligned} Flow_{i,t} = {} & \beta_0 + \theta \sum_{j=1}^{n} W_{ij} Perf_{i,t-1} + \beta_1 Perf_{i,t-1} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Risk_{i,t-1} \\ & + \beta_5 Expense_{i,t} + \beta_6 Semiannual\_Dummy + \beta_7 Best\_Worst_{t-1} \\ & + \beta_8 Best\_WorstxPerformance + \vartheta_{i,t} \end{aligned} \tag{3}$$

Where $\vartheta_{i,t} \sim N(0,\sigma^2)$

Expectations for the coefficients of control variables are the same as those in the first model. However, the performance increase in the neighboring funds is hypothesized to have a negative effect on the flow directed to fund *i,* i.e., θ is expected to be less than *0*.

The final equation investigating the determinants of fund flow considers all of the variables mentioned above. That is, the full model becomes a Spatial Durbin model which contains both the endogenous and the exogenous effects on the decisions of mutual fund investors. The same weight matrix *(W)* is used to scale both the performance and flow variables based on their locations in the risk – return space:

$$Flow_{i,t} = \varphi_0 + \delta_1 \sum_{j=1}^{n} W_{ij} Flow_{i,t} + \delta_2 \sum_{j=1}^{n} W_{ij} Perf_{i,t} + \varphi_1 Perf_{i,t-1} + \varphi_2 Age_{i,t-1} + \varphi_3 Size_{i,t-1}$$
$$+ \varphi_4 Risk_{i,t-1} + \varphi_5 Expense_{i,t} + \varphi_6 Semiannual\_Dummy + \varphi_7 Best\_Worst_{t-1}$$
$$+ \varphi_8 Best\_WorstxPerformanc\ e + \eta_{i,t} \tag{4}$$

Where $\eta_{i,t} \sim iid(0, \sigma^2)$

All of the spatial regressions given by equations (2), (3) and (4) have one common null hypothesis: Neighborhood variables are not influential on the flow to a mutual fund. The significance and the sign of the spatial coefficients in these equations will indicate the possible effect of these variables on the fund flows and the direction of this effect, respectively.

Similar to Koski and Pontiff (1999) and Kempf and Ruenzi (2008), the last group of equations measure the change in the risk ($\Delta RISK$) of mutual fund *i* while taking into account the control variables, namely prior risk, age, size and expense ratio. In addition, for the possible intercept and slope changes *Best-Worst* dummy and the interactive variable (*Best-Worst x Performance*) are included in the model. The definitions of these variables are the same as those given for the flow models 1 to 4. First, the OLS model shown below will be estimated:

$$\Delta RISK_{i,t} = a_0 + a_1 Risk_{i,t-1} + a_2 Age_{i,t-1} + a_3 Size_{i,t-1} + a_4 Expense_{i,t} + a_5 Perf_{i,t-1}$$
$$+ a_6 Flow_{i,t-1} + a_7 Best\_Worst_{t-1} + a_8 Best\_WorstxPerformance + u_{i,t} \quad (5)$$

Where the error term is independently and identically distributed.

Here, the research question becomes: “Do the Turkish fund managers change the risk of their portfolio at the end of the year based on the performance of the fund in the previous period?” To answer this question, risk changes due to the fund’s age, size and expense ratios should be controlled for as in Koski and Pontiff (1999). If Turkish fund managers are eager to alter portfolio risk as suggested by many papers (for instance; Chevalier and Ellison (1997); Brown, et al. (1996); Sirri and Tufano (1998)), then the impact of past period performance on the change in risk will be negative. Another possible explanation for the risk alterations may be the flow into and out of the fund. In this case, contrary to the performance related ones, risk changes are out of the control of the fund manager, and they may be undesirable (Koski & Pontiff, 1999). To control for this effect, lagged flow variable is added to the equation as an exogenous variable.

Koski and Pontiff (1999) and Kempf and Ruenzi (2008) explicitly indicate that funds’ risk tends to show mean reversion when the main cause of the portfolio risk change is exogenous. Therefore, apart from the performance and flow variables, lagged risk of fund *i* is added to the regressions in order to capture the possible mean reversion.

Brown et al (1996) emphasize that mutual fund managers try to exploit the convex flow-performance relation by altering the portfolio composition based on their relative performance during the year. This suggests including the neighbor’s prior performance into the model as an explanatory variable. As a result, the following model is obtained:

$$\Delta RISK_{i,t} = \psi_0 + \psi_1 Risk_{i,t-1} + \psi_2 Age_{i,t-1} + \psi_3 Size_{i,t-1} + \psi_4 Expense_{i,t} + \psi_5 Perf_{i,t-1}$$
$$+ \tau \sum_{j=1}^{n} W_{ij} Perf_{i,t-1} + \psi_6 Flow_{i,t-1} + \psi_7 Best\_Worst_{t-1} + \psi_8 Best\_Worst x Performanc\ e$$
$$+ v_{i,t} \tag{6}$$

Where v_i is a well behaved error term.

In Equation (6), expectations regarding the coefficients of nonperformance related variables, including flow variable, are the same as those in the OLS model given by equation (5) above. If the performance of the neighboring funds matters for the managers in their risk change decisions, then the coefficient of spatially lagged performance variable will be different from zero. More specifically, if neighboring funds show good performance, the manager of fund *i* may choose to increase the risk of her portfolio in order to be placed in the winner group. As a result, the change in the fund risk may be greater.

If the coefficient of the lagged flow variable in this equation is found to be significant in the presence of performance variables, then the neighboring fund flows defined as the spatially scaled flow variable will be added to the model as another explanatory variable. Last but not least, a possible risk shifting behavior is shown to occur usually at the end of the year. Therefore, the risk regressions, namely Models 5 and 6, will be estimated only for the second half of the year.

The Equations (1) and (5) are well known regression specifications. As long as the assumptions are satisfied, OLS is the best estimation procedure. Since the Equation (2) and Equation (4) are spatial lag and spatial Durbin models, maximum likelihood method and generalized spatial two-stage least squares method are used in estimating these equations. Here, the coefficients of spatial lags reflect the strength of spatial effects in these regressions. In the models where only exogenous variables are scaled through a weight matrix, namely equations (3) and (6), spatial lag of X model specification is employed. Then, OLS can be used for the estimations. The spatial coefficients, such as ρ, θ and τ show the change in the dependent variables as the average value of the neighbors represented by the spatial variable gets higher.

Model proxies used in the specifications mentioned above are explained in the next section. Furthermore, short definition for all proxies are provided in Tables 2a and 2b.

3.2.1. Model Proxies

In all specifications from Eq. (1) to Eq. (6), Age is the fund age in years from its foundation and Size represents the natural logarithm of the fund's total net assets. Expense is defined as the percentage of total fees that a fund applies to its total assets in the relevant year. There is no consensus on the most salient risk and performance measures for the investors (Sirri & Tufano, 1998). Therefore the literature suggests several proxies to measure the performance and the risk of a fund. Performance is often proxied by the difference between the fund's return and the value weighted market return at time t (Chevalier & Ellison, 1997), raw return (Brown, et al. 1996; Sirri and Tufano 1998; Busse 2001; Goriaev, et al. 2005; Ferreira et al. 2012), one factor and four-factor excess return (Huang, et al. 2007 and Ferreira et al. 2012). The most frequently used risk proxy in the literature is the standard deviation of raw returns (Brown, et al. 1996; Chevalier and Ellison 1997; Koski and Pontiff 1999; Busse 2001; Goriaev, et al. 2005). Additionally, Koski and Pontiff (1999) employ idiosyncratic risk, which is the standard deviation of the residuals from a market model, and systematic risk, which is the beta coefficient. Del Guercio and Tkac (2002) and Chen and Pennacchi (2009) also take into account the standard deviation of tracking error from a market index as a risk measure.

Considering the alternative proxies for performance and risk measurement, this dissertation will employ excess return from a market model (Jensen's alpha) and a Four-Factor model (Four-Factor alpha) as performance proxies and standard deviation of daily returns and beta as risk proxies, respectively.

To compute the Jensen's alpha, fund excess return in the previous 36 months is regressed on the market excess return over the same time period. Monthly BIST-ALL is selected as the market proxy. As suggested by Ferreira et al. (2012, 2012b), twenty four or more monthly return observations over a 36 month time period is required in order to estimate a Jensen's alpha measure for a fund. Using the betas from these regressions, and the realized market return at that time, the predicted fund return is estimated in the subsequent period. The semiannual Jensen's alpha becomes the difference between the realized return and the predicted return for that fund. Four-Factor alphas are estimated by employing the same methodology. However, this time, small minus big, high minus low and winners minus losers are used factors alongside the market factor. These factors have been estimated in the study of Danışoğlu (2013) and graciously provided by the author for use in the analyses of this dissertation. Regressions for all specifications are estimated on a semiannual basis. Total number of Jensen's alpha estimates and the number of these estimates that are significantly different from zero at the 5% and 10% significance levels are provided in Table 1a for each estimation period. As can be seen from this Table, between 30% (2009-Half 1) and 51.2% (2006-Half 2) of Jensen's alphas estimated are statistically significantly different from zero at the 10% level in any given period.

Table 1a. Number of Significant Alphas from Jensen's Alpha Measure

	Significant at 0.05	Significant at 0.10	Total Number of Alphas
2005 - Half 1	9	14	39
2005 - Half 2	10	14	39
2006 - Half 1	9	13	40
2006 - Half 2	15	21	41
2007 - Half 1	15	22	43
2007 - Half 2	11	15	44
2008 - Half 1	12	17	45
2008 - Half 2	12	18	46
2009 - Half 1	13	14	46
2009 - Half 2	9	14	52
2010 - Half 1	11	18	52
2010 - Half 2	13	19	57
2011 - Half 1	14	19	59
2011 - Half 2	22	24	62

Similarly, the total number of alpha estimates from the Four-Factor model and the number of these estimates that are significantly different from zero at the 5% and 10% significance levels are provided in Table 1b for each estimation period. As expected, statistical significance of alpha estimates decreases significantly when more factors are used to estimate the expected returns. In any given time period, as low as 4.6% and as high as 30.7% of Four-Factor alpha estimates are statistically significantly different from zero at the 10%.

Table 1b. Number of Significant Alphas from Four-Factor Measure

	Significant at 0.05	Significant at 0.10	Total Number of Alphas
2005 - Half 1	2	3	39
2005 - Half 2	1	2	39
2006 - Half 1	2	4	40
2006 - Half 2	3	3	41
2007 - Half 1	1	2	43
2007 - Half 2	1	4	44
2008 - Half 1	5	8	45
2008 - Half 2	5	7	46
2009 - Half 1	5	7	46
2009 - Half 2	1	6	52
2010 - Half 1	6	16	52
2010 - Half 2	3	5	57
2011 - Half 1	3	6	59
2011 - Half 2	2	5	62

Table 1a and 1b show the number of significant alphas and the total number of alphas that are obtained from the single-factor and the Four-Factor models that are used to compute the performance variables.

The significance of alphas obtained from these models is important when analyzing the mutual fund manager's skill. However, the aim of using this analysis in this dissertation is to obtain the excess returns for funds. Therefore, all the alphas without regarding their significance levels are used in following models of this dissertation.

The first risk proxy used in all of the models mentioned above is the standard deviation of daily returns in the first and the second semiannual of a specific year. The second proxy is a fund's beta in a semiannual for every year in the sample. These betas are obtained from the same monthly regressions that are used to compute the Jensen's alpha measure. The risk models, on the other hand, use change in the risk as the dependent variable. Hence, the change in these two risk proxies are calculated from the first half of the year to the second, and used as the dependent variable in the risk models of this dissertation.

The variables and the proxies of the flow and risk models presented in equations 1 through 6 are summarized in the next two tables. Brief descriptions of these variables are also given.

Table 2a. Variable Definitions for the Flow Models

	Variables	Proxies
Dependent Variable	$Flow_t$	Cash Flow (CF) obtained through financial statements ($CF_{i,t}/TNA_{i,t-1}$) Change in number of investors (Δ number of $investors_{i,t}$/number of $investors_{i,t-1}$)
Independent Variables	$Performance_{t-1}$	Excess return from a market model ($JensensAlphaExcessRet_{t-1}$) Excess return from a Four-Factor model ($4FactorExcessRet_{t-1}$)
	Age_{t-1}	Fund age from its foundation in the previous period ($age_{i,t-1}$)
	$Size_{t-1}$	Natural logarithm of total net assets in the previous period (TNA_{t-1}) The ratio of market value of fund *i* to market value of all funds in the sample
	$Risk_{t-1}$	Standard deviation of daily returns in the previous period ($StdDev_{t-1}$) Beta from market model in the previous period ($Beta_{t-1}$)
	$Flow_{t-1}$	One period lagged flow as defined in the dependent variable
	$Expense_t$	Percentage of total fees that a fund applies to its total assets in the current period ($Expense_t$)
	Semiannual Dummy	{ Semiannual dummy=1 if the second half of the year Semiannual dummy=0 if the first half of the year
	$Best\text{-}Worst_{t-1}$	{ Best-Worst=1 if fund performance is higher than the median in the previous period Best-Worst=0 if fund performance is lower than the median in the previous period
	Best-Worst x Performance	Performance variable x best_worst
	Crisis Dummy	{ Crisis Dummy =1 if the semiannual of the year belongs to 2009 or later Crisis Dummy =0 if the semiannual of the year belongs to the years between 2005 and 2008.
	Bank Dummy	{ Bank Dummy=1 if fund is owned by a bank Bank Dummy=0 if fund is owned by a non-bank institution.

Table 2b. Variable Definitions for the Risk Models

	Variables	Proxies
Dependent Variable	Change in Risk	Δ in semiannual standard deviation of daily returns Δ 24 month beta
Independent Variables	$Performance_{t-1}$	Excess return from a market model ($JensensAlphaExcessRet_{t-1}$) Excess return from a Four-Factor model ($4FactorExcessRet_{t-1}$)
	Age_{t-1}	Fund age from its foundation in the previous period ($age_{i,t-1}$)
	$Size_{t-1}$	Natural logarithm of total net assets in the previous period (TNA_{t-1}) The ratio of market value of fund *i* to market value of all funds in the sample
	$Risk_{t-1}$	Standard deviation of daily returns in the previous period ($StdDev_{t-1}$) Beta from market model in the previous period ($Beta_{t-1}$)
	$Expense_{t}$	Percentage of total fees that a fund applies to its total assets in the current period ($Expense_{t}$)
	$Flow_{t-1}$	Cash Flow (CF) obtained through financial statements ($CF_{i,t}/TNA_{i,t-1}$) Change in number of investors (Δ number of $investors_{i,t}$/number of $investors_{i,t-1}$)
	$Best\text{-}Worst_{t-1}$	{ Best-Worst=1 if fund performance is higher than the median in the previous period Best-Worst=0 if fund performance is lower than the median in the previous period
	Best-Worst x Performance	Performance variable x Best-Worst
	Crisis Dummy	{ Crisis Dummy =1 if the semiannual of the year belongs to 2009 or later Crisis Dummy =0 if the semiannual of the year belongs to the years between 2005 and 2008.
	Bank Dummy	{ Bank Dummy=1 if fund is owned by a bank Bank Dummy=0 if fund is owned by a non-bank institution.

3.2.2. Determining the Spatial Weight Matrix

Upon determining the proxies, the next step is to establish the spatial weight matrix used in the analysis. Anselin, Gallo, and Jayet (2008) define the spatial weight matrix as a positive n x n matrix in which the elements show the power of the interaction between two locations. A binary spatial weight matrix indicates the presence of neighborhood or not similar to dummy variables. A general spatial weight matrix, on the other hand, demonstrate a combination of distance based associations (Anselin, 1988). This matrix is used to weight the observations according to their proximity to each other. In other words, a degree of relation is assigned to each observation. In this sense, this is in fact a solution to the well-known problem that is caused by Gauss Markov's total independence assumption between observations.

The proximity among locations can be defined based on the geographical as well as economical distance concepts (Anselin et al., 2008; Anselin, 1988). This dissertation aims to contribute to the spatial econometrics literature by introducing a new definition of economical distance. I use a general spatial weight matrix based on mutual fund efficiencies. The fund i is considered as neighbor to the funds in its peer group. The distance between the fund i and its neighbors is the multiplicative inverse of its inefficiency values. The reason to take the multiplicative inverse is to obtain a decaying distance matrix. These peer group determinations and the degree of efficiencies are based on the data envelopment analysis (DEA) of mutual funds. According to Cooper, Seiford, and Tone (2006), DEA does not only provide an efficiency evaluation of the decision making units, but also a "reference set" that they can reach if they operate at the full efficiency level. In this dissertation, taking each mutual fund as a decision making unit in terms of DEA, I compute its efficiency. The inverse of the inefficiency value of each fund reflects the distance between the reference group, the most efficient funds, and the fund i. The reference set of each fund obtained from DEA constitute the peer groups that the funds are likely to be in when they are managed efficiently. Anselin (1988) indicates the similarities between input – output models and the spatial weight matrix (pg.28-29). He specifically notes that "interconnectedness that are based on the technical measures would seem applicable to summarize the overall connectivity reflected in a spatial weight matrix." Hence, one may conclude that in both theoretical and applied sense, using DEA output as a spatial weight matrix is appropriate for the analyses carried out in this dissertation. Upon the construction of the weight matrix, I employ a row standardization of the weights so that they sum up to 1.

In many studies, the specification of spatial weight matrix is shown to be the crucial point of spatial models. Anselin (1988) indicate that the weights should have an economical meaning that is closely related to the underlying theory instead of informal representation of the spatial pattern. Here, the DEA method becomes very useful for the topic examined in this dissertation. DEA is a commonly used method to evaluate the performances of decision making units (DMUs), while considering several efficiency measures at a time. By the aid of linear programming techniques, it creates virtual outputs and virtual inputs, and then computes the radial distance of the DMUs from the efficient frontier (Cooper et al., 2006). A DEA score up to 1 is assigned to each DMU based on its relative performance among all other DMUs. Since this method calculates the relative position of a DMU according to the efficient frontier, the application of this method to assess the performance of mutual funds can be consistent with the spatial nature of relations analyzed in this dissertation. Hence, the spatial distance among our DMUs in this dissertation can be obtained from the DEA method.

The use of ratios, such as Sharpe ratio or Treynor ratio is a conventional way to rank the mutual funds based on their performance. Choi and Murthi (2001) and Basso and Funari (2001) criticize these traditional ratios because they are bounded by strong assumptions on market and investor behavior, and they are inadequate to incorporate several indicators of performance such as redemption costs at the same time. Choi and Murthi (2001) make an analogy with DEA and Sharpe ratio and indicate that DEA provides a Sharpe ratio for a fund "relative" to the best performing, that is, winner fund, in its most basic form. Moreover, they note that DEA method is open for improvements by adding other scale and cost functions. Basso and Funari (2001), additionally, indicate that the traditional measures, namely Sharpe and Treynor ratio and Jensen alpha may suffer from the bias that is caused by the need of estimating investors' investment horizon. DEA measure, on the other hand, is free from a holding period assumption, which makes it a better measure of the fund performance than the conventional methods. In fact, Murthi et al. (1997) also suggest that DEA is an appropriate technique for evaluating the efficiency of a fund relative to a best group without a priori underlying theory. Accordingly, Choi and Murthi (2001) refer to well-known tournament behavior study by Brown et al. (1996) to indicate the suitability of DEA measure for the mutual fund industry. From this point of view, the ranking nature of tournament hypothesis and the relative measurement of performance in the DEA method are totally consistent with each other. Last but not least, this dissertation benefits from the "reference set" computation of DEA in constructing the spatial weight matrix, which is not available in any of the conventional performance evaluation methods mentioned above.

Another requirement of this model is to establish the DEA inputs and outputs in order to assess the location of mutual funds in a Euclidian space. Murthi et al. (1997) employ return as output, and expense ratio, load, turnover and standard deviation as inputs. They note that since the return of the riskless asset is constant, the usage of excess return or actual return does not make any difference in DEA efficiency analysis. Basso and Funari (2001) have integrated another output – the stochastic dominance indicator – besides the expected return to the model by Murthi et al. (1997). The inputs in their model are portfolio standard deviation, the square root of the half variance, and the beta coefficient. Choi and Murthi (2001) also use traditional cost and risk measures to improve the Sharpe ratio in mutual fund performance evaluation. Tarım and Karan (2001) use a single output-three input model to evaluate the performance of Turkish type-A and type-B funds for the January-August 1998 period. In this model, expense ratio, standard deviation, and turnover ratio are taken as the inputs, while the output is the monthly fund returns. In a recent study on Turkish mutual funds, Gökgöz (2009) takes standard deviation, beta, expenses and turnover rate as inputs, and excess return defined as the difference between the return on a mutual fund and risk free security as the only output. Following the literature on the performance evaluation of mutual funds with DEA approach, in this dissertation, I use the standard deviation, beta coefficient and expense ratio as inputs; and the excess return of mutual funds as defined in Gökgöz (2009) as the output.

Last, based on the mutual fund performance evaluation literature, one should decide on the computational method for the DEA efficient frontier. In their seminal work, Cooper et al (2006) mention two methods for this computation, namely Charnes, Cooper, Rhodes (CCR) model and Banker, Charnes, Cooper (BCC) model. The *inefficiency* in these models is defined as the excess usage of inputs or shortfalls in the outputs (Cooper et al., 2006).

Both CCR and BCC models assess this efficiency of decision making unit by solving a linear programming model in the envelopment form, so the inefficient units are plot below the efficient frontier. The basic difference between these two models lies in their returns to scale assumptions. The CCR model is based on the constant returns to scale assumption for the production possibility set. That is, if (x,y) is feasible, for any positive t, (tx,ty) is also feasible. In contrast, the BCC model assumes varying returns to scale, in which the production possibility set is concave and consists of different piecewise linear parts. These piecewise linear parts represent increasing returns to scale, decreasing returns to scale and constant returns to scale, respectively. In other words, the efficiency computed by CCR model is a global technical efficiency. By adding a new convexity constraint to the CCR model, however, BCC model is able to isolate the technical efficiency values of CCR from the scale differences (Gökgöz, 2009). Studies analyzing the performance of mutual funds using the DEA method utilize both estimation methods. For instance, Murthi, Choi, and Desai (1997); Tarım and Karan (2001); Basso and Funari (2001) employ the CCR method, while Choi and Murthi (2001) use the BCC method. Gökgöz (2009) applies both of these methods to evaluate the performance of Turkish mutual funds. However, he does not show which one of these methods is better suited for the analysis of Turkish mutual funds. Cooper, Seiford, and Tone (2006) point out that if a DMU is efficient according to the CCR method, it will also be efficient according to the BCC method, because the CCR score indicates global technical efficiency. However, the reverse is not necessarily valid for every case, since the BCC method operates in a piecewise linear efficient frontier. In other words, the BCC efficient frontier is either on the CCR linear frontier or below it. This is why, the efficiency expressed in the BCC method is called as *pure technical* *efficiency* (Cooper et al., 2006). As in the basic CCR model, BBC also provides a reference set for decision making units, which indicates their peer groups if they operate with full efficiency. This property of BCC allows me to use DEA as a new distance metric for spatial econometric analysis.

For the choice between these two alternative methods, Cooper, Seiford, and Tone (2006) designate the relevant prior literature as a benchmark. In particular, they note that if the prior studies identify a form for the efficient frontier, like a production frontier defined according to the Cobb-Douglas production function, than a DEA method that suits to the structure of the frontier can be chosen. Choi and Murthi (2001) point out that mutual funds can operate at all kinds of returns to scale. Because the CCR method makes no attempt to consider the scale effect, these scale differences cannot be correctly addressed when one uses the CCR method for mutual fund performance evaluation (Choi & Murthi, 2001).

Since the CCR and the BCC methods identify different types of inefficiencies in a DMU as stated in Banker et al. (2004), the source of differences in the results of the CCR and the BCC model would be important for studies evaluating purely the fund performances. However, this dissertation focuses on the distances between mutual funds as DMUs. Given the arguments provided by Choi and Murthi (2001), this dissertation uses the BCC model while generating the elements of spatial weight matrix.

The last point in the specification of DEA models is the orientation. Two most frequently used types of DEAs are input oriented and output oriented ones. Input oriented models keep the output level constant while trying to reduce the inputs as much as they can. Output oriented models aims to maximize the output level while keeping the inputs constant (Cooper et al., 2006). Following the prior Turkish mutual fund efficiency literature such as Gökgöz

(2009) and Yıldız (2006), this dissertation employs input oriented DEA model.

As pointed out by many authors, determining the spatial weight matrix is a crucial part of spatial analyses. Anselin (1988) and LeSage and Pace (2009), among others, explicitly state that the distance that is used to show the neighboring impact should be meaningful and closely related to the units of analysis. This requirement of spatial analysis is not a problem when the distance is geographically determined. In this case, even different distance metrics can be provided and compared, such as a binary weight matrix, indicating the existence of a common border, versus a decaying distance matrix, demonstrating the exact distances between two units. Geographical distance metrics are exogenous by definition and do not create endogeneity problems for the analyses. However, most of the time, the close relation between theory and spatial weights requirement makes exogenously determined weight matrices difficult to justify (Kelejian & Piras, 2014).

When employing an economic distance concept, however, overcoming the endogeneity problem may not be easy. Possible reasons and solutions for the endogeneity problem have very recently been discussed in the spatial econometrics literature (Kelejian & Piras, 2014; Qu & Lee, 2015). This dissertation uses DEA to measure the distances between funds on an analytical surface. The characteristics of DEA in terms of providing reference sets by the aid of relative measurement techniques are appropriate for the nature of analyses carried out in this dissertation. However, since DEA is an economic distance metric and it uses fund characteristics as inputs and outputs, it would be difficult to assume exogeneity. Although some new estimation methods are offered to overcome this issue, such as two stage instrumental variable or quasi-maximum likelihood estimation methods (Qu & Lee, 2015), these estimation techniques are not available in commercial statistical package programs, yet. Therefore, following Keiler and Eder (2013), this dissertation employs a spatial weight matrix that is lagged by one period in an attempt to decrease the severity of the problems associated with the mentioned endogeneity in the spatial models. LeSage and Pace (2009) and Keiler and Eder (2013) also suggest focusing on the model itself rather than the distance metrics. In future studies, this endogeneity problem can be addressed by analyzing alternative economic distance concepts as well.

CHAPTER 4

FINDINGS

This dissertation aims to understand how the mutual fund investors make their investment decisions among alternative funds; and based on this decision how the fund managers react/change their portfolio risk and return structure. Literature mainly suggests a convex relation between flows and past performance that makes managers to alter their portfolio at the end of the first semiannual period. However, this relation varies across different countries (Ferreira et al., 2012b). This dissertation, first, investigates the determinants of flows to mutual funds to understand whether an asymmetric association between fund flows and past fund performance exists in the Turkish mutual fund industry. Next, effects of flows to neighboring funds and their performance on flows to a fund is examined by using spatial models. Finally, fund managers' risk altering behavior in the second half of the year is examined. The effects of spatial variables on the risk altering behavior of fund managers are also evaluated. The basic models analyzed in this dissertation are augmented by new variables and modified to check the robustness of main findings of this dissertation. The results based on these robustness checks are presented in the last section of this chapter.

4.1. Descriptive Statistics

As explained before, the sample of this dissertation includes three different types of funds, namely equity funds, variable funds and mixed funds. Although they heavily invest in equity and their investment objectives are quite similar, a general look at some characteristics of these funds would highlight the similarities and differences between these fund types. Table 3a, 3b and 3c show the descriptive statistics on some fund characteristics for each fund group. These statistics are calculated for the period from 2005 to 2011, because main analyses of this dissertation are conducted for this time period as well.

Table 3a. Descriptive Statistics for Equity Funds

Variable	Obs.	Mean	Std. Dev.	Min	Max
Flow 1	236	0.34	1.85	-0.93	19.24
Flow 2 (Δ in Number of Investors)	232	27.29	156.35	-1.00	1084.80
Jensen's Alpha Excess Return	153	0.49	0.19	-0.34	1.05
Four Factor Excess Return	153	0.01	0.09	-0.48	0.22
Age	236	10.10	5.30	0.99	23.01
Size	250	14.76	1.52	10.85	17.58
Size2	250	0.02	0.02	0.00	0.12
Expense Ratio	169	0.08	0.11	0.00	0.98
Std. Dev.	236	0.02	0.01	0.00	0.17
Beta	153	0.71	0.14	0.19	1.05
Market Return	235	0.11	0.25	-0.33	0.67
Market Risk Premium	221	-0.01	0.30	-0.55	0.54
Rf	229	0.01	0.02	0.01	0.05
Bank Dummy	250	0.80	0.39	0.00	1.00

Table 3b. Descriptive Statistics for Mixed Funds

Variable	Obs.	Mean	Std. Dev.	Min	Max
Flow 1	246	0.19	1.43	-0.84	19.66
Flow 2 (Δ in Number of Investors)	240	24.00	158.83	-1.00	1366.54
Jensen's Alpha Excess Return	166	0.31	0.09	0.07	0.56
Four Factor Excess Return	166	0.03	0.07	-0.10	0.28
Age	246	9.61	4.66	0.49	22.01
Size	258	14.73	1.56	10.37	19.41
Size2	258	0.03	0.07	0.00	0.43
Expense Ratio	154	0.06	0.03	0.00	0.24
Std. Dev.	246	0.01	0.05	0.00	0.82
Beta	166	0.40	0.09	0.14	0.71
Market Return	238	0.11	0.26	-0.33	0.67
Bank Dummy	258	0.53	0.49	0.00	1.00

Table 3c. Descriptive Statistics for Variable Funds

Variable	Obs.	Mean	Std. Dev.	Min	Max
Flow 1	593	0.95	14.65	-1.02	350.58
Flow 2 (Δ in Number of Investors)	584	19.67	131.68	-1.00	1040.33
Jensen's Alpha Excess Return	384	0.40	0.16	-0.08	1.10
Four Factor Excess Return	384	0.04	0.10	-0.41	0.42
Age	597	9.12	5.15	-0.00	23.00
Size	629	14.35	1.69	9.07	18.06
Size2	629	0.02	0.03	0.00	0.34
Expense Ratio	408	0.07	0.04	0.00	0.33
Std. Dev.	593	0.01	0.04	0.00	0.70
Beta	384	0.52	0.16	0.03	1.19
Market Return	597	0.12	0.25	-0.33	0.67
Bank Dummy	633	0.61	0.49	0.00	1.00

Table 3a, 3b and 3c report the descriptive statistics on some fund characteristics for equity, mixed and variable funds, respectively for the period from 2005 to 2011.

From these descriptive statistics, one may observe that these fund groups have similar characteristics. For instance, mean standard deviation of daily returns for equity funds is 1.47%, while for mixed and variable funds; the means are 1.23% and 1.53% respectively. The highest average beta, 0.71, is obtained for equity fund category. This is followed by variable funds with an average beta of 0.5259. However, the highest beta value is observed for a variable fund. These findings are consistent with expectations.

Similarly, the highest mean flow goes to the variable funds. On the other hand, net cash flows that are obtained from CMB reports are very similar for the equity and mixed fund categories. However, the highest mean account numbers are seen in the equity funds. Although change in number of investors is a generally accepted flow proxy, this analysis shows that it may not be very highly correlated with the TL fund flow. These fund categories have similar age, size and expense ratios as well. However, a larger percentage of equity funds (80.40%) are owned by banks than variable (60.98%) and mixed funds (53.49%).

The most important conclusion that can be drawn from these descriptive statistics is that comprising a sample from these fund categories is acceptable because of the similarity in their characteristics. As a result, descriptive statistics for the entire sample is also given in Table 4.

Table 4. Descriptive Statistics for Entire Sample

Variable	Mean	Std. Dev.	Min	Max
Flow 1	0.1858	1.3569	-0.9295	19.6637
Flow 2 (Δ in Number of Investors)	21.7378	141.5522	-1.0000	1184.3170
Jensen's Alpha Excess Return	0.4103	0.1705	-0.3411	1.1056
Four Factor Excess Return	0.0334	0.0959	-0.4859	0.3242
Age	11.4243	4.6526	2.4904	23.0082
Size	14.7052	1.6051	9.1562	19.4099
Size2	0.0202	0.0501	0.0000	0.4325
Expense Ratio	0.0731	0.0662	0.0000	0.9800
Std Dev	0.0101	0.0046	0.0000	0.0381
Beta	0.5453	0.1776	0.0325	1.1939
Market Return	0.0917	0.2406	-0.3326	0.4891
Bank Dummy	0.6688	0.4710	0.0000	1.0000

Table 4 provides the descriptive statistics on some fund characteristics for the entire sample of funds between the years 2005 and 2011.

The descriptive statistics for the entire sample indicates that 66.88% of funds analyzed in this dissertation are owned by banks. There is a wider range of betas observed for the sample funds. On the other hand, the variability in total risks of these funds is quite low. Overall, descriptive statistics for the entire sample, as expected, are consistent with the numbers reported for the three different fund categories.

To further examine the similarity between these fund categories, their portfolio allocations to the broad asset classes are also analyzed. The descriptive statistics on asset allocations of these funds on a semiannual basis are reported in Tables 5a, 5b and 5c.

Table 5a. Asset Allocation of Equity Funds

Variable	Obs.	Mean	Std. Dev.	Min	Max
Equity	187	79.54	11.18	51.88	100.00
Treasury bills and bonds	187	4.05	7.83	0.00	38.34
Reverse repo	187	15.45	11.63	0.00	43.66
Money market	187	0.77	2.99	0.00	19.62
Foreign markets	187	0.00	0.00	0.00	0.00
Other investment options	187	0.19	1.87	0.00	18.47

Table 5b. Asset Allocation of Mixed Funds

Variable	Obs.	Mean	Std. Dev.	Min	Max
Equity	176	43.09	12.12	18.63	80.40
Treasury bills and bonds	176	31.19	18.50	0.00	70.53
Reverse repo	176	24.42	17.71	0.00	70.48
Money market	176	0.38	2.15	0.00	18.22
Foreign markets	176	0.00	0.00	0.00	0.00
Other investment options	176	0.92	3.19	0.00	20.43

Table 5c. Asset Allocation of Variable Funds

Variable	Obs.	Mean	Std. Dev.	Min	Max
Equity	464	57.85	19.16	0.40	100.00
Treasury bills and bonds	464	13.91	17.83	0.00	74.12
Reverse repo	464	26.91	20.54	0.00	99.60
Money market	464	0.71	2.68	0.00	20.24
Foreign markets	464	0.22	1.72	0.00	16.24
Other investment options	464	0.40	2.56	0.00	33.97

Table 5a, 5b and 5c provide a general view on allocations to the broad asset classes by equity, mixed and variable funds from 2005 to 2011.

Examining these tables for allocations to asset classes indicates that the equity funds have the highest allocation to the equity asset class. This finding is consistent with the equity funds having the highest average beta estimate reported in Tables 3a, 3b and 3c. Equity funds are followed by variable (57.85%) and mixed funds (43.09%) in terms of mean value of equity investments. Here, one may notice that the lowest investments in equity class for variable (0.4%) and mixed funds (18.63%) are significantly lower than the minimum 25% investment requirement in equity class imposed by the CMB of Turkey on type-A funds. A closer examination of the data reveals that these extreme values belong to the portfolio rebalancing intervals during the sample period analyzed in this dissertation. In a few days, these extreme values return back to the normal investment levels that are required by the CMB communiqué. Again, descriptive statistics for the general portfolio holdings of these three fund types show that these funds invest a significant percentage of their portfolios in the equity class. Therefore, constructing a sample with these three types of funds is appropriate for the purposes of this dissertation because these fund types have high investments in equity class and similar characteristics.

The correlations between different fund characteristics might be interesting as well. These correlations and their significance levels are given in Table 6.

Table 6. Piecewise Correlations between Fund Characteristics

	Flow 1	Flow 2 (Δ in Number of Investors)	Jensen’s Alpha Excess Return	Four Factor Excess Return	Age
Flow 1 (TL Flow)	1				
Flow 2 (Δ in Number of Investors)	-0.0144	1			
Jensen’s Alpha Excess Return	-0.0118	-0.0025	1		
Four Factor Excess Return	0.0072	-0.0421	0.4328*	1	
Age	-0.1072*	-0.0201	0.0221	0.025	1
Size	0.0000	0.1233*	-0.0249	-0.2075*	0.1718*
Size2	-0.0178	0.1607*	-0.0911*	-0.0933*	-0.009
Expense Ratio	-0.0426	-0.0042	0.044	-0.0162	-0.029
Std. Dev.	0.0303	0.0379	0.5981*	0.1000*	-0.1396*
Beta	-0.0056	0.0116	0.6515*	-0.2268*	-0.0136
Market Return	0.0880*	-0.0613	-0.5208*	-0.3053*	-0.0611
Market Risk Premium	0.0855*	-0.0389	-0.5839*	-0.3967*	-0.0906*
Risk free rate	-0.029	-0.0141	0.5344*	0.4967*	0.1411*
Bank Dummy	-0.0026	0.0957*	0.0684	-0.1356*	0.1449*
Crisis Dummy	0.0323	-0.1244*	0.0069	0.1000*	0.2066*

Table 6 (Cont'd). Piecewise Correlations between Fund Characteristics

	Size	Size2	Expense Ratio	Std. Dev.	Beta	Market Return	Market Risk Premium	Risk free rate	Bank Dummy	Crisis Dummy
Size	1									
Size2	0.5473*	1								
Expense Ratio	-0.2253*	-0.1167*	1							
Std. Dev.	-0.0855*	-0.0697	0.0176	1						
Beta	0.1004*	-0.0656	0.1419*	0.4860*	1					
Market Return	0.0646	0.0048	0.0548	-0.3666*	-0.0426	1				
Market Risk Premium	0.0331	0.0103	0.0733*	-0.3691*	-0.0418	0.9703*	1			
Risk free rate	0.0692	-0.0135	-0.1037*	0.2247*	0.0206	-0.4875*	-0.6821*	1		
Bank Dummy	0.1557*	0.1089*	-0.0214	0.0791*	0.1862*	-0.0016	0.0019	-0.0081	1	
Crisis Dummy	0.1133*	-0.0468	-0.0932*	-0.0917*	-0.0614	0.2621*	0.1284*	0.2322*	-0.0339	1

Table 6 provides the correlations among fund characteristics. The correlation coefficients that are significantly different from zero at the 5% significance level are indicated by *.

Table 6 shows that the fund flow obtained from the financial statements is negatively and significantly correlated with fund's age but no other fund characteristics. The second flow definition, on the other hand, is significantly and positively correlated only with measures of fund size. Performance variables are mostly positively and significantly related to the risk variables, as expected. Interestingly, size variables mostly negatively related to the performance variables. This negative correlation may indicate that an increase in the size does not necessarily create productivity and performance for fund investors. The second definition of size, namely *Size 2*, has a positive and significant correlation with *Size*. Consistently, *Size 2* has negatively related to performance variables as well.

The correlations among fund characteristics and some other market variables are also examined. Here, market return is the semiannual return on the BIST ALL index. The market risk premium is computed by subtracting the risk free rate from the market return. The crisis dummy variable becomes one for the period after the first half of 2009 to indicate the post-subprime mortgage crisis era. As expected, the market return and the market risk premium are highly and positively correlated, while the risk free rate is negatively related to the market risk premium. The crisis dummy variable also positively and significantly correlated with all of these market variables. The market return and the market risk premium are negatively and statistically significantly correlated with both of the fund performance variables, whereas the crisis dummy variable is positively and significantly correlated with only the Four-Factor excess return. Furthermore, the correlation between the crisis dummy variable and the Four-Factor excess return is much lower in magnitude than that between the market return and both of the performance measures or that between the market risk premium and both of the performance measures. As a result of significant and positive correlations of the crisis dummy variable with the market return and the market risk premium, and low or no correlation of this variable with fund performance measures, the crisis dummy variable is considered to be a good proxy for overall market conditions. Therefore, it is added to the main models of this dissertation as a robustness check.

It is well known that Turkey has a bank based financial system. The dominance of bank ownership for mutual funds is documented in Tables 3a, 3b and 3c. Correlations reported in Table 6 indicate that bank ownership is only positively related to the second flow definition. This might be due to investors finding it easier to open investment accounts in bank owned mutual funds. Furthermore, bank ownership is positively and statistically significantly correlated with the age, the size, both risk measures and negatively correlated with the Four-Factor excess return of the funds.

Given these correlations between fund characteristics and bank ownership, it makes sense to analyze the similarities and differences between characteristics of the bank and the non-bank owned mutual funds more closely. The summary statistics on characteristics of bank and non-bank owned mutual funds are given separately in Tables 7a and 7b, respectively. Furthermore, the statistical significance of differences in characteristics of bank and non-bank owned funds based on Wilcoxon rank sum test, a non-parametric test, are shown in Table 8.

Table 7a. Fund Characteristics for Bank Owned Mutual Funds

Variable	Obs.	Mean	Std. Dev.	Min	Max
Flow 1	508	0.3402	2.7551	-0.9295	50.5551
Flow 2 (Δ in Number of Investors)	503	29.4684	164.9172	-1.0000	1184.3170
Jensen's Alpha Excess Return	428	0.4188	0.1674	0.0012	1.0476
Four Factor Excess Return	428	0.0259	0.0870	-0.2637	0.3170
Age	483	11.0970	5.4117	0.4904	23.0082
Size	519	14.7766	1.5510	9.9472	19.4099
Size 2	519	0.0219	0.0565	0.0001	0.4325
Expense Ratio	479	0.0699	0.0677	0.0000	0.9800
Std. Dev.	481	0.0109	0.0071	0.0000	0.1264
Beta	428	0.5656	0.1717	0.1614	1.0520
Market Return	521	0.1041	0.2368	-0.3326	0.4891
Market Risk Premium	483	-0.0051	0.2877	-0.4901	0.4188
Rf	483	0.0164	0.0140	0.0054	0.0553

Table 7b. Fund Characteristics for Non-Bank Owned Mutual Funds

Variable	Obs.	Mean	Std. Dev.	Min	Max
Flow 1	299	0.3542	2.2791	-1.0238	21.3241
Flow 2 (Δ in Number of Investors)	298	2.8549	48.1800	-1.0000	831.7032
Jensen's Alpha Excess Return	237	0.3944	0.1771	-0.3411	1.1056
Four Factor Excess Return	237	0.0532	0.1099	-0.4859	0.4268
Age	285	9.5622	4.4287	-0.0027	19.0055
Size	308	14.2336	1.8474	9.0752	17.8568
Size 2	308	0.0115	0.0168	0.0000	0.0907
Expense Ratio	252	0.0727	0.0512	0.0000	0.3423
Std. Dev.	284	0.0099	0.0049	0.0013	0.0284
Beta	237	0.4955	0.1867	0.0325	1.1939
Market Return	309	0.1049	0.2364	-0.3326	0.4891
Market Risk Premium	285	-0.0063	0.2905	-0.4901	0.4188
Rf	285	0.0166	0.0145	0.0054	0.0553

Table 7a and 7b provides the fund characteristics separately for bank owned and non-bank owned mutual funds.

Table 8. Wilcoxon Rank Sum Test for Bank Ownership

	Wilcoxon Rank Sum Test
Flow 1	0.8143
Flow 2 (Δ in Number of Investors)	0.1847
Jensen's Alpha Excess Return	0.0671
Four Factor Excess Return	0.0000
Age	0.0004
Size	0.0024
Size2	0.0019
Expense Ratio	0.0441
Std. Dev.	0.0021
Beta	0.0000
Market Return	0.9780
Market Risk Premium	0.9330
Rf	0.9065

Table 8 provides the test statistics from Wilcoxon rank sum test for the difference between characteristics of bank owned and non-bank owned funds.

Table 8 demonstrates that none of the flow definitions differ significantly based on the ownership type. Furthermore, the Jensen's alpha excess return is not statistically significantly different for bank and non-bank owned funds. However, Four-Factor excess return is significantly higher for non-bank owned funds. As one may expect, bank owned mutual funds are older and larger than their non-bank owned counterparts. Moreover, bank owned mutual funds have statistically significantly higher mean for total risk and systematic risk variables. On the other hand, non-bank owned funds have significantly higher expense ratios. Because of these statistically significant differences in fund characteristics of bank and non-bank owned funds, a bank dummy variable having a value of 1 for bank owned funds and 0 otherwise is added to the main models of this dissertation as a robustness check.

The next step is to examine the relationship between flow – past performance for Turkish mutual funds during the sample period of this dissertation. Figure 1 represents the general nonlinear relation between past performance and fund flows for Turkish variable, mixed and equity funds included in the sample, between the years 2005 and 2011. Funds are ranked into 10 groups based on their Jensen's alpha excess returns in each semiannual period. Then, for each performance group, new money growth scaled by fund's total net assets is computed as the median of flow for that group. Actual flow data is used for this figure.

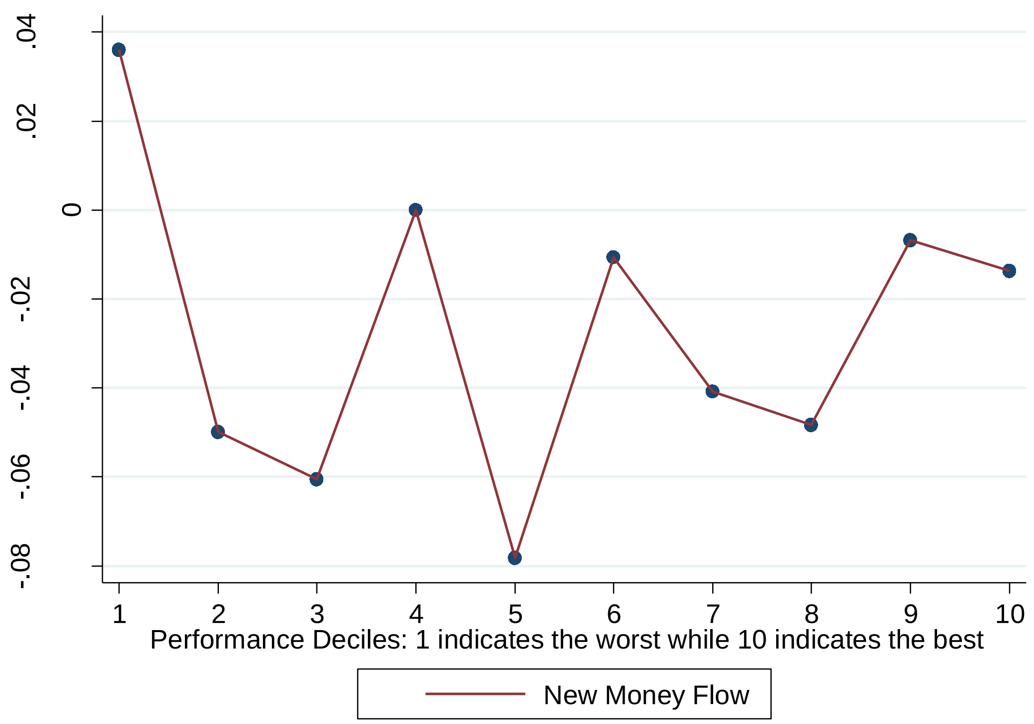


Figure 1. This graph illustrates the median of new money flow to funds according to the Jensen's alpha excess returns in the previous semiannual. The worst performing funds are in the Group 1; while the Group 10 consists of the best performing funds.

This figure is obtained by using the Jensen's alpha excess return definition; however, Four-Factor excess return and the flow definition based on "the change in numbers of investor" also show a similar pattern. To conserve space, these additional figures are not included in the dissertation, however, are available from the author upon request. The nonlinear relation between fund flows and past performance can be observed in Figure 1. Cash flow to the funds is negative up to the funds with average performance, and cash outflows only begin to decrease from this point on. It seems that best performers prevent withdrawals at the least.

4.2. Flow Models

According to the Türkiye Sermaye Piyasası Raporu (2009), 96.6% of the mutual fund investors are domestic individuals. Zheng (2008) underlines the importance of the individual investors' decisions for the overall market stability. Therefore, this study first examines the determinants of the Turkish fund flow by using Eq (1). The findings from the regression model that associates flow to the fund characteristics are presented in Tables 9a and 9b.

The regressions reported in Tables 9a and 9b are checked for the regression assumptions. The variance of the residuals is found to be not constant. Therefore, the White estimator is used for the computation of standard errors of estimates. Moreover, since there are dummy and interaction variables in the model, special attention is paid to the multi-collinearity issue. However, variance inflation factor is always found to be below the critical value. Hence, no multi-collinearity problem is detected in any of the models.

However, residuals from these regressions are not normally distributed. This problem, in fact, exists in other studies, such as Busse (2001) and Goriaev et al. (2005). Busse (2001) reports p-values obtained from Monte Carlo simulations, which are free from the normality assumption as well as p-values obtained by assuming normal distribution and, he points out that simulated p-values are not substantially different than those obtained from assuming normal distribution. Goriaev et al. (2005) states that Monte Carlo simulation approach is computationally intensive. Given arguments in Goriaev et al. (2005) and findings of Busse (2001) regarding simulated and regular p-values, I also assume normality for coefficent tests. Since number of observations used in the analyses of this dissertation are large enough for the central limit theorem to hold, the violation of normality assumption are considered to be not important enough to alter the main conclusions of this dissertation.

Table 9a. Flow Models

VARIABLES	(1)	(2)	(3)	(4)
Constant	3.146***	3.499***	3.165***	3.441***
	(1.217)	(1.329)	(1.223)	(1.286)
Jensen's Alpha Excess Ret$_{t-1}$	-0.980**		-0.944**	
	(0.421)		(0.448)	
4 Factor Excess Ret$_{t-1}$		-0.996		-0.984
		(0.613)		(0.599)
Std. Dev $_{t-1}$	16.57	7.953		
	(10.44)	(10.72)		
Beta $_{t-1}$			0.551*	0.316
			(0.309)	(0.222)
Flow$_{t-1}$	-0.0397**	-0.0352**	-0.0376**	-0.0351**
	(0.0167)	(0.0147)	(0.0160)	(0.0146)
Best-Worst $_{t-1}$	0.143	-0.142	0.0948	-0.134
	(0.163)	(0.154)	(0.167)	(0.148)
Best-Worst x Jensen's	0.417*		0.300	
	(0.249)		(0.264)	
Best-Worst x 4Factor		-0.817		-0.731
		(0.565)		(0.560)
Semiannual Dummy	0.0226	0.00354	0.0326	0.00787
	(0.120)	(0.112)	(0.120)	(0.112)
Age $_{t-1}$	-0.00119	-0.00166	-0.00165	-0.00185
	(0.00992)	(0.00992)	(0.00983)	(0.00986)
Size $_{t-1}$	-0.188**	-0.211***	-0.196***	-0.214***
	(0.0745)	(0.0810)	(0.0743)	(0.0813)
Expense Ratio $_{t}$	-1.909	-1.791	-1.949	-1.872
	(1.692)	(1.556)	(1.667)	(1.576)
R-squared	0.059	0.064	0.059	0.065
Observations	611	611	611	611
t test (Jensen's + B-W x Jensen's)	-0.5630			
	(0.3995)			

*** p<0.01, ** p<0.05, * p<0.1

This table shows the findings from the flow model that relates the fund flow to the fund characteristics, such as performance, age, size, risk, and expense ratio as well as one period lagged flow. The formal model can be represented as follows:

$$Flow_{i,t} = \gamma_0 + \gamma_1 Perf_{i,t-1} + \gamma_2 Age_{i,t-1} + \gamma_3 Size_{i,t-1} + \gamma_4 Risk_{i,t-1} + \gamma_5 Expense_{i,t} + \gamma_6 Flow_{i,t-1}$$
$$+ \gamma_7 Semiannual\_Dummy + \gamma_8 Best\_Worst_{t-1} + \gamma_9 Best\_WorstxPerformance + \varepsilon_{i,t}$$

Here, the dependent variable is the cash flow obtained from daily reports to CMB. Models presented in this Table alternate the performance proxies, namely Jensen's alpha excess returns and Four-Factor excess returns, as well as risk proxies, namely standard deviation and beta. Robust standard errors are presented in parenthesis.

Table 9b. Flow Models

VARIABLES	(1)	(2)	(3)	(4)
Constant	-165.4***	-125.4*	-176.5***	-137.3**
	(63.90)	(64.40)	(65.95)	(66.22)
Jensen's Alpha Excess Ret$_{t-1}$	59.87		33.53	
	(44.24)		(28.60)	
4 Factor Excess Ret$_{t-1}$		132.4**		127.2**
		(65.44)		(63.44)
Std. Dev $_{t-1}$	-1,655	-1,494		
	(1,615)	(1,375)		
Beta $_{t-1}$			6.102	-16.94
			(46.89)	(28.71)
Flow$_{t-1}$	-0.0475***	-0.0473***	-0.0479***	-0.0480***
	(0.0153)	(0.0155)	(0.0153)	(0.0157)
Best-Worst $_{t-1}$	-5.417	-25.46	-4.707	-24.63
	(16.04)	(15.88)	(17.46)	(15.86)
Best-Worst x Jensen's	-14.98		-18.62	
	(28.38)		(34.61)	
Best-Worst x 4Factor		-125.3**		-121.9**
		(51.67)		(48.89)
Semiannual Dummy	-12.87	-11.12	-12.58	-11.98
	(11.84)	(11.66)	(12.08)	(11.54)
Age $_{t-1}$	-1.544	-1.505	-1.481	-1.454
	(1.424)	(1.418)	(1.396)	(1.391)
Size $_{t-1}$	14.08***	13.27***	14.23***	13.70***
	(4.964)	(4.847)	(5.134)	(4.991)
Expense Ratio $_{t}$	55.97	65.41	49.20	62.91
	(52.23)	(56.27)	(53.78)	(56.40)
R-squared	0.030	0.036	0.029	0.035
Observations	603	603	603	603
t test (4 Factor Excess Ret. + B-W x 4 Factor Excess Ret.)		7.0720		5.2732
		(41.487)		(40.801)

*** p<0.01, ** p<0.05, * p<0.1

Table 9b is prepared using the formal model defined in Eq (1):

$$Flow_{i,t} = \gamma_0 + \gamma_1 Perf_{i,t-1} + \gamma_2 Age_{i,t-1} + \gamma_3 Size_{i,t-1} + \gamma_4 Risk_{i,t-1} + \gamma_5 Expense_{i,t} + \gamma_6 Flow_{i,t-1}$$
$$+ \gamma_7 Semiannual\_Dummy + \gamma_8 Best\_Worst_{t-1} + \gamma_9 Best\_WorstxPerformance + \varepsilon_{i,t}$$

Dependent variables in this table are the change in the number of investors scaled by the previous period's number of investors (number of investors $_{i,t}$/number of investors$_{i,t-1}$). Models presented in this Table alternate the performance proxies, namely Jensen's alpha excess returns and Four-Factor excess returns, as well as risk proxies, namely standard deviation and beta. Robust standard errors are shown in parenthesis.

Literature suggests that investors are sensitive to the past performance of funds in a non-linear way. They do not flee when funds exhibit bad performance, but they invest more to the funds with good performance. Brown et al. (1996) and Chevalier and Ellison (1997) indicate that this convex performance – flow structure creates an implicit compensation scheme. That is, fund managers alter the risk of their portfolios to be in the winners' side. Based on this discussion in the literature, one may begin to interpret effect of past performance on flows to Turkish mutual funds.

Findings from the flow model show that investors do not pay attention to alphas from the Four-Factor model as a risk adjusted performance measure in their fund investments, since this variables does not have a significant coefficient in any of the flow models. Excess returns obtained from the Jensen's alpha measure have a significant relation with the first flow definition in Table 9a. Contrary to the discussion in the previous paragraph, there is not a convex relation between fund flows and past performance for the Turkish mutual funds[3]. It seems that past performance and fund flows are negatively related as opposed to the positive relation reported in the literature. Investors withdraw their money from the funds that have shown good performance in the previous 6-month period. This could be due to the profit realization motivation of Turkish mutual fund investors between the years 2005 and 2011. According to the Turkish Capital Markets Association's report, domestic individual investors in Turkey had a tendency to sell their assets and realize their profits between the years 2005 and 2008 (Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği (2006, 2007, 2008, 2009)). The heavy consequences of the crises in the beginning of 2000s were

[3] In order to test the convex structure in the fund flow-past performance relation, funds are divided into performance deciles, and these deciles are compiled into "high", "mid" and "low" groups. Although different "high", "mid" and "low" group definitions are used, significant results cannot be obtained. Hence, this dissertation only includes *Best-Worst* dummy in the models to account for the asymmetric relation between fund flow and past performance.

influential on this selling decision. Domestic individual investors became a net buyer only in the year 2008, however the economic fluctuations in the May – June of 2009 forced them to realize their net gains again (Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği (2009, 2010)).

It seems that the relative bull market experienced in the Borsa Istanbul between the years 2005 and 2011 may also have contributed to this net profit realization behavior of fund investors. In Figure 2, the level of BIST ALL index and total flow to mutual funds analyzed in this dissertation are plotted together for the sample period analyzed in this dissertation. From this figure, one may observe that the stock market of Turkey usually has an upward trend during the sample period of this dissertation. It seems that total flow to mutual funds has a similar trend with the stock market. Since the funds included in the sample of this dissertation heavily invest in equity asset class, the higher gains in the stock market might allow investors in these mutual funds to withdraw their money to realize their profits from their investments in these funds.

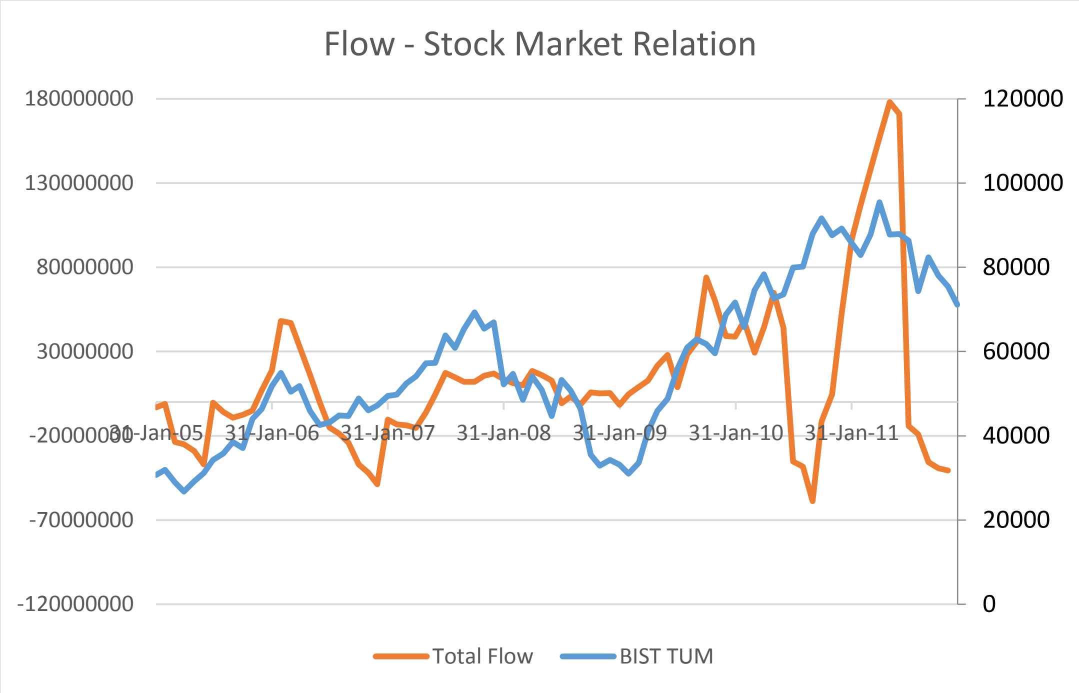
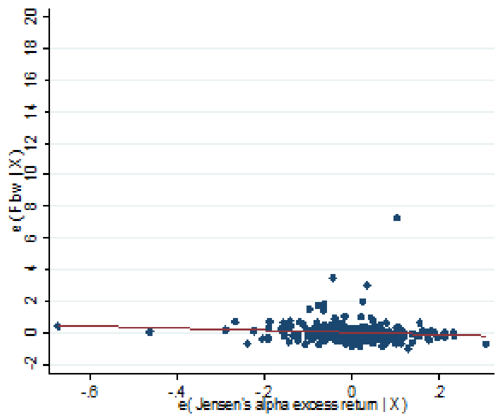


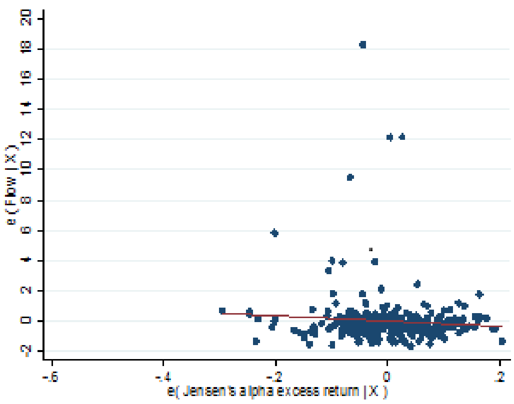
Figure 2. The blue line in the graph shows the level of BIST ALL index from 2005 to 2011, while the orange line shows the total flow to mutual fund analyzed in this dissertation on a monthly basis. Source: BIST and author's calculations.

The holding period of an average individual investor was 50 days in the 2002 (Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği, 2003). Although it has fluctuated throughout the years, it became 1 month on average in 2010 (Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği, 2011). From the reports of the Turkish Capital Markets Association, one may observe that individual investors are also very cautious while buying equity shares. Hence, it might be conceivable for these individual investors to be cautious when investing in mutual funds mainly holding equity securities. Therefore, outflow from sample funds may be explained by these behaviors of domestic individual investors.

Before concluding about the performance – flow relation for the Turkish mutual fund investors, one may look at the coefficient of the dummy variable (*Best-Worst*) and the interactive variable (*Best-Worst x Performance* variables). The *Best-Worst* dummy variable has a value of *1* for funds exhibiting above median performance and *0* otherwise. The interactive variable is the multiplication of the performance proxy in the respective regression with the *Best-Worst* dummy variable. *Best-Worst* dummy variable has an insignificant coefficient; that is, there is no difference in intercepts of the regression lines for the best and worst performing funds. However, *Best-Worst x Performance* for Jensen's alpha is significant and positive at least in the first model in Table 9a. This means that the funds with above median performance have a less negative slope than those with below median performance. Putting it differently, the cash outflow from the best performers is less than the cash outflow from the worst performers. A separate t-test is conducted to understand whether the sum of the coefficients for the Jensen's alpha excess return and the interactive variable is significantly different from zero. This test is conducted only when the coefficients of Jensen's alpha and the interactive variable are individually significant and have the opposite signs. The null hypothesis of this summed coefficient being zero cannot be rejected. That is, for best performing funds, performance does not negatively affect the new cash flow to the funds. Instead, performance loses its overall impact on flows for these funds. However, the positive and statistically significant constant terms in these models indicate that best performing funds still attract more cash inflow than worst performing ones.

The relation between fund flow and performance for best and worst performing funds are depicted in Figure 3:





Regression line for the worst performers   Regression line for the best performers

Figure 3. Added variable plots for Jensen's alpha excess returns are shown in figure 3. The first graph shows the relation of performance with the flow conditional on the control variables when the *Best-Worst* dummy is 0. The second one illustrates the same relation when the *Best-Worst* dummy is 1.

Figure 3 exhibits the regression lines for fund flow and the Jensen's alpha excess return as a performance proxy while holding other explanatory variables as constant. The first graph shows this association only for the funds with below median performance, whereas the second one depicts the same relation for funds with above median performance. From these figures, changing flow-performance structure discussed above can be seen more clearly. The fact that funds with good performance experience a smaller outflow than the bad performing ones may also induce an implicit compensation scheme similar to the one caused by the convex relation between fund flows and past performance. Funds with bad performances may shift their risk level in the next period to be among the winner funds.

Öztürkkal and Erdem (2012) previously indicated that semiannual tournaments exist in the Turkish mutual fund market by comparing the return volatility of funds with below and above median performance. They note that managers of the loser funds alter the portfolio risk at the end of the first half of the year. Given this evidence, it is conceivable to see a difference in flows to funds in the first and the second half of the year. Therefore, this dissertation also compares the flows to funds in the first and the second half of the year by adding a semiannual dummy to the regression models. The semiannual dummy takes the value of *1* if the data is from the second half of the year and *0* otherwise. However, the coefficient for this explanatory variable is found to be insignificant. In other words, fund flows are not sensitive to the periods of the year.

Previous literature documents either an insignificant (Kempf & Ruenzi, 2008) or a negative (Chevalier & Ellison, 1997; Ferreira et al., 2012b) relation between a fund's age and its flow. Fund age in our flow models never has a significant coefficient. Results reported in Table 9a indicate that investors do not consider funds' age when they make investment/disinvestment decisions.

Size of a fund may also affect its flow, because many studies have found that larger funds experience a slower new cash flow causing a smaller growth rate for these funds (i.e. Chevalier and Ellison 1997; Sirri and Tufano 1998). Some studies, on the other hand, point out that larger funds are more likely to draw more cash flow (Ferreira et al., 2012b). Regarding the bank ownership of the larger mutual funds in the Turkish market, a positive association is expected to be observed between new cash flows and fund size. Contrary to the expectations, findings consistently demonstrate a negative and significant effect of size on the fund flows. As in Li and Tiwari (2006), smaller funds in the Turkish mutual fund market attract more cash flow than larger funds. Öztürkkal and Erdem (2012) note that banks may force the funds that they own to shift their portfolio risk in order to draw more flow. Because larger funds are usually bank related; investors may not prefer to invest in these funds. On the other hand, customers of bank related funds may invest their excess money when they receive their salary at the beginning of the month in the funds of their banks instead of leaving it idle in their bank accounts, but withdraw it towards the end of the month when they are out of cash. The ability to invest and disinvest easily in bank related mutual funds might result in higher cash outflow from the larger mutual funds relative to smaller non-bank owned funds.

Another determinant of funds' cash flow is the risk structure of a fund's portfolio. Naturally, a negative impact of risk increase on new cash flow to the funds suggests a risk averse behavior for investors. Literature has used many risk proxies to determine this association. This dissertation employs semiannual standard deviation of daily fund returns and each fund's beta based on last 36 month returns. Results demonstrate an insignificant coefficient for both of these risk proxies. In only one model, coefficient of systematic risk is positive and significant at 10% level. This weak evidence indicates that increased systematic risk may attract more cash flows to the funds, implying a risk taking rather than risk averse behavior for fund investors. Overall findings suggest that Turkish fund investors are not sensitive to either the total or the systematic risk while considering alternative funds in the sample for investment purposes. No evidence for risk aversion is detected for the mutual fund investors. This finding may be attributed to the sample of funds analyzed in this dissertation. Type-A funds in the Turkish mutual fund market are riskier than type-B funds. Among the type-A funds, the sample of this dissertation consists of the ones which invest heavily in the equity market. Considering the decreasing tendency of individual investors to invest in shares trading in the Turkish capital markets beginning from the 2000s (Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği 2003, 2004, 2005, 2006, 2007, 2008), the investors of variable, mixed and equity funds are the ones who are more willing to take on risk. Hence, it may be natural to observe a lack of risk aversion for these investors. This finding implies that mutual fund managers are not be able to attract more investors by changing their total or systematic risk levels.

Previously, it has been suggested that the negative coefficient for size variable may have two explanations. First, bank related funds, which are usually the largest ones, are likely to increase the fund's portfolio risk and investors may not welcome this tendency. Second, investors of bank related funds may find it easier to withdraw their money from these funds and invest it in other options, since they may also have demand deposits with the bank. Since the findings shown in Table 9a and 9b indicate that investors do not pay attention to the risk structure of the fund's portfolio, the negative impact of size variables on flows are more likely to be explained by the ease of withdrawals from bank related funds.

This finding is similar to those put forth in Sirri and Tufano (1998) and Del Guercio and Tkac (2002). Sirri and Tufano (1998) use the standard deviation of monthly returns as a risk proxy and show very weak or insignificant effect of this variable on the fund flows. Del Guercio and Tkac (2002) find that, contrary to the pension fund investors, mutual fund investors do not take into account the risk variable while allocating their investments.

Literature mainly finds significant and positive coefficient for one period lagged flow (Del Guercio & Tkac, 2002; Ferreira et al., 2012b; Li & Tiwari, 2006). This positive association means that investors prefer to allocate their money to the funds that appealed more to investors in the past. The results from Table 9 indicate that lagged flow is always significant in all of the models supporting the autocorrelation argument and enhances the R^2 of the regressions. However, the coefficient for this variable is always negative stating that if a fund draws more flow one period before, this trend will be reversed in the subsequent period, and the fund will experience outflows. This contrary finding can only be explained by the unique structure of Turkish mutual fund industry. The market experiences a high amount of cash outflows during the period analyzed. Individual investors are interested in realizing their net profits over their very short investment horizon. Hence, the withdrawals in the subsequent period are expected in such an environment.

Both Sirri and Tufano (1998) and Huang et al. (2007) point out the negative effect of fund expenses on the fund growth rates in terms of new cash flow. Flow models in Tables 9a, however, show that fund fees are not influential on the cash flows, because expense ratio variable does not have a significant coefficient in any of the models. Again, this finding can be explained by the fee structure of the Turkish mutual fund. Fund expenses can be determined by the fund itself as long as they are clearly stated in their internal regulations. However, CMB puts an upper limit on the fund expenses by its communiqués (*Yatırım Fonlarına İlişkin Esaslar Tebliği Seri:VIII, No:10*, 1996). The general attitude of fund managers, then, is to determine an expense structure close to the upper limit and the expense structures of other funds. As a result, fund expenses do not show much variability, and hence may not have an effect on the flow allocation decision of investors. This finding is also consistent with the world-wide evidence shown by Ferreira et al. (2012b).

Table 9b shows the results of the same analysis with the second proxy of cash flow, i.e. change in the number of investors. In these analyses, effects of the same independent variables on this alternative measure of fund flow are examined. Findings indicate that fund size positively affects the change in number of investors. In other words, larger funds are more likely to grow in terms of number of investors. Based on the bank-related nature of the large funds, this finding may not be surprising. Yet, given the results reported in Table 9a, one may conclude that an increase in the number of investors does not always mean a higher TL flow to the fund. Performance in terms of Four-Factor excess return seems to positively affect the change in number of investors. For funds with high performance, the number of accounts increases. The interactive variable for Four-Factor excess return is negative, however. To observe the overall impact of performance on this second flow definition for best performing funds, a separate t tests on the sum of the coefficients for the Four-Factor alpha and the interactive variable is conducted. This statistic points out that for best performing funds the impact of performance is not significantly different from zero. This finding is consistent with that for the first flow measure.

4.3. Spatial Flow Models

As explained before, Manski (2000) states that individuals consider others' choices when choosing among many alternatives. He called this relation among individuals as preference interactions. In order to take into account the preference interactions in the mutual fund choices, one may look at cash flows to other funds which reflect individuals' investment decisions.

In fact, the existence of high autocorrelation among mutual fund flows has been well documented. Del Guercio and Tkac (2002) note that this situation is unique to mutual funds and not observed for pension funds. They suggest the "*herding behavior toward specific funds*" as a possible explanation for this correlation. This herding behavior may be seen as a result of the preference interactions noted in Manski (2000). However, conventional methods are insufficient to model this interaction between individual investors. Therefore, besides including one period lagged flow variable as an additional independent variable in conventional regressions, this dissertation also utilize three types of spatial modeling for fund flows in order to explore the existence of preference interactions as mentioned in Manski (2000).

The beginning point of the spatial analysis can be considered as the construction of a spatial weight matrix (W). A general spatial weight matrix, which displays the proximity among observations, is created by the aid of data envelopment analysis explained in the methodology section. In all of the spatial analyses of flow and risk, the same W matrix is employed. Next, based on this matrix, the existence of spatial autocorrelation among observations is investigated. Anselin (1992) points out Moran's *I* and Geary's *C* measures as the classical spatial autocorrelation tests. Although they mostly provide the same conclusions about the existence of spatial autocorrelation, Getis (2010) notes that Moran's *I* is the leading and most powerful test for this type of spatial interaction. Hence, this dissertation employs Moran's *I* statistic to detect the global spatial autocorrelation in the variables. As in the OLS models, the time dimension is ignored and a pooling regression specification is used in the spatial models as well. Moran's *I* statistic is also computed without this time dimension. The results are presented in Table 10.

Table 10. Moran's *I* Results

Variables	I	E(I)	sd(I)	z	p-value
Age	0.038	-0.002	0.025	1.577	0.057
Beta	0.065	-0.002	0.025	2.667	0.004
Standard Deviation	0.201	-0.002	0.025	8.145	0.000
Flow 1	0.046	-0.002	0.023	2.087	0.018
Flow 2	0.000	-0.002	0.024	0.061	0.476
Four-Factor Excess Return	0.586	-0.002	0.025	23.583	0.000
Jensen' s Alpha Excess Return	0.208	-0.002	0.025	8.396	0.000
Expense Ratio	0.429	-0.002	0.025	17.271	0.000
Size	0.037	-0.002	0.025	1.550	0.061

This table shows the Moran's *I* statistics for the flow model variables. The null hypothesis for this statistic is that there is no spatial autocorrelation. *Flow 1* is computed from data provided in financial statements of funds and scaled by the past period's *TNA*. *Flow 2* is defined as the change in number of investors scaled by one period lagged number of investors. *Age* is a fund's age in years from its foundation. Beta and standard deviation are the risk proxies, while Four-Factor excess return and Jensen's excess return are performance proxies. A general spatial weight matrix based on mutual fund efficiencies is obtained by the aid of DEAs. The fund *i* is accepted as a neighbor to its peer group. The distance between them is the inverse of fund *i*' s efficiency value.

A positive and significant Z value indicates the presence of positive spatial autocorrelation and rejects the null hypothesis of no spatial autocorrelation. Putting it differently, a positive value of this statistic means that high values of variables move together, while the low values make another cluster. Findings in Table 10 reject the null hypothesis for all but the second flow definition and indicate the existence of positive spatial autocorrelation. Naturally, a higher Moran's *I* statistic points out a stronger relation.

The scatter plots, presented below, help to visualize the extent of spatial autocorrelation for performance and risk variables. The Moran's *I* scatter plots for the other variables can be found in the appendix A. The highest clustering among high and low values can be seen in the performance proxies.

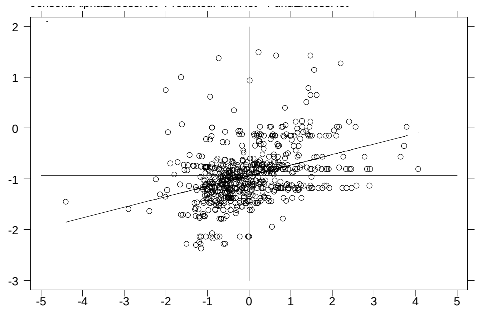


Figure 4.a Jensen's alpha excess return

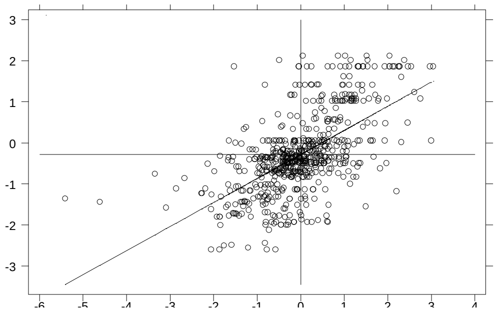


Figure 4.b Four-Factor excess return

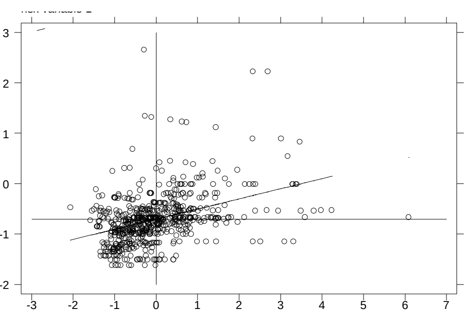


Figure 4.c Standard Deviation

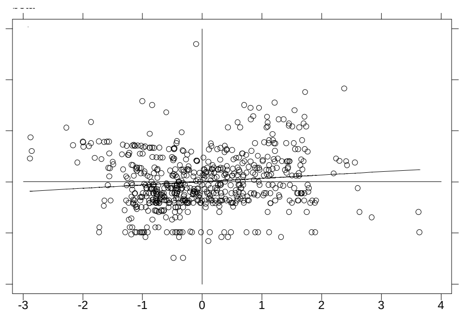


Figure 4.d 24 month beta

Figure 4. Moran's *I* scatter plots for performance and risk variables. The standardized variable, which has zero mean and 1 variance, is on the horizontal axis, while its spatial lag is shown on the vertical axis. The values of the variable over the mean are displayed in the upper right quadrant, while low values are plotted on the lower left one. Clustering in these quadrants indicate a positive spatial autocorrelation. A random distribution in all four quadrants cannot reject null hypothesis of no spatial autocorrelation. A distribution in the other two quadrants indicates a negative spatial autocorrelation.

One may recall that initial flow models estimated in this dissertation are heteroskedastic and have significant coefficients on lagged flows indicating the existence of autocorrelation. This finding is not surprising, given the Moran's *I* results indicating the existence of positive spatial autocorrelation for variables of these models. Hence, three types of spatial modeling are applied to the flow models.

First, a spatial lag model, where the spatial lag of flow is included as shown in Eq (2), is considered. Two different models, one for each flow definition used in this dissertation, are estimated as in the traditional flow models. The findings from this specification can be seen in Tables 11a and 11b for the TL flow and the change in the number of investors, respectively. To correct for heteroskedasticity, robust standard errors are used and reported in the parentheses. Since R^2 values for these models are not comparable to the ones for the OLS models (Anselin, 1988; Leenders, 2002), Akaike Information Criteria (AIC) values as a goodness of fit statistic are reported in these tables.

Table 11a. Spatial Lag Model of Flow

VARIABLES	(1)	(2)	(3)	(4)
Constant	3.360*	3.500*	3.351*	3.521*
	(1.38)	(1.41)	(1.39)	(1.45)
Spatial Lag of Flow (Rho)	0.057	0.049	0.065	0.050
	(0.12)	(0.12)	(0.12)	(0.12)
Jensen's Alpha Excess Ret$_{t-1}$	-0.969*		-0.960*	
	(0.43)		(0.44)	
4 Factor Excess Ret$_{t-1}$		-1.664*		-1.686
		(0.75)		(0.88)
Std. Dev $_{t-1}$	14.176	1.061		
	(11.34)	(11.54)		
Beta $_{t-1}$			0.511	-0.027
			(0.32)	(0.42)
Best-Worst $_{t-1}$	0.136	0.185	0.091	0.195
	(0.17)	(0.16)	(0.18)	(0.22)
Best-Worst x Jensen's	0.437		0.331	
	(0.26)		(0.28)	
Best-Worst x 4Factor		-0.563		-0.566
		(0.62)		(0.62)
Semiannual Dummy	0.000	-0.005	0.008	-0.004
	(0.12)	(0.12)	(0.12)	(0.12)
Age $_{t-1}$	-0.001	-0.002	-0.001	-0.002
	(0.01)	(0.01)	(0.01)	(0.01)
Size $_{t-1}$	-0.201*	-0.217*	-0.207*	-0.217*
	(0.08)	(0.09)	(0.08)	(0.09)
Expense Ratio $_t$	-2.149	-2.178	-2.166	-2.170
	(1.88)	(1.81)	(1.84)	(1.80)
AIC	2059.789	2056.582	2059.597	2056.583
Observations	599	599	599	599

***p<0.01, ** p<0.05, * p<0.1

This table displays the findings from the spatial lag model. The formal specification of this model can be seen as follows:

$$Flow_{i,t} = \varphi_0 + \rho\sum_{j=1}^{n} W_{ij} Flow_{i,t} + \varphi_1 Perf_{i,t-1} + \varphi_2 Age_{i,t-1} + \varphi_3 Size_{i,t-1} + \varphi_4 Risk_{i,t-1} + \varphi_5 Expense_{i,t}$$
$$+ \varphi_6 Semiannual\_Dummy + \varphi_7 Best\_Worst_{t-1} + \varphi_8 Best\_WorstxPerformanc\ e + \xi_{i,t}$$

In these specifications, flow is computed from the CMB daily reports. Models vary by the alternative performance and risk variables used. *W* is computed from DEAs based on the fund efficiencies. The fund *i* is accepted as a neighbor to its peer group. The distance between two funds is the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parenthesis.

Table 11b. Spatial Lag Model of Flow

VARIABLES	(1)	(2)	(3)	(4)
Constant	-172.718*	-155.521*	-184.587**	-172.483*
	(67.70)	(66.22)	(70.05)	(69.61)
Spatial Lag of Flow (Rho)	-0.008	-0.007	-0.008	-0.007
	(0.21)	(0.21)	(0.21)	(0.21)
Jensen's Alpha Excess Ret$_{t-1}$	62.740		34.453	
	(44.07)		(28.96)	
4 Factor Excess Ret$_{t-1}$		52.866		65.733
		(36.96)		(53.05)
Std. Dev $_{t-1}$	-1736.504	-1072.922		
	(1613.87)	(1497.70)		
Beta $_{t-1}$			9.035	11.962
			(46.73)	(47.03)
Best-Worst $_{t-1}$	-7.293	-5.633	-6.872	-11.694
	(16.30)	(13.37)	(17.75)	(19.39)
Best-Worst x Jensen's	-13.841		-18.589	
	(27.84)		(34.17)	
Best-Worst x 4Factor		-125.737*		-121.983*
		(51.81)		(50.29)
Semiannual Dummy	-13.541	-10.756	-13.239	-11.703
	(11.93)	(12.05)	(12.14)	(11.76)
Age $_{t-1}$	-1.422	-1.336	-1.360	-1.281
	(1.40)	(1.39)	(1.37)	(1.37)
Size $_{t-1}$	14.374**	14.221**	14.490**	14.420**
	(5.15)	(5.11)	(5.28)	(5.23)
Expense Ratio $_t$	64.013	71.632	56.777	66.585
	(54.60)	(58.18)	(56.20)	(58.75)
AIC	7634.924	7634.042	7635.927	7634.475
Observations	599	599	599	599

***p<0.01, ** p<0.05, * p<0.1

This table reports the findings from the spatial lag model which can formally be expressed as follows:

$$Flow_{i,t} = \varphi_0 + \rho\sum_{j=1}^{n} W_{ij}Flow_{i,t} + \varphi_1 Perf_{i,t-1} + \varphi_2 Age_{i,t-1} + \varphi_3 Size_{i,t-1} + \varphi_4 Risk_{i,t-1} + \varphi_5 Expense_{i,t}$$
$$+ \varphi_6 Semiannual\_Dummy + \varphi_7 Best\_Worst_{t-1} + \varphi_8 Best\_WorstxPerformanc\ e + \xi_{i,t}$$

In these specifications, flow is the change in the number of investors in subsequent periods. Models vary by the alternative performance and risk variables used. *W* is computed from DEAs based on the fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is computed as the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parenthesis.

The LM test shows that there is no spatial autocorrelation left after spatial modeling, although the initial analyses have indicated significant and positive spatial autocorrelation. AIC values as goodness of fit measure are smaller than those obtained but not reported from the OLS flow models, so they indicate an improved fit.

Despite the results of initial Moran's *I* test, models in Tables 4a and 4b do not show a significant *rho*. It means that flow to a fund is not affected from flow to its peer funds. This indicates that, contrary to the expectations, individuals make their investment decisions independently and do not take into account how other investors distribute their money across funds. Therefore, the feedback mechanism expected from the spatial lag models cannot be detected in these models. These results do not indicate any herding behavior for Turkish individual investors towards specific fund managers as claimed in Del Guercio and Tkac (2002). In other words, Turkish mutual fund investors are not affected from endogenous interactions as defined in Manski (1993).

Under these conditions, these spatial lag models revert back to classical OLS models, and present results very similar to those reported in Tables 9a and 9b. The most important performance proxy that the investors take into account is the Jensen's alpha and it is negatively related to the TL flow variable. In only one model, Four-Factor excess return becomes significant and negative like Jensen's alpha measure. Consistent with the OLS results, *Size* is negatively associated with the net flow as well in these models. However, it seems that *Size* improves the number of accounts opened, since it has a positive and significant coefficient in models reported in Table 11b. Performance measured by Four-Factor excess return has no impact on this second flow definition, but coefficient of the interactive variable indicates that the incremental effect of this performance measure for best performing funds is negative.

Up to this point, the analyses show that flow and prior performance is related, but not as suggested in the literature. Furthermore, there is spatial autocorrelation in the model that cannot be explained by endogenous interactions. Then, the spatial autocorrelation may be explained by exogenous interactions. To test this hypothesis, a spatial lag of X model as shown in Eq (3) is constructed by adding a spatial lag of past performance variable to the models. These models have the ability to account for the spatial autocorrelation (Rey & Montouri, 1999), but they can be estimated by the OLS method. The results are given in Tables 12a and 12b for the two flow measures of this dissertation, respectively. Robust standard errors are estimated and given in the parentheses.

Table 12a. Spatial Lag of X Model of Flow

VARIABLES	(1)	(2)	(3)	(4)
Constant	3.626**	4.026***	3.693**	4.012***
	(1.415)	(1.554)	(1.431)	(1.516)
Spatial Lag of Perf. (Jensen's$_{t-1}$)	0.106		-0.0304	
	(0.427)		(0.415)	
Jensen's Alpha Excess Ret$_{t-1}$	-1.180**		-1.084**	
	(0.466)		(0.487)	
Spatial Lag of Perf. (4Factor$_{t-1}$)		0.900		0.751
		(0.656)		(0.655)
4 Factor ExcessRet$_{t-1}$		-1.499**		-1.406**
		(0.707)		(0.670)
Std. Dev $_{t-1}$	17.44	11.79		
	(11.80)	(11.34)		
Beta $_{t-1}$			0.399	0.276
			(0.331)	(0.240)
Flow 1$_{t-1}$	-0.0373*	-0.0381*	-0.0365*	-0.0378*
	(0.0214)	(0.0219)	(0.0209)	(0.0216)
Best-Worst $_{t-1}$	0.180	-0.110	0.140	-0.112
	(0.179)	(0.157)	(0.184)	(0.151)
Best-Worst x Jensen's	0.477*		0.416	
	(0.247)		(0.255)	
Best-Worst x 4Factor		-0.905		-0.796
		(0.785)		(0.782)
Semiannual Dummy	0.00621	-0.0208	0.0122	-0.0138
	(0.130)	(0.120)	(0.130)	(0.121)
Age $_{t-1}$	-0.00272	-0.00490	-0.00327	-0.00501
	(0.0105)	(0.0108)	(0.0104)	(0.0106)
Size $_{t-1}$	-0.216**	-0.244**	-0.221**	-0.246**
	(0.0891)	(0.0959)	(0.0890)	(0.0963)
Expense Ratio $_t$	-2.060	-1.956	-2.085	-2.000
	(1.952)	(1.789)	(1.936)	(1.816)
R-squared	0.066	0.070	0.065	0.070
Observations	554	554	554	554
t test (Jensen's + B-W x Jensen's)	-0.7027			
	(0.422)			

*** p<0.01, ** p<0.05, * p<0.1

This table shows the results of spatial lag of X model for fund flow. One period lagged performance variables are scaled by the spatial weight matrix. Fund characteristics are age, size, expense ratio and risk. Dependent variable, Flow 1, is the flow computed from the daily reports of funds to CMB. *W* is constructed by the aid of DEAs based on fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is computed as the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parentheses. The formal model can be seen below:

$$Flow_{i,t} = \beta_0 + \theta \sum_{j=1}^{n} W_{ij} Pef_{i,t-1} + \beta_1 Perf_{i,t-1} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Risk_{i,t-1} + \beta_5 Expense_{i,t}$$

$$+ \beta_6 Semiannual\_Dummy + \beta_7 Best\_Worst_{t-1} + \beta_8 Best\_Worst\ x\ Performance + \vartheta_{i,t}$$

Table 12b. Spatial Lag of X Model of Flow

VARIABLES	(1)	(2)	(3)	(4)
Constant	-141.0**	-138.9*	-165.6**	-153.7*
	(66.83)	(82.34)	(71.45)	(85.91)
Spatial Lag of Perf. (Jensen's$_{t-1}$)	-117.0***		-83.02*	
	(45.11)		(43.30)	
Jensen's Alpha Excess Ret$_{t-1}$	44.51		6.596	
	(42.79)		(30.58)	
Spatial Lag of Perf. (4Factor$_{t-1}$)		-8.631		3.855
		(70.11)		(73.56)
4 Factor ExcessRet$_{t-1}$		68.71		60.23
		(75.27)		(70.94)
Std. Dev $_{t-1}$	-2,322	-1,157		
	(1,746)	(1,305)		
Beta $_{t-1}$			18.49	-0.354
			(55.15)	(29.87)
Flow 2$_{t-1}$	-0.0491***	-0.0475***	-0.0501***	-0.0484***
	(0.0173)	(0.0172)	(0.0176)	(0.0175)
Best-Worst $_{t-1}$	4.877	-12.75	5.115	-11.07
	(16.43)	(15.48)	(19.22)	(14.97)
Best-Worst x Jensen's	-12.04		-23.41	
	(28.20)		(30.41)	
Best-Worst x 4Factor		-87.47		-84.59
		(69.59)		(72.82)
Semiannual Dummy	-6.321	-2.827	-5.186	-3.488
	(11.42)	(11.50)	(11.62)	(11.53)
Age $_{t-1}$	-1.090	-1.236	-0.976	-1.143
	(1.561)	(1.656)	(1.525)	(1.618)
Size $_{t-1}$	15.23***	13.76**	15.15**	13.96**
	(5.863)	(5.948)	(6.037)	(6.026)
Expense Ratio $_{t}$	-3.174	-2.262	-3.200	-2.457
	(2.032)	(1.971)	(2.058)	(1.913)
R-squared	0.038	0.033	0.036	0.032
Observations	554	554	554	554
t test (4 Factor + B-W x 4 Factor)		-6.2813		-23.547
		(59.588)		(55.070)

*** p<0.01, ** p<0.05, * p<0.1

The findings from the spatial lag of X model are presented in this table. The formal model can be seen below.

$$Flow_{i,t} = \beta_0 + \theta\sum_{j=1}^{n} W_{ij} Pef_{i,t-1} + \beta_1 Perf_{i,t-1} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Risk_{i,t-1} + \beta_5 Expense_{i,t}$$

$$+ \beta_6 Semiannual\_Dummy + \beta_7 Best\_Worst_{t-1} + \beta_8 Best\_Worst\ x\ Performanc\ e + \vartheta_{i,t}$$

Fund characteristics are age, size, expense ratio and risk. Dependent variables in all models, Flow 2, are the change in the number of investors in two subsequent periods. One period lagged performance variables are scaled by the spatial weight matrix. *W* is constructed by the aid of DEAs based on fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is computed as the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parentheses.

All models in Tables 12a and 12b have a higher R2 indicating a better fit. This increase in the goodness of fit is even more dramatic for models reported in Table 12b where the dependent variable is the change in number of investors of a fund.

However, findings presented in Table 12a shows that flow to a fund is not affected from the performance of funds in its peer group, because spatial lag for both performance variables has an insignificant coefficient estimate. Putting it differently, individual investors are not under the influence of exogenous effects measured by performance of neighboring funds. The only performance that investors consider is the fund's own prior performance, which has a negative impact on flows as shown in traditional flow models estimated with OLS. Taking into account the interaction terms and slope differences, one may again conclude that funds with good prior performance experience a lower outflow. This negative relation between fund flow and performance can be attributed to the length of investment horizon of Turkish investors as explained before.

As in the OLS models, a separate t-test is conducted for the sum of the coefficients on Jensen's alpha excess return and the interactive variable. Results indicate that sum of these two coefficients is not significantly different from zero. That is, for best performing funds, performance does not negatively affect the new cash flow to the funds. Instead, it loses its overall impact. Yet, the constant terms indicate that best performing funds still attract more cash inflow than worst performing ones, because they have positive and significant coefficients.

The insignificance of spatial lag of performance variable reduces the models in Table 12a to the classical OLS models. Hence, the findings in Table 12a are consistent with those reported in Table 9a. Besides the performance variables, *Size* and lagged flow are inversely related to current fund flow. In other words, small funds attract more flow, which may be explained by the ownership of large funds by banks. The negative association between lagged and current flow may be due to short investment horizon of investors and their desire to realize their net profit immediately.

The findings in Table 12b, on the other hand, paint another picture. In this table, flow is defined as the change in the number of investors of a fund. It shows that spatial lag of Jensen's alpha excess return has a negative and significant coefficient. It means that a performance increase in neighboring funds induce a decrease in the number of investors of a fund. This finding is in line with the expectations of this dissertation and tournament hypothesis. Change in number of investors is also affected from *Size* and one period lagged flow. *Size* is positively related, indicating that larger funds have more investor accounts. This may be again related with the ownership structure of larger funds as explained before. Again, it should be noted that although the change in number of investors might be proxy of flow, it may not be the same as the actual TL flow.

One period lagged flow has a negative influence on the fund flow as expected. This again can be attributed to the gain realization incentive of Turkish mutual fund investors.

Consistent with the classical OLS models, investors take into account funds' own performance measured by Four-Factor excess return while opening new accounts. However, the incremental effect of this variable for best performing funds is not significantly different from zero.

Based on the arguments of Manski (1993), one may conclude that Turkish mutual fund investors are not alike in terms of obeying the group norms, because no endogenous effect is detected. From this point of view, they act as independent decision makers. However, evidence of exogenous effects on the number of investors is documented. This means that the performance of neighboring investment options is still important for these investors in making their allocation decisions to mutual funds.

It is also possible that endogenous and exogenous effects are not separable (Elhorst, 2010; Manski, 1993). In this case, Elhorst (2010) underlines the importance of spatial Durbin modeling in order to account for the possible spatial interactions among the independent variables and the error terms. As a result, this dissertation models flow – performance relation by using spatial Durbin specification as presented in Eq (4). In this specification, both the impact of neighboring fund's flow and performance are taken into consideration. The results are presented in Tables 13a and 13b for the two flow measures of this dissertation, respectively.

Table 13a. Spatial Durbin Model of Flow

VARIABLES	(1)	(2)	(3)	(4)
Constant	6.508**	6.875**	6.444**	6.636*
	(2.33)	(2.54)	(2.37)	(2.60)
Spatial Lag of Flow (Rho)	0.398	0.371	0.391	0.352
	(0.28)	(0.28)	(0.27)	(0.29)
Spatial Lag of Perf. (Jensen's$_{t-1}$)	1.016		1.008	
	(1.05)		(1.06)	
Jensen's Alpha Excess Ret$_{t-1}$	-1.584		-1.700*	
	(0.83)		(0.83)	
Spatial Lag of Perf. (4Factor$_{t-1}$)		1.539		1.287
		(1.04)		(1.00)
4 Factor Excess Ret$_{t-1}$		-3.266*		-3.055
		(1.53)		(1.79)
Std. Dev $_{t-1}$	-9.224	-20.766		
	(25.39)	(26.80)		
Beta$_{t-1}$			0.017	-0.010
			(0.70)	(0.87)
Best-Worst $_{t-1}$	0.133	0.437	0.143	0.390
	(0.36)	(0.33)	(0.36)	(0.49)
Best-Worst x Jensen's	1.411*		1.384*	
	(0.59)		(0.66)	
Best-Worst x 4Factor		0.223		0.262
		(1.42)		(1.40)
Semiannual Dummy	0.107	0.095	0.105	0.067
	(0.27)	(0.26)	(0.26)	(0.25)
Age $_{t-1}$	-0.028	-0.035	-0.028	-0.034
	(0.02)	(0.02)	(0.02)	(0.02)
Size $_{t-1}$	-0.370*	-0.390*	-0.369*	-0.385*
	(0.15)	(0.16)	(0.14)	(0.15)
Expense Ratio $_{t}$	-2.448	-2.527	-2.489	-2.650
	(3.60)	(3.43)	(3.57)	(3.41)
AIC	1024.671	1027.171	1024.738	1027.571
Observations	599	599	599	599

*** p<0.01, ** p<0.05, * p<0.1

This table illustrates the findings from the spatial Durbin model of flow where both flow and performance variables are scaled by the spatial weight matrix. The model is given below:

$$Flow_{i,t} = \varphi_0 + \delta_1 \sum_{j=1}^{n} W_{ij} Flow_{i,t} + \delta_2 \sum_{j=1}^{n} W_{ij} Perf_{i,t} + \varphi_1 Perf_{i,t-1} + \varphi_2 Age_{i,t-1} + \varphi_3 Size_{i,t-1} + \varphi_4 Risk_{i,t-1}$$
$$+ \varphi_5 Expense_{i,t} + \varphi_6 Semiannual\_Dummy + \varphi_7 Best\_Worst_{t-1} + \varphi_8 Best\_Worst\ x\ Performanc\ e + \eta_{i,t}$$

Fund characteristics are age, size, expense ratio and risk. Dependent variable is the cash flow obtained from the daily reports to the CMB. Models include either Jensen's alpha excess returns or Four-Factor excess returns as performance variables. *W* is constructed by the aid of DEAs based on fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parentheses.

Table 13b. Spatial Durbin Model of Flow

VARIABLES	(1)	(2)	(3)	(4)
Constant	-226.424	-226.856	-250.322	-272.828
	(148.55)	(144.49)	(151.49)	(148.04)
Spatial Lag of Flow (Rho)	-0.008	-0.009	-0.009	-0.010
	(0.21)	(0.21)	(0.21)	(0.21)
Spatial Lag of Perf. (Jensen's$_{t-1}$)	-32.764		-77.681	
	(106.50)		(113.51)	
Jensen's Alpha Excess Ret$_{t-1}$	210.305		206.034*	
	(117.48)		(101.52)	
Spatial Lag of Perf. (4Factor$_{t-1}$)		66.202		54.055
		(178.55)		(178.20)
4 Factor Excess Ret$_{t-1}$		177.779		212.618
		(119.47)		(147.60)
Std. Dev $_{t-1}$	-6788.515*	-3138.389		
	(3203.34)	(3145.86)		
Beta$_{t-1}$			-193.176	-10.447
			(104.87)	(102.89)
Best-Worst $_{t-1}$	-36.741	-10.347	-20.619	-17.777
	(41.55)	(32.89)	(43.09)	(47.56)
Best-Worst x Jensen's	16.554		65.391	
	(69.28)		(83.04)	
Best-Worst x 4Factor		-92.374		-87.962
		(194.28)		(195.10)
Semiannual Dummy	-25.419	-15.139	-28.081	-15.180
	(29.81)	(37.05)	(30.41)	(37.27)
Age $_{t-1}$	-3.130	-3.344	-3.271	-3.209
	(3.00)	(2.98)	(3.03)	(3.04)
Size $_{t-1}$	24.215*	25.624*	28.265**	27.214*
	(10.00)	(10.36)	(10.93)	(10.65)
Expense Ratio $_t$	73.302	83.549	95.403	79.186
	(104.34)	(108.69)	(108.54)	(109.14)
AIC	3079.939	3081.26	3080.684	3081.987
Observations	599	599	599	599

*** p<0.01, ** p<0.05, * p<0.1

The spatial Durbin model of flow, where flow is defined as the change in the number of investors, is presented in this table. The formal model can be seen below:

$$Flow_{i,t} = \varphi_0 + \delta_1 \sum_{j=1}^{n} W_{ij} Flow_{i,t} + \delta_2 \sum_{j=1}^{n} W_{ij} Perf_{i,t} + \varphi_1 Perf_{i,t-1} + \varphi_2 Age_{i,t-1} + \varphi_3 Size_{i,t-1} + \varphi_4 Risk_{i,t-1}$$
$$+ \varphi_5 Expense_{i,t} + \varphi_6 Semiannual\_Dummy + \varphi_7 Best\_Worst_{t-1} + \varphi_8 Best\_Worst \ x \ Performance + \eta_{i,t}$$

Fund characteristics are age, size, expense ratio and risk. Models include either Jensen's alpha excess return or Four-Factor excess returns as performance variables. Both flow and performance variables are scaled by the spatial weight matrix (*W*) which is generated by the aid of DEAs based on fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parentheses.

To provide a comparison with other models, AIC values for all models are presented in Tables 6a and 6b. Although lower values of AIC, which indicate a better fit, are obtained for all spatial Durbin models, none of the coefficients for spatial lags in models reported in these tables are different from zero. That is, the spatial Durbin models employed in this dissertation reverts back to the classical OLS models. The coefficients and signs of other independent variables verify this inference, since they have almost the same size and sign with the OLS models displayed in Tables 9a and 9b, respectively. The only difference between classical OLS models and those reported in Tables 13a and 13b is the significant coefficient on Four-Factor excess return in one of the models. Consistent with previous findings, this coefficient also indicates a negative impact of fund performance on new cash flows to funds.

To summarize, investors of Turkish mutual funds decide independently from exogenous and endogenous effects. They do not consider either the impact of neighboring funds' performance or how the other investors allocate their money. Accordingly, one may conclude that Turkish mutual fund investors are rational in terms of maximizing their own utility when allocating their capital across mutual funds. Therefore, not considering social effects, as pointed out by Akerlof (1997), is not a costly mistake for studies analyzing the behavior of Turkish mutual fund investors as rational agents.

Since the spatial lags are not significant in fund flow modeling, OLS will continue to be the best specification. Only evidence for a significant spatial lag comes from the spatial lag of X models when the fund flow is proxied by the change in the numbers of investor. Performances of neighboring funds affect the change in number of investors negatively but do not have any effect on the TL flow. A fund's flow and its past performance are inversely related. By including the interactive variable in the models, one can observe that funds with better performance experience less cash outflow. *Age* is not a determinant of fund flow. Although smaller funds have higher TL flows, large funds have more investors. Last but not least, individuals do not consider either the total or systematic risk of a fund's portfolio when they are choosing among alternative funds.

4.4. Risk Models

The determinants of mutual fund flow is important for the stability of the fund market, because flow affects fund managers' decisions as well as asset prices (Zheng, 2008). Therefore, it is possible to conclude that the well-functioning of the mutual fund market does not only depend on the decisions of the fund managers, but also that of fund investors. Based on this reasoning, the first part of the analysis conducted in this dissertation investigates which characteristics of mutual funds and their peers, investors take into account while allocating their money among funds.

Literature indicates that individuals do not withdraw as much from the loser funds as they invest into the winner funds. This convex relation is the main motivation for the fund managers to alter the risk of their portfolios. Contrary to the fund flow – performance literature, the flow analyses of this dissertation show that Turkish mutual fund investors do not chase performance when allocating their money across funds. There is a continuous trend of withdrawals from the mutual funds during the analysis period of this dissertation. However, the interaction term indicates that funds with better performance experience lower withdrawals than those with worse performance. This may constitute an incentive for Turkish fund managers to increase the risk of their portfolios in order to be among funds with better performance. In addition, Koski and Pontiff (1999) indicate that fund managers may not be willing to change the risk structure immediately when new cash flow comes to fund due to market timing strategies. Hence, the next parts of this dissertation focus on fund managers and how they react to fund flows and change the risk – return structure of a fund.

Tables 14a and 14b illustrate the determinants of risk changes for the two different risk definitions used in this dissertation. Table 14a represents the determinants of risk change decision of fund managers when the risk is defined as the semiannual standard deviation of daily returns. On the other hand, the dependent variable of Table 14b is the change in the betas from first half of the year to the second. These betas are computed from the regressions using monthly data as explained in the methodology section. Similar to the flow models, the regression assumptions are checked first. To account for the heteroskedasticity, White standard errors are computed and reported in the parentheses. Variance inflation factor shows no multi-collinearity. Furthermore, residuals of the models are normally distributed. Regressions reported in both Tables 14a and 14b are run by using data only from the second half of the year. That is, I investigate whether a fund changes its risk in the second half of the year depending on its characteristics in the first half of the year.

Table 14a. Risk Change Models

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	5.84e-05	0.000538	-0.000107	0.000438
	(0.00168)	(0.00214)	(0.00168)	(0.00218)
Std. Dev $_{t-1}$	-0.418***	-0.103	-0.423***	-0.130
	(0.148)	(0.124)	(0.148)	(0.125)
Jensen's Alpha Excess Ret$_{t-1}$	0.0163***		0.0156***	
	(0.00306)		(0.00302)	
4 Factor Excess Ret$_{t-1}$		0.0169***		0.0163***
		(0.00456)		(0.00452)
Best-Worst $_{t-1}$	-0.00240***	-0.00254***	-0.00239***	-0.00247***
	(0.000645)	(0.000752)	(0.000651)	(0.000733)
Best-Worst x Jensen's	0.00164		0.00168	
	(0.00122)		(0.00125)	
Best-Worst x 4Factor		0.00649*		0.00693**
		(0.00351)		(0.00349)
Flow 1$_{t-1}$	0.000141	-2.68e-05		
	(0.000160)	(0.000179)		
Flow 2$_{t-1}$			-5.74e-07	-6.47e-07
			(1.25e-06)	(1.73e-06)
Age $_{t-1}$	-2.77e-05	-3.70e-05	-2.94e-05	-4.26e-05
	(6.35e-05)	(6.80e-05)	(6.33e-05)	(6.79e-05)
Size $_{t-1}$	-5.01e-05	0.000140	-1.72e-05	0.000161
	(0.000122)	(0.000122)	(0.000121)	(0.000119)
Expense Ratio $_t$	-0.00500**	-0.00439*	-0.00511**	-0.00422*
	(0.00229)	(0.00250)	(0.00222)	(0.00245)
R-squared	0.291	0.155	0.287	0.165
Observations	309	309	305	305

***p<0.01, ** p<0.05, * p<0.1

Table 14a. Risk Change Models

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.00207	-0.00254	-0.00224	-0.00265
	(0.00190)	(0.00181)	(0.00189)	(0.00180)
Beta $_{t-1}$	-0.00482***	0.00343***	-0.00477***	0.00293**
	(0.00185)	(0.00130)	(0.00182)	(0.00128)
Jensen's Alpha Excess Ret$_{t-1}$	0.0147***		0.0142***	
	(0.00219)		(0.00221)	
4 Factor Excess Ret$_{t-1}$		0.0163***		0.0157***
		(0.00429)		(0.00425)
Best-Worst $_{t-1}$	-0.00212***	-0.00216***	-0.00210***	-0.00212***
	(0.000697)	(0.000694)	(0.000702)	(0.000677)
Best-Worst x Jensen's	0.00151		0.00140	
	(0.00162)		(0.00168)	
Best-Worst x 4Factor		0.00848***		0.00890***
		(0.00290)		(0.00287)
Flow 1$_{t-1}$	2.05e-05	-4.26e-05		
	(0.000184)	(0.000196)		
Flow 2$_{t-1}$			-1.21e-06	-7.45e-07
			(1.58e-06)	(1.75e-06)
Age $_{t-1}$	4.24e-06	-2.26e-05	1.42e-06	-2.64e-05
	(5.96e-05)	(6.14e-05)	(5.97e-05)	(6.17e-05)
Size $_{t-1}$	6.51e-06	0.000135	3.33e-05	0.000157
	(0.000132)	(0.000128)	(0.000130)	(0.000124)
Expense Ratio $_t$	-0.00567**	-0.00638**	-0.00566**	-0.00615**
	(0.00274)	(0.00266)	(0.00266)	(0.00258)
R-squared	0.215	0.166	0.205	0.166
Observations	309	309	305	305

***p<0.01, ** p<0.05, * p<0.1

This table illustrates the findings from the risk models that associate the risk change decisions of fund managers to the fund characteristics, such as flow, performance, age, size, risk, and expense ratio. The formal model is as follows:

$$\Delta RISK_{i,t} = a_0 + a_1 Risk_{i,t-1} + a_2 Age_{i,t-1} + a_3 Size_{i,t-1} + a_4 Expense_{i,t}$$

$$+ a_5 Perf_{i,t-1} + a_6 Flow_{i,t-1} + a_7 Best\_Worst_{t-1} + a_8 Best\_Worst\ x\ Performanc\ e + u_{i,t}$$

Here, the dependent variable is the change in the semiannual standard deviation of daily returns. Models presented in Panel A and Panel B of this table only differ by the lagged risk proxies, namely standard deviation or beta, used as a control variable. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns. Robust standard errors are reported in parenthesis.

The models in the Table 14a explain the semiannual change in the standard deviation of daily returns from the first to the second part of the year. Findings from this table show that funds' performance in the first semiannual, measured by both the Jensen's alpha excess returns and Four-Factor excess returns, is positively and significantly related to the risk alteration behavior of managers. In other words, good past performance in the first interim causes an increase in the fund risk in the second half of the year. This is in fact contrary to the existing risk change – performance association in the literature. For instance, Koski and Pontiff (1999) find a negative coefficient on past performance when the dependent variable is the change in portfolio risk as measure by either standard deviation or beta indicating a tendency to increase risk for loser funds. Therefore, the evidence from the Turkish mutual fund industry does not support the tournament behavior for fund managers.

Nevertheless, there is a significant difference between the best performing and worst performing funds' risk altering behavior since the dummy variable, namely *Best-Worst*, is always significant in all of the models in Table 14a. This variable has a negative coefficient which indicates a lower constant term for best performing funds. Putting it differently, when there is no other impact, best performing funds have a tendency to decrease the total risk of their portfolios. The worst performing ones, however, do not have a statistically significant intercept, meaning that these funds do not change their risk level from the first to the second half of the year, all else being equal. The interaction terms for both performance definitions are mostly significant and positive. Here, one should pay special attention to the direction of the coefficients. In none of the models reported in Panels A and B of Table 14a, the coefficients of performance and interactive variables (*Best-Worst x Performance)* have contradictory sign. They always have positive coefficients, when they are significant. This situation creates an incremental increase in the slope of the performance variable for the best funds. In other words, the relation between past performance and risk change decision is stronger for best funds, since the coefficient of performance variable is higher for these funds. When a fund exhibits good performance in the first half of the year, managers of best performers are willing to increase the change in portfolio risk more than the managers of worst performers. These findings are inconsistent with the predictions of the tournament hypothesis.

Following the methodology of Brown et al. (1996), Öztürkkal and Erdem (2012) report tournament like behavior for Turkish mutual funds. . However, they do not benefit from a regression analysis, and only compare the standard deviation ratios as noted in Brown et al. (1996). Moreover, they look at only the equity portion of all type-A funds' portfolios. This approach has been criticized before in this dissertation based on the potential biases created by their sampling method. This dissertation, on the other hand, finds no evidence of tournament behavior for the Turkish mutual fund market so far. In fact, results of this dissertation are consistent with the contrary arguments put forth by Busse (2001).

Busse (2001) cannot show any evidence of tournament behavior by using daily data. Actually, he demonstrates that above median funds may take higher total risk than below median ones. Taylor (2003) rationalizes this behavior as such: winners and losers decide to gamble with respect to each other's positions. Therefore, the manager of a winner fund decides to gamble with a certain probability when she expects a gambling behavior from the manager of a loser fund as well. This might explain higher risk taking by Turkish mutual fund managers with increasing performance. Kempf and Ruenzi (2008) also state that in declining markets, unlike managers of winner funds, loser fund managers are not willing to increase the risk level due to career concerns. Considering the constant outflow from the Turkish Type-A mutual fund market in the analyzed period, it is natural to observe such unwillingness for loser funds.

The interaction between loser and winner funds, and their relative positions, are taken into account from a different angle in Li and Tiwari (2006). They note that regression analyses with monthly data indicate a tournament like behavior for the US aggressive growth, long term growth and growth and income mutual funds for the years between 1962 and 2004. Worst funds increase their idiosyncratic risk, whereas the coefficient of the past performance variable is negative in the risk equation for the best funds. They explain this behavior by the performance gap between the leader fund and its followers. The risk taking behavior is observed only when the follower funds are not too far away from the leader so that they have an expectation of catching up with the leader and being ranked among the best funds. The contradictory findings from the Turkish mutual fund market may also be the result of this performance gap mentioned in the study of Li and Tiwari (2006).

The inferences made by Li and Tiwari (2006) and the implications of Taylor (2003) model, once more, highlight the need for spatial analysis which considers the distance between funds in the mutual fund industry. In fact, the "performance gap" concept, discussed in Li and Tiwari (2006), is taken into account in the spatial weight construction of this dissertation. The spatial analyses are conducted in the next section. However, first, the risk alteration behavior of best and worst funds that is depicted in the Table 14a should be examined thoroughly. This behavior is also illustrated in Figure 5.

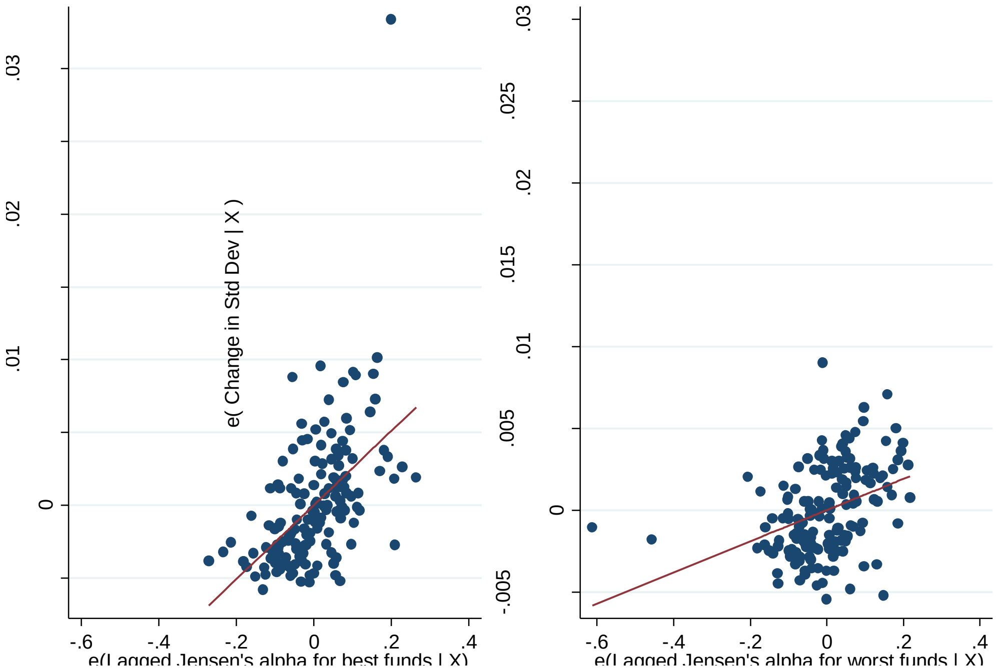


Figure 5. Added variable plots for Jensen's alpha excess returns are shown in figure 4. The first graph demonstrates the change in risk based on the one period lagged performance conditional on the control variables when the *Best-Worst* dummy is 0. The second one illustrates the same relation when the *Best-Worst* dummy is 1.

Table 14a also shows that as the expense ratio, that is the cost of operating a fund, increases, the tendency to enhance the fund's total risk change decreases.

Koski and Pontiff (1999) expect a mean reversion in risk changing behavior of mutual funds and include a lagged risk variable in their models. To capture this behavior, our risk models contain either one period lagged semiannual standard deviation (Panel A) or beta (Panel B). Panels A and B of Table 14a show often significant and negative coefficients for lagged standard deviation and beta. Fund managers seem to decrease the change in the total risk of their portfolios in the next period when the total risk or the systematic risk of their portfolios has already been high in the first half of the year. In other words, a mean reversion process in risk changes is seen for Turkish mutual funds.

From the results reported in Table 14a, it is clear that fund managers' decision for the alteration of total risk is not affected from either *Age* or *Size* of the fund. In fact, both Chevalier and Ellison (1997) and Huang et al. (2011) point out that younger funds are more open to risk alterations in comparison to older ones. This dissertation cannot provide such evidence, however. Last but not least, managers do not consider the flow, defined in either ways, in the first half of the year when deciding to change their portfolio's total risk.

Up to this point, the effects of past performance and other control variables on the managers' total risk change decision are discussed. Table 14b, presented below, however, shows the determinants of managers' systematic risk, i.e. beta, change decisions.

Table 14b. Risk Change Models

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.0740***	-0.0730***	-0.0760***	-0.0753***
	(0.0230)	(0.0240)	(0.0229)	(0.0240)
Std. Dev $_{t-1}$	7.510***	5.066***	7.512***	5.195***
	(0.980)	(0.812)	(0.982)	(0.824)
Jensen's Alpha Excess Ret$_{t-1}$	-0.0940***		-0.0918***	
	(0.0171)		(0.0172)	
4 Factor Excess Ret$_{t-1}$		-0.0172		-0.0165
		(0.0534)		(0.0536)
Best-Worst $_{t-1}$	0.0209***	0.0191***	0.0206***	0.0185***
	(0.00499)	(0.00616)	(0.00500)	(0.00611)
Best-Worst x Jensen's	-0.00711		-0.00746	
	(0.00976)		(0.00981)	
Best-Worst x 4Factor		-0.00266		-0.00238
		(0.0514)		(0.0515)
Flow 1$_{t-1}$	9.22e-05	0.000970		
	(0.00259)	(0.00217)		
Flow 2$_{t-1}$			-2.93e-06	-2.72e-06
			(2.30e-05)	(2.54e-05)
Age $_{t-1}$	0.000440	0.000392	0.000546	0.000532
	(0.000507)	(0.000534)	(0.000501)	(0.000523)
Size $_{t-1}$	0.00238*	0.00165	0.00238*	0.00167
	(0.00130)	(0.00134)	(0.00129)	(0.00133)
Expense Ratio $_{t}$	-0.00929	-0.0166	-0.00484	-0.0130
	(0.0187)	(0.0199)	(0.0184)	(0.0195)
R-squared	0.270	0.193	0.269	0.196
Observations	309	309	305	305
t test (Constant + B-W)	-0.0565**	-0.0580**	-0.0597***	-0.0616***
	(.0221)	(0.023)	(0.022)	(0.023)

***p<0.01, ** p<0.05, * p<0.1

Table 14b. Risk Change Models

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.00566	-0.00302	-0.00859	-0.00584
	(0.0235)	(0.0236)	(0.0231)	(0.0234)
Beta $_{t-1}$	-0.00557	-0.0150	-0.00520	-0.0136
	(0.0251)	(0.0150)	(0.0251)	(0.0152)
Jensen's Alpha Excess Ret$_{t-1}$	-0.00250		-0.00166	
	(0.0294)		(0.0299)	
4 Factor Excess Ret$_{t-1}$		0.0249		0.0236
		(0.0602)		(0.0606)
Best-Worst $_{t-1}$	0.0103*	0.00871	0.00878	0.00746
	(0.00565)	(0.00659)	(0.00555)	(0.00651)
Best-Worst x Jensen's	-0.0199*		-0.0182*	
	(0.0105)		(0.0106)	
Best-Worst x 4Factor		-0.114***		-0.110***
		(0.0385)		(0.0385)
Flow 1$_{t-1}$	0.00206	0.00217		
	(0.00270)	(0.00264)		
Flow 2$_{t-1}$			4.73e-06	3.36e-06
			(2.89e-05)	(2.89e-05)
Age $_{t-1}$	-0.000162	-8.25e-05	-3.44e-05	5.54e-05
	(0.000514)	(0.000525)	(0.000510)	(0.000518)
Size $_{t-1}$	0.00122	0.00134	0.00132	0.00142
	(0.00147)	(0.00147)	(0.00143)	(0.00144)
Expense Ratio $_t$	0.0194	0.0223	0.0212	0.0240
	(0.0240)	(0.0233)	(0.0234)	(0.0225)
R-squared	0.028	0.046	0.021	0.039
Observations	309	309	305	305

***p<0.01, ** p<0.05, * p<0.1

The determinants of the risk change decision of managers are modeled in this table as follows:

$$\Delta RISK_{i,t} = a_0 + a_1 Risk_{i,t-1} + a_2 Age_{i,t-1} + a_3 Size_{i,t-1} + a_4 Expense_{i,t} + a_5 Perf_{i,t-1}$$
$$+ a_6 Flow_{i,t-1} + a_7 Best\_Worst_{t-1} + a_8 Best\_Worst\ x\ Performance + u_{i,t}$$

Fund characteristics, namely flow, performance, age, size, risk, and expense ratio, are explanatory variables, whereas the dependent variable is the semiannual change in a fund's betas. The difference between Panel A and Panel B is the lagged risk proxies used among the explanatory variables. One period lagged risk is defined as standard deviation of daily returns in Panel A and as beta in Panel B. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns.

Similar to the flow models shown in Tables 9a and 9b, fund managers only take into account one period lagged Jensen's alpha excess return as the performance proxy while altering the systematic risk of their portfolios. Four-Factor excess returns do not have a significant coefficient in any of the models reported in Panels A and B of Table 14b. Contrary to the evidence presented in Table 14a for total risk change decisions, past performance and change in systematic risk are negatively related indicating that as the performance of a fund enhances, managers are decreasing the systematic risk of their portfolios. In line with Koski and Pontiff (1999), this finding can be considered as supporting evidence for tournament hypothesis. In all of the models reported in Panels A and B of Table 14b, the constant term for the best and the worst performing funds are different. All funds exhibit a negative change in their betas from the first half to the second half of the year. However, best funds consistently have less negative intercept terms, meaning that all things being equal, best funds begin with a smaller decline in their systematic risk. Here, special attention is paid to the significance of constant terms for the best funds, because the coefficient of *Best-Worst* dummy variable in all models is consistently positive, while constant terms of these models are negative. Separate t tests on the sum of the coefficients for the *Best-Worst* dummy variable and the constant term in the models reported in Panel A of Table 14bare conducted. For all models, these t statistics are significant and the overall constant terms are negative. As a result, the earlier conclusion, indicating a smaller decline in the best funds' systematic risk, has not been changed.

Interactive variables in Table 14b, indicating the gradual impact of performance for above median funds, usually have significant and negative coefficients. In other words, beta change decisions of best performing funds are inversely affected from their past performance over and above the effect coming from them being better than a median fund. This is in line with predictions of the tournament behavior. However, performance variables mostly do not have a significant effect on the systematic risk change decisions of mutual fund managers. In only two out of the eight models of systematic risk change, performance variables have negative and statistically significant coefficients supporting the tournament behavior. Only the results reported in Table 14b, but not the ones in Table 14a, provide a weak support for tournament behavior. Therefore, overall evidence supporting the tournament behavior is not very strong for the Turkish market.

To investigate the effect of fund characteristics on the risk change decisions, one may look at *Age*, *Size* and *Expense Ratio*. Table 14b mostly displays a positive effect of *Size* positively on the systematic risk change decisions of managers. In other words, older funds decrease the systematic risk of their portfolios by a smaller amount. Ferreira et al. (2012b) indicate that older and larger funds usually draw less flow from investors. Although *Age* is not a determinant of Turkish investor flows, *Size* has shown to be negatively related to fund flows as well in this market. Hence, the reluctance of larger funds to decrease the systematic portfolio risk may be explained by the desire of these funds to attract more investor flow. *Age* and *Expense Ratio* are not significant in any of these models.

It is also interesting to note that one period lagged standard deviation has a positive coefficient, while one period lagged beta does not have a significant coefficient in model presented in Table 14b. Putting it differently, fund managers only consider the total risk in the first semiannual, while deciding on how much to change the systematic risk of their portfolios in the second half of the year. The first period change in beta, on the other hand, has no impact on this decision.

Last but not least, Table 14b shows that managers of funds that have a higher expense ratio are not likely to alter the portfolio's systematic risk. This is different than results reported in Table 14a. However, in line with the previous risk models, individual flows are not influential on the systematic risk change decision of fund managers.

4.5. Spatial Risk Models

Literature suggests that fund managers have to compete with each other to attract more cash flow and this competition cause in a convex relation between performance and flow (Brown et al., 1996; Chevalier & Ellison, 1997; Sirri & Tufano, 1998). Kempf and Ruenzi (2008) indicate that such a competition even exists inside mutual fund families. All of these papers argue that relative position of a fund among other mutual funds inside or outside a family influences fund managers' decisions.

The previous section of this dissertation examines the risk change decision in the Turkish mutual fund industry. Results indicate that fund performance and risk in the first half of the year are the two most important factors affecting the risk alteration decision of managers in the second half the year. Based on the discussion above, this section takes into account the impact of performance of neighboring funds on the managers' risk change decisions. The impact of neighboring funds is included in the analysis by the aid of a spatial lag of X model as shown in Eq (6). As it is the case in all of the spatial models above, this analysis also employs a spatial weight matrix generated by data envelopment analyses. The same W matrix is used for all the spatial risk and spatial flow models. Findings are reported in Tables 15a and 15b, respectively for the two risk measures analyzed in this dissertation. Table 15a investigates the determinants of the change in the semiannual standard deviation of daily returns, while Table 15b examines the change in the betas. The regressions are run by using the data from the second half of the year in order to see how funds change their risk structure at the end of the year. Robust standard errors are estimated. No multi-collinearity problem is detected. Residuals of these regressions are normally distributed.

Table 15a. Spatial Lag of X Model of Risk Change

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.000591	0.00444*	-0.000641	0.00485**
	(0.00186)	(0.00234)	(0.00183)	(0.00242)
Std. Dev $_{t-1}$	-0.407***	-0.131	-0.414***	-0.163
	(0.150)	(0.113)	(0.150)	(0.113)
Jensen's Alpha Excess Ret$_{t-1}$	0.0156***		0.0150***	
	(0.00312)		(0.00309)	
Spatial Lag (Jensen's$_{t-1}$)	0.00376*		0.00326	
	(0.00223)		(0.00218)	
4 Factor ExcessRet$_{t-1}$		0.00710**		0.00646**
		(0.00301)		(0.00297)
Spatial Lag (4Factor$_{t-1}$)		0.0201***		0.0200***
		(0.00359)		(0.00356)
Best-Worst $_{t-1}$	-0.00222***	-0.00151***	-0.00224***	-0.00140**
	(0.000670)	(0.000576)	(0.000672)	(0.000558)
Best-Worst x Jensen's	0.00150		0.00157	
	(0.00120)		(0.00123)	
Best-Worst x 4Factor		-0.00173		-0.00103
		(0.00449)		(0.00444)
Flow 1$_{t-1}$	0.000117	-0.000134		
	(0.000172)	(0.000198)		
Flow 2$_{t-1}$			-5.39e-07	4.50e-07
			(1.30e-06)	(1.52e-06)
Age $_{t-1}$	-2.65e-05	-8.43e-05	-2.81e-05	-9.31e-05
	(6.34e-05)	(6.59e-05)	(6.33e-05)	(6.64e-05)
Size $_{t-1}$	-6.20e-05	-7.81e-05	-3.03e-05	-9.09e-05
	(0.000127)	(0.000113)	(0.000127)	(0.000110)
Expense Ratio $_t$	-0.00463**	-0.00270	-0.00476**	-0.00266
	(0.00229)	(0.00239)	(0.00222)	(0.00219)
R-squared	0.296	0.300	0.290	0.313
Observations	304	304	300	300
t test (Constant + B-W)		0.003		0.0034
		(0.0021)		(0.0022)

***p<0.01, ** p<0.05, * p<0.1

Table 15a. Spatial Lag of X Model of Risk Change

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.00291	0.00131	-0.00294	0.00159
	(0.00209)	(0.00189)	(0.00204)	(0.00193)
Beta $_{t-1}$	-0.00409**	0.00282**	-0.00415**	0.00237**
	(0.00190)	(0.00119)	(0.00188)	(0.00117)
Jensen's Alpha Excess Ret$_{t-1}$	0.0139***		0.0135***	
	(0.00221)		(0.00225)	
Spatial Lag (Jensen's$_{t-1}$)	0.00435*		0.00376	
	(0.00238)		(0.00234)	
4 Factor ExcessRet$_{t-1}$		0.00672**		0.00605**
		(0.00295)		(0.00289)
Spatial Lag (4Factor$_{t-1}$)		0.0194***		0.0192***
		(0.00357)		(0.00350)
Best-Worst $_{t-1}$	-0.00199***	-0.00119**	-0.00200***	-0.00110**
	(0.000720)	(0.000546)	(0.000722)	(0.000530)
Best-Worst x Jensen's	0.00115		0.00109	
	(0.00165)		(0.00171)	
Best-Worst x 4Factor		0.000565		0.00131
		(0.00383)		(0.00375)
Flow 1$_{t-1}$	-2.57e-06	-0.000152		
	(0.000193)	(0.000223)		
Flow 2$_{t-1}$			-1.15e-06	2.61e-07
			(1.62e-06)	(1.53e-06)
Age $_{t-1}$	2.90e-06	-6.63e-05	3.09e-07	-7.29e-05
	(6.00e-05)	(6.02e-05)	(6.03e-05)	(6.11e-05)
Size $_{t-1}$	-1.13e-05	-7.71e-05	1.46e-05	-8.67e-05
	(0.000137)	(0.000120)	(0.000135)	(0.000116)
Expense Ratio $_{t}$	-0.00512*	-0.00480*	-0.00513**	-0.00471**
	(0.00265)	(0.00249)	(0.00257)	(0.00233)
R-squared	0.221	0.300	0.209	0.303
Observations	304	304	300	300

***p<0.01, ** p<0.05, * p<0.1

The findings from the spatial lag of X model are presented in Panel A and Panel B of this table. The model specification is shown below:

$$\Delta RISK_{i,t} = \psi_0 + \psi_1 Risk_{i,t-1} + \psi_2 Age_{i,t-1} + \psi_3 Size_{i,t-1} + \psi_4 Expense_{i,t} + \psi_5 Perf_{i,t-1}$$

$$+ \tau \sum_{j=1}^{n} W_{ij} Perf_{i,t-1} + \psi_6 Flow_{i,t-1} + \psi_7 Best\_Worst_{t-1} + \psi_8 Best-Worst\ x\ Performanc\ e \quad + \upsilon_{i,t}$$

Dependent variable is defined as the change in the semiannual standard deviation of daily returns. Fund characteristics are flow, performance, age, size, risk, and expense ratio. Fund performance is scaled by a spatial weight matrix (*W*) which is obtained from DEAs based on fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is the multiplicative inverse of fund *i*'s inefficiency value. Models in Panel A and Panel B differ by lagged risk proxies, namely standard deviation and beta, used. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns. Robust standard errors are presented in parenthesis.

Table 15b. Spatial Lag of X Model of Risk Change

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.0838***	-0.0798***	-0.0860***	-0.0828***
	(0.0252)	(0.0276)	(0.0250)	(0.0281)
Std. Dev $_{t-1}$	7.739***	5.114***	7.743***	5.248***
	(1.009)	(0.817)	(1.012)	(0.832)
Jensen's Alpha Excess Ret$_{t-1}$	-0.103***		-0.101***	
	(0.0182)		(0.0184)	
Spatial Lag (Jensen's$_{t-1}$)	0.0437		0.0463*	
	(0.0272)		(0.0274)	
4 Factor ExcessRet$_{t-1}$		0.00875		0.00892
		(0.0631)		(0.0637)
Spatial Lag (4Factor$_{t-1}$)		-0.0215		-0.0206
		(0.0375)		(0.0381)
Best-Worst $_{t-1}$	0.0186***	0.0136**	0.0174***	0.0122*
	(0.00531)	(0.00666)	(0.00528)	(0.00666)
Best-Worst x Jensen's	-0.00609		-0.00412	
	(0.0102)		(0.0102)	
Best-Worst x 4Factor		-0.0600		-0.0590
		(0.0380)		(0.0378)
Flow 1$_{t-1}$	-4.70e-05	0.00109		
	(0.00252)	(0.00217)		
Flow 2$_{t-1}$			-2.01e-06	-3.98e-06
			(2.22e-05)	(2.53e-05)
Age $_{t-1}$	0.000391	0.000431	0.000500	0.000575
	(0.000504)	(0.000575)	(0.000496)	(0.000570)
Size $_{t-1}$	0.00235*	0.00204	0.00231*	0.00211
	(0.00139)	(0.00152)	(0.00138)	(0.00153)
Expense Ratio $_{t}$	0.00399	-0.0142	0.00896	-0.0101
	(0.0218)	(0.0206)	(0.0229)	(0.0203)
R-squared	0.279	0.196	0.279	0.199
Observations	304	304	300	300
t test (Constant + B-W)	-0.0652***	-0.0662**	-0.0686***	-0.070**
	(0.0244)	(0.028)	(0.024)	(0.028)

***p<0.01, ** p<0.05, * p<0.1

Table 15b. Spatial Lag of X Model of Risk Change

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.00868	-0.00777	-0.0129	-0.0106
	(0.0267)	(0.0272)	(0.0261)	(0.0274)
Beta $_{t-1}$	-0.00383	-0.0151	-0.00273	-0.0139
	(0.0280)	(0.0155)	(0.0280)	(0.0156)
Jensen's Alpha Excess Ret$_{t-1}$	-0.00495		-0.00505	
	(0.0336)		(0.0342)	
Spatial Lag (Jensen's$_{t-1}$)	0.00617		0.00990	
	(0.0300)		(0.0304)	
4 Factor ExcessRet$_{t-1}$		0.0292		0.0266
		(0.0739)		(0.0748)
Spatial Lag (4Factor$_{t-1}$)		-0.00649		-0.00301
		(0.0407)		(0.0409)
Best-Worst $_{t-1}$	0.0104*	0.00795	0.00908	0.00680
	(0.00609)	(0.00729)	(0.00601)	(0.00728)
Best-Worst x Jensen's	-0.0200*		-0.0184*	
	(0.0107)		(0.0108)	
Best-Worst x 4Factor		-0.114***		-0.112***
		(0.0384)		(0.0379)
Flow 1$_{t-1}$	0.00209	0.00220		
	(0.00273)	(0.00272)		
Flow 2$_{t-1}$			4.97e-06	3.02e-06
			(2.88e-05)	(2.89e-05)
Age $_{t-1}$	-0.000176	-7.82e-05	-4.56e-05	5.52e-05
	(0.000520)	(0.000567)	(0.000516)	(0.000565)
Size $_{t-1}$	0.00130	0.00164	0.00142	0.00174
	(0.00157)	(0.00165)	(0.00153)	(0.00165)
Expense Ratio $_{t}$	0.0233	0.0270	0.0260	0.0296
	(0.0252)	(0.0235)	(0.0250)	(0.0232)
R-squared	0.029	0.047	0.022	0.040
Observations	304	304	300	300

***p<0.01, ** p<0.05, * p<0.1

The findings from the spatial lag of X model are presented in Panel A and Panel B of this table. The model specification is shown below:

$$\Delta RISK_{i,t} = \psi_0 + \psi_1 Risk_{i,t-1} + \psi_2 Age_{i,t-1} + \psi_3 Size_{i,t-1} + \psi_4 Expense_{i,t} + \psi_5 Perf_{i,t-1}$$

$$+ \tau \sum_{j=1}^{n} W_{ij} Perf_{i,t-1} + \psi_6 Flow_{i,t-1} + \psi_7 Best\_Worst_{t-1} + \psi_8 Best-Worst\ x\ Performanc\ e \quad + \upsilon_{i,t}$$

Dependent variable is defined as the change in a fund's betas. Fund characteristics are flow, performance, age, size, risk, and expense ratio. Fund performance is scaled by a spatial weight matrix (*W*) which is obtained from DEAs based on fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is the multiplicative inverse of fund *i*'s inefficiency value. Models in Panel A and Panel B differ by the lagged risk proxies, namely standard deviation and beta, used. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns. Robust standard errors are presented in parenthesis.

First of all, comparisons of R^2 values exhibit a better goodness of fit for most of the spatial lag of X models than classical OLS models shown in Tables 14a and 14b. This statistic shows that the spatial models are more successful in explaining the variation in the risk change decision of managers. Similarly, findings from Table 15a show that the spatial lag of each performance variable significantly and positively affects the change in standard deviation decision of managers. It indicates that mutual fund managers pay attention to the performance of their rivals when they make the total risk change decision for their portfolios. It seems that fund managers are more likely to increase their portfolio's total risk when their neighboring funds, i.e. their peer group, have better performance. This increase in the total risk of their portfolio can be explained by their desire to enhance their performance levels and to be among winners to attract more flows to their funds. From the classical flow regressions reported in Tables 9a and 9b, it is clear that fund flows are usually not affected from risk taken by managers. Therefore, such a change in the portfolio risk does not negatively impact flows directly, but it may increase it indirectly by resulting in a better performance.

Apart from the spatial lags, performance variables, namely Jensen's alpha excess returns and Four-Factor excess returns, consistently exhibit a positive impact on change in the semiannual standard deviations. This finding is in stark contrast with the tournament behavior. Funds inside the tournament are more likely to have negative prior performance coefficients as noted in Koski and Pontiff (1999). In fact, this result from Table 15a is in line with previous OLS analysis for risk change behavior shown in Table 14a. The OLS analysis presented in Table 14a also suggest that although best performing funds initially have lower change in their risk, other things are being equal, they tend to increase their risk more as their performance gets higher.

Consistently, spatial modeling in Table 15a points out that in all specifications, *Best-Worst* dummy is negative and interactive variables are insignificant. This finding indicates that worst funds have a higher intercept than best ones. This finding is also verified by separate t tests. These tests are conducted when coefficient *Best-Worst* dummy and the constant term have opposite signs. These tests cannot reject the null hypothesis; that is the sum of these two coefficients is equal to zero for best performing funds. As a result, worst performing funds will have a higher risk than best performing funds when all other things being equal because best performing funds decrease their risk more than worst performing ones. This attitude may be seen as evidence for tournament behavior.

Yet, Cullen et al. (2012) note that mutual fund managers may change the portfolio risk for several reasons other than involving in a tournament behavior, for instance, for portfolio rebalancing and altering industry weights. They specifically question whether portfolio risk alterations are intentional or a result of mean reversion in risk of mutual funds. To distinguish these two effects from one another, they examine the mutual fund portfolios on a fund by fund basis, and then determine the impact of each stock on the overall portfolio risk. Their results show that involving in a mutual fund tournament is a less common behavior than it is assumed in previous studies such as Brown et al. (1996). Furthermore, they show that the mean reversion in risks of mutual funds may cause spurious tournament like associations between risk alterations and previous performance. Examining findings reported in Table 15a thoroughly reveals that funds usually decrease the change in their portfolio risk when the previous period's total or systematic risk is high. Koski and Pontiff (1999) and Kempf and Ruenzi (2008) note that this is an indication of mean reversion in fund risk, when managers' risk alteration decision is strongly affected from exogenous factors. As mentioned before, spatial lag of X model includes the exogenous interactions as defined by Manski (1993). The findings from Panels A and B of Table 15a consistently show significant spatial lags, i.e. exogenous interactions. Then, it is natural to find evidence supporting mean reversion behavior for Turkish mutual funds. Since the exact portfolio holdings of these funds are not known, one cannot conclude whether the worst portfolios' tendency to have ahigher risk is a result of tournament behavior or a spurious finding due to mean reversion as shown by Cullen et al. (2012). Hence, evidence supporting tournament behavior for Turkish mutual fund industry is weak or inconclusive.

Since spatial modeling takes the exogenous interactions into account which are not been considered in the OLS models, the results reported in Table 15a may more accurately show the relation between risk change and fund performance. All in all, it can be said that the risk change decisions of the Turkish fund managers display a weak evidence of tournament like behavior.

In line with risk change regressions estimated by OLS, *Expense Ratio* has a negative effect on total risk alteration behavior of managers. However, *Size*, *Age* and either definition of *Flow* do not have any effect on this decision.

Similar to Table 15a, Table 15b shows determinants of the systematic risk change decisions of fund managers. Findings from this table are comparable to those reported in Table 14b with OLS modeling. Results show a somewhat better fit as indicated by slightly higher R^2 in Panel A of Table 15b, where one period lagged risk is defined as standard deviation. On the other hand, in panel B of Table 15b, there is very little change in R^2 values compared to those reported in Panel B of Table 14b. Consistent with slight or no improvement in R^2 results with the addition of spatially lagged performance variables, neighboring funds' performance does not affect the systematic risk change decision of a fund's manager. The only exception comes from the third model reported in Table 15b Panel A. Only in this model, neighboring funds' performance becomes a significant determinant of systematic risk change decision of fund managers. Consistent with the models reported in Table 15a, when neighboring funds show good performance, fund managers are likely to increase the change in their systematic risk in the expectation of attracting more cash inflow. In sum, Table 15b notes that no or very slight exogenous interaction can be detected among fund managers. Therefore, it is possible to conclude that spatial modeling is not necessary in this case and OLS estimations provide accurate results

In line with Table 14b, results reported in Table 15b exhibit that fund managers only take Jensen's alpha excess return into account as the performance variable while deciding upon the change in systematic risk of their portfolios. Four-Factor excess returns consistently have insignificant coefficients in all the models. Contrary to the Four-Factor excess return variable, Jensen's alpha excess returns have a negative coefficient indicating that one period lagged performance is inversely related to the change in systematic risk of a fund. The interactive variables for both performance proxies also point out a negative risk change behavior for the managers of best performing funds (Panel B of Table 15b). This result is also consistent with the tournament like behavior as stated in the literature (e.g. Koski and Pontiff 1999).

Best-Worst dummy is another variable of interest in explaining the association between past performance and risk change decision. It has a positive coefficient indicating a lower decline in the systematic risk of best performing funds compared to worst ones. Separate t tests verify this conclusion. For best performing funds, the constant terms are still negative and significant, but higher than the constant terms of worst performing funds. In most of the models, the interaction term is insignificant. In other words, performance of best and worst funds has the same impact on the change in the systematic risk of their respective portfolios. All in all, it seems that best funds tend to change their systematic risk more slowly than worst funds, though the performance level of these funds in the first semiannual has the same effect on the change in their systematic risks.

It is interesting to note that fund managers bear in mind one period lagged total risk, but not the beta, of their portfolios in the first half of the year when they are deciding on how much to change the systematic risk of their portfolios. Managers are likely to increase the change in systematic risk when their funds have a higher total risk in the first half of the year. Yet, alongside the negative coefficients of standard deviation in Table 15a, it is possible to observe that fund managers do not prefer to have a higher increase in total risk of the portfolio either.

Age, *Size* and *Expense Ratio* are the other fund characteristics that are influential on the systematic risk change decision of managers. There is some evidence that larger funds are more willing to decrease systematic risk of their portfolios less in the second half of the year, because size variable mostly have have significant and positive coefficients. Yet, age and operating costs do not have any effect on systematic risk changing behavior of managers. In line with above analysis, flow amount is not a determinant of systematic risk change, either.

It is previously indicated that a spatially lagged flow variable will be added to the model if the lagged flow variable has a significant coefficient when there are performance variables in the model. However, all of the lagged flow variables are found to be insignificant. Therefore, such a modeling modification is not considered.

To sum up, the spatial analyses of risk change behavior of mutual fund managers show exogenous interactions in the decision making process of fund managers. Spatial lag of performance significantly affects the total risk change decisions. Putting it differently, fund managers pay attention to the performance of their rivals when deciding on how much to change the total risk of their portfolios. The performance of neighboring funds, i.e. the funds in the peer group, in the first semiannual period, positively affects the change in portfolios' total risk in the second half of the year. Managers are likely to decrease the total risk of their portfolio less in the second semiannual, when neighboring funds are performing better, in the anticipation of exhibiting a better performance in the second half of the year by taking on higher risk. Based on these results, one may conclude that the basic argument of this dissertation claiming that mutual fund managers try to maximize their gains by changing the portfolio risk according to their relative positions is supported. Hence, classical OLS modeling is not sufficient when one tries to understand the dynamics of risk alteration in mutual fund portfolios. Spatial modeling is a must to avoid the biases caused by location in analyzing this issue.

However, this risk alteration behavior depending on the peer group performance cannot be detected while examining the determinants systematic risk change decisions of managers. Li and Tiwari (2006) note the importance of performance gap between the leader/peer group and the fund itself. Funds are only involved in a risk alteration behavior when they believe that they can catch the leaders and be ranked among the best funds. Based on this explanation, fund managers may think that their relative position can only be enhanced by changing the fund's total risk, since all mutual funds have to invest in Turkish stocks and, hence, carry more or less the same systematic risk during the sample period analyzed in this dissertation. This conclusion is actually in line with Li and Tiwari (2006), because they note that managers tend to alter the idiosyncratic risk when they want to catch the best performing funds.

Besides the effect of performance of neighboring funds on risk change decision of managers, this dissertation cannot find strong evidence in favor of tournament behavior. Literature suggests a negative relation between past performance and risk change for funds that involve in a tournament. However, this dissertation mostly finds a positive impact of past performance on the risk alteration behavior. Negative coefficients are observed only in the models examining the association between one period lagged Jensen’s alpha excess returns and change in systematic risk.

CHAPTER 5

ROBUSTNESS CHECK

Results from flow and risk models reported in Chapter 4 mostly find evidence inconsistent with the tournament behavior. To test the robustness of these results, two sets of models are estimated. In the first set of models, a new size variable, *Size 2*, defined as the ratio of market value of fund *i* to market value of all funds in the sample; replaces the original size variable in all flow and risk models estimated in Chapter 4. In the second set of models, two additional variables are added to the ones estimated in the previous chapter. These are a Crisis Dummy variable to account for the impact of subprime mortgage crisis in the US at the beginning of 2009 and a Bank Dummy variable to differentiate the funds that are owned by banks from those that are owned by non-bank institutions. Overall, the main conclusion of this dissertation is mostly verified by these additional models. Results from these additional models are reported in the following sections.

5.1. Size Definition

Literature indicates that size may affect fund flows and risk changes of funds. Traditional flow and risk models include size as the natural logarithm of funds' total net assets among other independent variables. However, cash flows to the funds, which are used as the dependent variable in the models, are also scaled by the funds' total net asset to control for the size effect on flows. In this dissertation, results from traditional models have mostly indicated a negative size impact on the cash flows to the funds. Having size on both sides of the flow equation, in the denominator on the right hand side and also in the numerator on the left hand side, might be the cause of this negative relationship between these two variables. To verify the negative relationship between size and flow, a new size variable, *Size 2*, defined as a funds' total net asset value as a percentage of total net asset value of all the funds included in the sample, is created. Flow and regression models are re-run using this second size definition as a robustness check.

5.1.1. Flow Models with Size 2 Variable

To provide a comparison with basic cash flow models reported in Tables 9a and 9b, these models are re-estimated with the new size variable, *Size 2, defined as* ($TNA_{i,t}$/the sum of TNAs at the end of a semiannual for all funds in the sample). The representation of the models reported in Tables 16a and 16b are shown in Eq. (7):

$$\begin{aligned} Flow_{i,t} = {} & \gamma_0 + \gamma_1 Perf_{i,t-1} + \gamma_2 Age_{i,t-1} + \gamma_3 Size2_{i,t-1} + \gamma_4 Risk_{i,t-1} + \gamma_5 Expense_{i,t} \\ & + \gamma_6 Flow_{i,t-1} + \gamma_7 Semiannual\_Dummy + \gamma_8 Best\_Worst_{t-1} \\ & + \gamma_9 Best\_WorstxPerformance + \varepsilon_{i,t} \end{aligned} \tag{7}$$

Definitions of remaining variables stay the same. For these definitions, readers can refer to Table 2a.

Table 16a. Flow Models with Size 2

VARIABLES	(1)	(2)	(3)	(4)
Constant	0.364*	0.337	0.421*	0.346
	(0.198)	(0.245)	(0.238)	(0.215)
Jensen's Alpha Excess Ret$_{t-1}$	-0.927**		-0.669	
	(0.426)		(0.422)	
4 Factor Excess Ret$_{t-1}$		-0.606		-0.554
		(0.573)		(0.551)
Std. Dev $_{t-1}$	20.39*	13.64		
	(11.04)	(11.68)		
Beta $_{t-1}$			0.107	0.231
			(0.360)	(0.214)
Flow$_{t-1}$	-0.0463**	-0.0422**	-0.0452**	-0.0417**
	(0.0186)	(0.0169)	(0.0182)	(0.0166)
Best-Worst $_{t-1}$	0.184	-0.0801	0.164	-0.0825
	(0.177)	(0.154)	(0.189)	(0.150)
Best-Worst x Jensen's	0.315		0.313	
	(0.240)		(0.268)	
Best-Worst x 4Factor		(0.573)		(0.551)
		-0.554		-0.546
Semiannual Dummy	0.0194	-0.00603	0.0194	0.00165
	(0.123)	(0.112)	(0.120)	(0.113)
Age $_{t-1}$	-0.00594	-0.00679	-0.00681	-0.00735
	(0.0107)	(0.0107)	(0.0106)	(0.0107)
Size 2 $_{t-1}$	-1.471**	-1.843***	-1.545***	-1.879***
	(0.582)	(0.687)	(0.579)	(0.687)
Expense Ratio $_t$	-1.219	-1.053	-1.158	-1.048
	(1.371)	(1.264)	(1.346)	(1.264)
R-squared	0.017	0.015	0.015	0.015
Observations	611	611	611	611

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table shows the findings from the flow model that relates the fund flow to the fund characteristics, such as performance, age, size, risk, and expense ratio as well as one period lagged flow. The formal model can be represented as follows:

$$Flow_{i,t} = \gamma_0 + \gamma_1 Perf_{i,t-1} + \gamma_2 Age_{i,t-1} + \gamma_3 Size2_{i,t-1} + \gamma_4 Risk_{i,t-1} + \gamma_5 Expense_{i,t}$$
$$+ \gamma_6 Flow_{i,t-1} + \gamma_7 Semiannual\_Dummy + \gamma_8 Best\_Worst_{t-1} + \gamma_9 Best\_WorstxPerformance + \varepsilon_{i,t}$$

Here, the dependent variable is the cash flow obtained from daily reports to CMB. Models presented in this Table alternate the performance proxies, namely Jensen's alpha excess returns and Four-Factor excess returns, as well as risk proxies, namely standard deviation and beta. Robust standard errors are presented in parenthesis.

Table 16b. Flow Models with Size 2

VARIABLES	(1)	(2)	(3)	(4)
Constant	23.19	53.04*	5.777	39.03
	(22.13)	(30.04)	(26.26)	(30.43)
Jensen's Alpha Excess Ret$_{t-1}$	56.09		19.72	
	(44.39)		(28.36)	
4 Factor Excess Ret$_{t-1}$		119.2*		113.0*
		(65.02)		(62.71)
Std. Dev $_{t-1}$	-1,664	-1,390		
	(1,653)	(1,357)		
Beta $_{t-1}$			33.13	-0.623
			(44.38)	(26.97)
Flow$_{t-1}$	-0.0558**	-0.0566**	-0.0566**	-0.0573**
	(0.0259)	(0.0260)	(0.0260)	(0.0262)
Best-Worst $_{t-1}$	-6.487	-27.86*	-7.541	-26.37*
	(15.95)	(15.98)	(17.22)	(15.94)
Best-Worst x Jensen's	-4.039		-14.54	
	(28.45)		(34.49)	
Best-Worst x 4Factor		-126.9**		-116.9**
		(52.47)		(48.44)
Semiannual Dummy	-12.59	-10.78	-11.72	-11.59
	(11.82)	(11.59)	(12.01)	(11.49)
Age $_{t-1}$	-0.796	-0.802	-0.724	-0.730
	(1.326)	(1.329)	(1.292)	(1.294)
Size 2 $_{t-1}$	511.0*	492.7*	514.9*	504.0*
	(289.6)	(285.8)	(289.9)	(287.8)
Expense Ratio $_t$	37.07	50.76	26.55	41.57
	(39.73)	(44.16)	(42.45)	(44.86)
R-squared	0.037	0.045	0.036	0.043
Observations	603	603	603	603
t test (Constant + B-W)		25.177		
		(21.575)		
t test (4 Factor Excess Ret. + B-W x 4 Factor Excess Ret.)		-7.701		-3.956
		(44.920)		(42.972)

*** p<0.01, ** p<0.05, * p<0.1

Table 16b is prepared using the formal model defined in Eq (1):

$$Flow_{i,t} = \gamma_0 + \gamma_1 Perf_{i,t-1} + \gamma_2 Age_{i,t-1} + \gamma_3 Size2_{i,t-1} + \gamma_4 Risk_{i,t-1} + \gamma_5 Expense_{i,t}$$
$$+ \gamma_6 Flow_{i,t-1} + \gamma_7 Semiannual\_Dummy + \gamma_8 Best\_Worst_{t-1} + \gamma_9 Best\_WorstxPerformance + \varepsilon_{i,t}$$

Dependent variables in this table are the change in the number of investors scaled by the previous period number of investors (number of investors $_{i,t}$/number of investors$_{i,t-1}$). Models presented in this Table alternate the performance proxies, namely Jensen's alpha excess returns and Four-Factor excess returns, as well as risk proxies, namely standard deviation and beta. Robust standard errors are presented in parenthesis.

In particular, models in Table 16a have much lower R^2 than those reported by using original size definition. It seems that models with the first size definition have a better fit. Moreover, results reported in Table 16a mostly confirm the conclusions reached by using the first *Size* variable. Investors only take into account the Jensen's alpha excess return as the performance measure while choosing among various mutual funds. As in the original models, this variable has a negative coefficient which might be attributed to the gain realization desire of fund investors. Although the intercept terms are mostly positive and significant, indicating a positive base flow to funds regardless of their characteristics, the interactive and *Best-Worst* dummy variables are not statistically significant. A weak evidence for risk taking behavior by the fund investors is documented because in only one out of eight fund flow models, the coefficient of total risk variable is positive and statistically significant. The coefficient of one period lagged flow continues to be negative and significant. Most importantly, coefficient of the *Size 2* variable remains to be negative and significant demonstrating that smaller funds are more successful in attracting new cash flows.

The analysis with the new size variable is also repeated for the second cash flow proxy, namely change in the number of investors, in Table 16b. As in the previous models, *Size 2* has positive and significant coefficients in all models, i.e. larger funds grow faster in terms of new investors. In two models, performance measured as Four-Factor excess return is found to be positively and significantly related to the number of investors. However, the negative and significant coefficient of interactive dummy variables makes the overall effect of fund performance not different from zero for best performing funds. The only difference from the models using the first size definition is the significant and negative coefficient on the *Best-Worst* dummy variable in two of the models reported in Table 16b. A separate t test on the summation of this coefficient with the constant term reveals that the negative impact of *Best-Worst* dummy variable is wiped out by the positive intercept term.

Overall, findings from Tables 16a and 16b mostly agree with those reported in Tables 9a and 9b. Hence, one may conclude that results from flow models are robust to different definitions of size variable.

Spatial models are also re-conducted by using *Size 2* definition. Before doing so, Moran I test is run for this variable. This statistic indicates the existence of spatial autocorrelation at 0.01 significance level with a Z value of 3.394. As in the previous spatial flow models, first endogenous effects, then exogenous effects, and finally a combination of these two effects are controlled for. The same spatial weight matrix obtained from the DEA efficiency scores are used in all of the spatial models of this dissertation. In other words, W term is the same in all spatial models with *Size* 2 variables. The findings are reported in the following tables.

Table 17a. Spatial Lag Model of Flow with Size 2

VARIABLES	(1)	(2)	(3)	(4)
Constant	0.357	0.267	0.379	0.389
	(0.20)	(0.18)	(0.25)	(0.24)
Spatial Lag of Flow (Rho)	-0.148	0.061	0.077	0.065
	(0.10)	(0.13)	(0.13)	(0.13)
Jensen's Alpha Excess Ret$_{t-1}$	-0.855*		-0.676	
	(0.43)		(0.40)	
4 Factor Excess Ret$_{t-1}$		-1.049		-1.180
		(0.56)		(0.74)
Std. Dev $_{t-1}$	20.878	5.989		
	(11.02)	(11.22)		
Beta $_{t-1}$			0.139	-0.166
			(0.37)	(0.46)
Best-Worst $_{t-1}$	0.157	0.154	0.130	0.212
	(0.18)	(0.16)	(0.19)	(0.24)
Best-Worst x Jensen's	0.292		0.324	
	(0.24)		(0.28)	
Best-Worst x 4Factor		-0.464		-0.488
		(0.64)		(0.63)
Semiannual Dummy	0.009	-0.020	-0.007	-0.015
	(0.12)	(0.12)	(0.12)	(0.12)
Age $_{t-1}$	-0.006	-0.006	-0.005	-0.006
	(0.01)	(0.01)	(0.01)	(0.01)
Size 2 $_{t-1}$	-1.327*	-1.651**	-1.466*	-1.704**
	(0.58)	(0.63)	(0.58)	(0.65)
Expense Ratio $_{t}$	-1.406	-1.212	-1.179	-1.164
	(1.46)	(1.37)	(1.40)	(1.36)
AIC	2087.236	2086.958	2088.084	2086.984
Observations	599	599	599	599

***p<0.01, ** p<0.05, * p<0.1

This table displays the findings from the spatial lag model. The formal specification of this model can be seen as below:

$$Flow_{i,t} = \varphi_0 + \rho \sum_{j=1}^{n} W_{ij} Flow_{i,t} + \varphi_1 Perf_{i,t-1} + \varphi_2 Age_{i,t-1} + \varphi_3 Size2_{i,t-1} + \varphi_4 Risk_{i,t-1} + \varphi_5 Expense_{i,t}$$

$$+ \varphi_6 Semiannual\_Dummy + \varphi_7 Best\_Worst_{t-1} + \varphi_8 Best\_WorstxPerformanc\ e + \xi_{i,t}$$

In these specifications, flow is computed from the CMB daily reports. Models vary by the alternative performance and risk variables used. *W* is computed from DEAs based on the fund efficiencies. The fund *i* is accepted as a neighbor to its peer group. The distance between two funds is the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parenthesis.

Table 17b. Spatial Lag Model of Flow with Size 2

VARIABLES	(1)	(2)	(3)	(4)
Constant	23.523	37.665	6.499	15.722
	(21.99)	(24.27)	(26.45)	(28.18)
Spatial Lag of Flow (Rho)	-0.007	-0.006	-0.006	-0.006
	(0.21)	(0.21)	(0.21)	(0.21)
Jensen's Alpha Excess Ret$_{t-1}$	55.716		19.588	
	(44.02)		(28.66)	
4 Factor Excess Ret$_{t-1}$		24.320		47.274
		(35.22)		(52.55)
Std. Dev $_{t-1}$	-1733.993	-1087.281		
	(1648.40)	(1523.96)		
Beta $_{t-1}$			30.722	29.161
			(44.72)	(47.04)
Best-Worst $_{t-1}$	-6.780	-1.570	-7.849	-11.840
	(16.23)	(13.14)	(17.61)	(19.21)
Best-Worst x Jensen's	-2.776		-12.990	
	(28.03)		(34.09)	
Best-Worst x 4Factor		-115.461*		-110.124*
		(50.09)		(48.36)
Semiannual Dummy	-13.201	-10.317	-12.448	-11.434
	(11.92)	(11.99)	(12.07)	(11.72)
Age $_{t-1}$	-0.768	-0.717	-0.698	-0.636
	(1.32)	(1.31)	(1.29)	(1.29)
Size 2 $_{t-1}$	479.950	469.563	483.882	479.707
	(276.84)	(275.14)	(277.26)	(276.50)
Expense Ratio $_t$	33.137	39.793	23.319	32.457
	(38.79)	(41.72)	(41.47)	(43.22)
AIC	7631.693	7630.933	7632.417	7631.063
Observations	599	599	599	599

***p<0.01, ** p<0.05, * p<0.1

This table reports the findings from the spatial lag model which can formally be expressed as below:

$$Flow_{i,t} = \varphi_0 + \rho\sum_{j=1}^{n} W_{ij}Flow_{i,t} + \varphi_1 Perf_{i,t-1} + \varphi_2 Age_{i,t-1} + \varphi_3 Size2_{i,t-1} + \varphi_4 Risk_{i,t-1} + \varphi_5 Expense_{i,t}$$
$$+ \varphi_6 Semiannual\_Dummy + \varphi_7 Best\_Worst_{t-1} + \varphi_8 Best\_Worst\ x\ Performance + \xi_{i,t}$$

In these specifications, flow is the change in the number of investors in subsequent periods. Models vary by the alternative performance and risk variables used. *W* is computed from DEAs based on the fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is computed as the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parenthesis.

First, as a measure of goodness of fit, the AIC statistic is calculated for all the models. The models reported in Tables 17a and 17b have more or less the same AIC statistic with those in Tables 11a and 11b. However, it seems that spatial lag model of flow has a better fit when the first *Size* variable is used, because the AIC statistics are slightly higher with new *Size 2* variable. Spatial lags are still insignificant in all of the models, so again, all models revert back to the OLS specification. Consistent with previous findings from the classical OLS flow models using original definition of size, performance variables have a negative coefficient. Furthermore, the coefficient of *Size 2* is still negative indicating that smaller funds are more successful in drawing new cash flows.

To observe the possible exogenous interactions in flow models, spatial lag of X models are also re-estimated with *Size 2* variable as well. The results are given in Tables 18a and 18b.

Table 18a. Spatial Lag of X Model of Flow with Size 2

VARIABLES	(1)	(2)	(3)	(4)
Constant	0.535**	0.399	0.723**	0.427*
	(0.266)	(0.265)	(0.315)	(0.244)
Spatial Lag of Perf. (Jensen's$_{t-1}$)	-0.255		-0.506	
	(0.395)		(0.408)	
Jensen's Alpha Excess Ret$_{t-1}$	-1.068**		-0.784*	
	(0.460)		(0.453)	
Spatial Lag of Perf. (4Factor$_{t-1}$)		0.0122		-0.147
		(0.667)		(0.688)
4 Factor ExcessRet$_{t-1}$		-0.712		-0.604
		(0.606)		(0.567)
Std. Dev $_{t-1}$	17.64	13.05		
	(12.00)	(11.95)		
Beta $_{t-1}$			-0.129	0.183
			(0.398)	(0.231)
Flow 1$_{t-1}$	-0.0492*	-0.0472*	-0.0486*	-0.0469*
	(0.0267)	(0.0257)	(0.0260)	(0.0252)
Best-Worst $_{t-1}$	0.208	-0.0979	0.204	-0.107
	(0.193)	(0.163)	(0.208)	(0.158)
Best-Worst x Jensen's	0.397*		0.479*	
	(0.238)		(0.267)	
Best-Worst x 4Factor		-0.293		-0.230
		(0.787)		(0.794)
Semiannual Dummy	-0.00298	-0.0306	-0.0117	-0.0236
	(0.131)	(0.121)	(0.127)	(0.121)
Age $_{t-1}$	-0.00807	-0.00932	-0.00884	-0.00966
	(0.0113)	(0.0116)	(0.0112)	(0.0115)
Size 2 $_{t-1}$	-1.427**	-1.802**	-1.469**	-1.832***
	(0.593)	(0.710)	(0.586)	(0.704)
Expense Ratio $_{t}$	-1.250	-1.078	-1.191	-1.068
	(1.550)	(1.437)	(1.540)	(1.450)
R-squared	0.018	0.014	0.017	0.014
Observations	554	554	554	554
t test (Jensen's + B-W x Jensen's)	-0.6715		-0.3045	
	(0.426)		(0.408)	

*** p<0.01, ** p<0.05, * p<0.1

This table shows the results of spatial lag of X model for fund flow. One period lagged performance variables are scaled by the spatial weight matrix. Fund characteristics are age, size, expense ratio and risk. Dependent variable, Flow 1, is the flow computed from the daily reports of funds to CMB. *W* is constructed by the aid of DEAs based on fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is computed as the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parentheses. The formal model can be seen below:

$$Flow_{i,t} = \beta_0 + \theta \sum_{j=1}^{n} W_{ij} Perf_{i,t-1} + \beta_1 Perf_{i,t-1} + \beta_2 Age_{i,t-1} + \beta_3 Size2_{i,t-1} + \beta_4 Risk_{i,t-1} + \beta_5 Expense_{i,t}$$
$$+ \beta_6 Semiannual\_Dummy + \beta_7 Best\_Worst_{t-1} + \beta_8 Best\_Worst\ x\ Performance + \vartheta_{i,t}$$

Table 18b. Spatial Lag of X Model of Flow with Size 2

VARIABLES	(1)	(2)	(3)	(4)
Constant	42.66	52.35	11.60	39.04
	(26.54)	(31.78)	(26.08)	(33.09)
Spatial Lag of Perf. (Jensen's$_{t-1}$)	-58.35*		-19.49	
	(33.44)		(29.17)	
Jensen's Alpha Excess Ret$_{t-1}$	62.26		19.47	
	(48.18)		(30.25)	
Spatial Lag of Perf. (4Factor$_{t-1}$)		38.37		51.33
		(55.73)		(58.79)
4 Factor ExcessRet$_{t-1}$		106.8		97.68
		(69.45)		(65.33)
Std. Dev $_{t-1}$	-2,369	-1,217		
	(1,922)	(1,432)		
Beta $_{t-1}$			31.60	1.226
			(46.39)	(29.41)
Flow 2$_{t-1}$	-0.0575**	-0.0602**	-0.0592**	-0.0610**
	(0.0277)	(0.0282)	(0.0280)	(0.0284)
Best-Worst $_{t-1}$	-0.119	-23.23	-0.440	-21.45
	(16.18)	(16.67)	(18.12)	(16.47)
Best-Worst x Jensen's	-7.694		-22.56	
	(27.95)		(35.50)	
Best-Worst x 4Factor		-168.9**		-165.6**
		(69.03)		(67.89)
Semiannual Dummy	-14.97	-12.08	-13.51	-12.63
	(12.72)	(12.49)	(13.00)	(12.39)
Age $_{t-1}$	(48.18)		(30.25)	
	-0.721	-0.784	-0.615	-0.725
Size 2 $_{t-1}$	(1.395)	(1.393)	(1.357)	(1.371)
	531.8*	514.4*	537.4*	523.5*
Expense Ratio $_t$	17.98	43.57	9.052	35.52
	(30.36)	(40.44)	(33.84)	(40.47)
R-squared	0.043	0.049	0.041	0.048
Observations	547	547	547	547

*** p<0.01, ** p<0.05, * p<0.1

The findings from the spatial lag of X model are presented in this table. The formal model can be seen below.

$$Flow_{i,t} = \beta_0 + \theta\sum_{j=1}^{n} W_{ij} Perf_{i,t-1} + \beta_1 Perf_{i,t-1} + \beta_2 Age_{i,t-1} + \beta_3 Size2_{i,t-1} + \beta_4 Risk_{i,t-1} + \beta_5 Expense_{i,t}$$
$$+ \beta_6 Semiannual\_Dummy + \beta_7 Best\_Worst_{t-1} + \beta_8 Best\_Worst\ x\ Performance + \vartheta_{i,t}$$

Fund characteristics are age, size, expense ratio and risk. Dependent variables in all models, Flow 2, are the change in the number of investors in two subsequent periods. One period lagged performance variables are scaled by the spatial weight matrix. *W* is constructed by the aid of DEAs based on fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is computed as the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parentheses.

No spatial lag can be detected in the models reported in Table 18a. It means that investors are not under the influence of neighboring funds' performances when cash flow is calculated from CMB reports. As a result, the models in Table 18a confirm results with the classical OLS modeling of flow. That is, investors only examine the Jensen's alpha excess return as a performance measure, when allocating their money across mutual funds. Consistent with earlier findings, this variable has a negative impact on TL cash flows, but it seems that best performing funds at least prevent some of the withdrawals. Consistently, *Size 2* has a negative impact on TL cash flows.

Contrary to Table 18a, Table 18b notes a decline in the number of accounts of a fund when neighboring funds perform better, so there may be a slight indication of exogenous interactions. The constant outflows from best performing funds can be seen from the negative coefficient of interactive dummy variable. As in Tables 12b, *Size 2* has a positive effect on the number of accounts.

Up to this point, cash flows to mutual funds are modeled by controlling only for either the endogenous or the exogenous interactions. However, sometimes these two effects may not be separable from each other. Hence, spatial Durbin models are re-conducted by using *Size 2* definition as well. The findings are shown in Tables 19a and 19b.

Table 19a. Spatial Durbin Model of Flow with Size 2

VARIABLES	(1)	(2)	(3)	(4)
Constant	0.782	1.004**	1.091*	1.099*
	(0.50)	(0.36)	(0.54)	(0.46)
Spatial Lag of Flow (Rho)	0.420	0.397	0.418	0.390
	(0.28)	(0.29)	(0.27)	(0.28)
Spatial Lag of Perf. (Jensen's$_{t-1}$)	1.353		1.185	
	(1.15)		(1.12)	
Jensen's Alpha Excess Ret$_{t-1}$	-1.136		-0.853	
	(0.79)		(0.71)	
Spatial Lag of Perf. (4Factor$_{t-1}$)		1.461		1.487
		(0.96)		(1.04)
4 Factor Excess Ret$_{t-1}$		-1.697		-1.885
		(1.03)		(1.45)
Std. Dev $_{t-1}$	-4.978	-9.310		
	(26.80)	(26.07)		
Beta$_{t-1}$			-0.947	-0.411
			(0.92)	(0.99)
Best-Worst $_{t-1}$	0.176	0.352	0.251	0.443
	(0.39)	(0.33)	(0.42)	(0.54)
Best-Worst x Jensen's	1.044		1.322	
	(0.56)		(0.68)	
Best-Worst x 4Factor		0.002		-0.024
		(1.43)		(1.41)
Semiannual Dummy	0.168	0.162	0.146	0.156
	(0.30)	(0.29)	(0.29)	(0.29)
Age $_{t-1}$	-0.029	-0.034	-0.029	-0.035
	(0.02)	(0.02)	(0.02)	(0.02)
Size 2 $_{t-1}$	-2.725***	-3.120***	-2.667***	-3.094***
	(0.80)	(0.89)	(0.80)	(0.90)
Expense Ratio $_{t}$	-0.843	-0.918	-0.781	-0.904
	(2.38)	(2.36)	(2.43)	(2.32)
AIC	1047.307	1043.454	1041.975	1052.962
Observations	599	599	599	599

*** p<0.01, ** p<0.05, * p<0.1

This table illustrates the findings from the spatial Durbin model of flow where both flow and performance variables are scaled by the spatial weight matrix. The model is given below:

$$Flow_{i,t} = \varphi_0 + \delta_1 \sum_{j=1}^{n} W_{ij} Flow_{i,t} + \delta_2 \sum_{j=1}^{n} W_{ij} Perf_{i,t} + \varphi_1 Perf_{i,t-1} + \varphi_2 Age_{i,t-1} + \varphi_3 Size2_{i,t-1}$$
$$+ \varphi_4 Risk_{i,t-1} + \varphi_5 Expense_{i,t} + \varphi_6 Semiannual\_Dummy + \varphi_7 Best\_Worst_{t-1}$$
$$+ \varphi_8 Best\_Worst\ x\ Performanc\ e + \eta_{i,t}$$

Fund characteristics are age, size, expense ratio and risk. Dependent variable is the cash flow obtained from the daily reports to the CMB. Models include either Jensen's alpha excess returns or Four-Factor excess returns as performance variables. *W* is constructed by the aid of DEAs based on fund efficiencies. The distance between two funds is the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parentheses.

Table 19b. Spatial Durbin Model of Flow with Size 2

VARIABLES	(1)	(2)	(3)	(4)
Constant	124.565	142.630*	134.618	102.211
	(66.31)	(58.53)	(77.01)	(67.30)
Spatial Lag of Flow (Rho)	-0.007	-0.008	-0.008	-0.008
	(0.21)	(0.21)	(0.21)	(0.21)
Spatial Lag of Perf. (Jensen's$_{t-1}$)	-34.054		-57.967	
	(106.80)		(113.74)	
Jensen's Alpha Excess Ret$_{t-1}$	158.207		111.833	
	(114.36)		(91.81)	
Spatial Lag of Perf. (4Factor$_{t-1}$)		55.329		36.839
		(182.03)		(182.47)
4 Factor Excess Ret$_{t-1}$		61.658		113.857
		(108.09)		(141.79)
Std. Dev $_{t-1}$	-6727.078*	-4211.506		
	(3398.85)	(3310.94)		
Beta$_{t-1}$			-120.456	5.523
			(94.67)	(103.58)
Best-Worst $_{t-1}$	-28.471	3.765	-15.117	-10.709
	(40.71)	(31.99)	(42.89)	(47.34)
Best-Worst x Jensen's	38.550		69.998	
	(71.65)		(84.74)	
Best-Worst x 4Factor		-73.151		-64.564
		(192.13)		(193.90)
Semiannual Dummy	-30.077	-23.253	-31.905	-23.590
	(29.99)	(37.48)	(30.61)	(37.72)
Age $_{t-1}$	-2.395	-2.726	-2.433	-2.429
	(2.99)	(2.95)	(3.02)	(3.00)
Size 2 $_{t-1}$	438.177	435.221	492.278	472.005
	(352.14)	(351.69)	(358.04)	(353.42)
Expense Ratio $_t$	51.897	52.913	52.481	40.554
	(87.13)	(90.85)	(89.42)	(90.52)
AIC	3083.505	3085.201	3085.497	3086.529
Observations	599	599	599	599

*** p<0.01, ** p<0.05, * p<0.1

The spatial Durbin model of flow, where flow is defined as the change in the number of investors, is presented in this table. The formal model can be seen below:

$$Flow_{i,t} = \varphi_0 + \delta_1 \sum_{j=1}^{n} W_{ij} Flow_{i,t} + \delta_2 \sum_{j=1}^{n} W_{ij} Perf_{i,t} + \varphi_1 Perf_{i,t-1} + \varphi_2 Age_{i,t-1} + \varphi_3 Size2_{i,t-1} + \varphi_4 Risk_{i,t-1} + \varphi_5 Expense_{i,t} + \varphi_6 Semiannual\_Dummy + \varphi_7 Best\_Worst_{t-1} + \varphi_8 Best-Worst\ x\ Performance + \eta_{i,t}$$

Fund characteristics are age, size, expense ratio and risk. Models include either Jensen's alpha excess return or Four-Factor excess returns as performance variables. Both flow and performance variables are scaled by the spatial weight matrix (*W*) which is generated by the aid of DEAs based on fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parentheses.

Findings presented in Tables 19a and 19b does not indicate the existence of a spatial interaction with new *Size 2* definition as well. Although the results are essentially the same with those obtained by using *Size* variable, the AIC statistics are much higher in Tables 19a and 19b. Hence, *Size 2* does not provide a better fit. In fact, OLS estimation procedure is sufficient for explaining the cash flow to the mutual funds. Considering all the models estimated with *Size* and *Size 2* variables together, one may conclude that the inferences from analyses of this dissertation are robust to different definitions of size variable. Very little evidence has been found for the existence of spatial interactions. It may be possible to say that mutual fund investors at best care about the past performance of a fund when choosing among various funds to invest in. Contrary to the tournament behavior implications, the relation between fund performance and fund flow is negative. This situation can be explained by the structure of the Turkish mutual fund market and the investor profile. Due to the short holding period and high tendency for gain realization of investors, Turkish mutual funds in general suffer from withdrawals. However, there is some evidence indicating that best performing funds experience lower withdrawals.

5.1.2. Risk Models with Size 2 Variable

Even though the basic inferences from flow models are the same with *Size 2* variable, the risk models are still re-estimated as a robustness check. The basic model can be seen in Eq. (8):

$$\Delta RISK_{i,t} = a_0 + a_1 Risk_{i,t-1} + a_2 Age_{i,t-1} + a_3 Size2_{i,t-1} + a_4 Expense_{i,t} + a_5 Perf_{i,t-1} + a_6 Flow_{i,t-1} + a_7 Best\_Worst_{t-1} + a_8 Best\_WorstxPerformance + u_{i,t} \tag{8}$$

With the exception of *Size 2,* the variable definitions stay the same. The readers can refer to Table 2b for these definitions. The risk change models are only estimated for the second interim of the year as previously stated. The findings are reported in Tables 20a and 20b.

Table 20a. Risk Change Models with Size 2

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.000480	0.00276	-0.000187	0.00295
	(0.00154)	(0.00236)	(0.00154)	(0.00236)
Std. Dev $_{t-1}$	-0.421***	-0.108	-0.426***	-0.134
	(0.149)	(0.127)	(0.149)	(0.128)
Jensen's Alpha Excess Ret$_{t-1}$	0.0163***		0.0156***	
	(0.00308)		(0.00304)	
4 Factor Excess Ret$_{t-1}$		0.0168***		0.0162***
		(0.00454)		(0.00451)
Best-Worst $_{t-1}$	-0.00239***	-0.00253***	-0.00238***	-0.00248***
	(0.000631)	(0.000749)	(0.000635)	(0.000734)
Best-Worst x Jensen's	0.00157		0.00162	
	(0.00127)		(0.00128)	
Best-Worst x 4Factor		0.00598		0.00641*
		(0.00372)		(0.00370)
Flow 1$_{t-1}$	0.000136	9.90e-06		
	(0.000155)	(0.000171)		
Flow 2$_{t-1}$			-4.06e-07	-3.47e-07
			(1.20e-06)	(1.66e-06)
Age $_{t-1}$	-3.32e-05	-3.53e-05	-3.37e-05	-3.95e-05
	(6.36e-05)	(6.84e-05)	(6.35e-05)	(6.85e-05)
Size 2 $_{t-1}$	-0.00414	-0.00221	-0.00363	-0.00167
	(0.00292)	(0.00279)	(0.00281)	(0.00272)
Expense Ratio $_{t}$	-0.00512**	-0.00535*	-0.00536**	-0.00532*
	(0.00247)	(0.00288)	(0.00244)	(0.00286)
R-squared	0.293	0.153	0.289	0.161
Observations	309	309	305	305

***p<0.01, ** p<0.05, * p<0.1

Table 20a. Risk Change Models with Size 2

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.00188*	-0.000536	-0.00171*	-0.000360
	(0.00104)	(0.00146)	(0.00101)	(0.00144)
Beta $_{t-1}$	-0.00479**	0.00346***	-0.00470**	0.00299**
	(0.00185)	(0.00130)	(0.00183)	(0.00129)
Jensen's Alpha Excess Ret$_{t-1}$	0.0148***		0.0142***	
	(0.00222)		(0.00224)	
4 Factor Excess Ret$_{t-1}$		0.0162***		0.0156***
		(0.00427)		(0.00424)
Best-Worst $_{t-1}$	-0.00212***	-0.00216***	-0.00212***	-0.0021***
	(0.000671)	(0.000694)	(0.000675)	(0.000680)
Best-Worst x Jensen's	0.00142		0.00133	
	(0.00171)		(0.00176)	
Best-Worst x 4Factor		0.00813***		0.00855***
		(0.00306)		(0.00303)
Flow 1$_{t-1}$	2.72e-05	-1.06e-05		
	(0.000175)	(0.000185)		
Flow 2$_{t-1}$			-1.07e-06	-5.52e-07
			(1.50e-06)	(1.68e-06)
Age $_{t-1}$	1.97e-06	-1.90e-05	6.05e-07	-2.13e-05
	(5.92e-05)	(6.10e-05)	(5.93e-05)	(6.15e-05)
Size 2 $_{t-1}$	-0.00266	-0.000444	-0.00189	0.000208
	(0.00313)	(0.00247)	(0.00278)	(0.00230)
Expense Ratio $_t$	-0.00597*	-0.00718**	-0.00606**	-0.00707**
	(0.00306)	(0.00305)	(0.00301)	(0.00300)
R-squared	0.216	0.163	0.205	0.163
Observations	309	309	305	305

***p<0.01, ** p<0.05, * p<0.1

This table illustrates the findings from the risk models that associate the risk change decisions of fund managers to the fund characteristics, such as flow, performance, age, size, risk, and expense ratio. The formal model is as follows:

$$\Delta RISK_{i,t} = a_0 + a_1 Risk_{i,t-1} + a_2 Age_{i,t-1} + a_3 Size2_{i,t-1} + a_4 Expense_{i,t}$$
$$+ a_5 Perf_{i,t-1} + a_6 Flow_{i,t-1} + a_7 Best\_Worst_{t-1} + a_8 Best\_Worst\ x\ Performanc\ e + u_{i,t}$$

Here, the dependent variable is the change in the semiannual standard deviation of daily returns. Models presented in Panel A and Panel B of this table only differ by the lagged risk proxies, namely standard deviation or beta, used as a control variable. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns. Robust standard errors are reported in parenthesis.

Table 20a presents the determinants of total risk change decision of mutual fund managers. These results can be compared to those reported in Table 14a with the first *Size* definition. Interestingly, total risk change decision of managers seems to be more robust than flow models to changes in size variable definition. The findings shown in Table 20a are almost the same with the findings presented in Table 14a. Basically, both the results indicate that performance, either measured by Jensen's alpha excess return or Four-factor excess return, is positively related to the risk change decisions. Fund managers seem to prefer a higher total risk when they have a good performance in the first half of the year. As noted before, the reverse is expected when managers engage in tournament like behavior. The positive and significant coefficients of the interactive terms indicate a stronger relation between past performance and risk change decision for best performing funds. In other words, when a fund shows good performance in the first half of the year, managers of best performers are willing to change the risk of their portfolios more than the managers of worst performers. The only evidence in favor of tournament like behavior in Panel A of Table 20a is the negative coefficient for *Best-Worst* dummy variable indicating that all else being equal, best performing funds have a lower constant term. Different from the analyses with the first *Size* variable presented in Table 14a, Panel B of Table 20a demonstrates a negative impact of *Beta* on total risk change decisions of managers in two models. This is an indication of mean reversion as well.

The same analyses are conducted for the systematic risk change decisions of fund managers by using *Size* 2 variable. The results are shown in Panels A and B of Table 20b.

Table 20b Risk Change Models with Size 2

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.0387***	-0.0487***	-0.0408***	-0.0509***
	(0.0115)	(0.0117)	(0.0115)	(0.0116)
Std. Dev $_{t-1}$	7.432***	5.057***	7.446***	5.195***
	(0.983)	(0.817)	(0.987)	(0.828)
Jensen's Alpha Excess Ret$_{t-1}$	-0.0914***		-0.0893***	
	(0.0171)		(0.0173)	
4 Factor Excess Ret$_{t-1}$		-0.00372		-0.00350
		(0.0516)		(0.0518)
Best-Worst $_{t-1}$	0.0171***	0.0149**	0.0158***	0.0135**
	(0.00514)	(0.00610)	(0.00508)	(0.00602)
Best-Worst x Jensen's	-0.00867		-0.00681	
	(0.0102)		(0.0102)	
Best-Worst x 4Factor		-0.0690*		-0.0669*
		(0.0365)		(0.0366)
Flow 1$_{t-1}$	0.000595	0.00134		
	(0.00256)	(0.00215)		
Flow 2$_{t-1}$			-5.90e-07	-1.19e-06
			(2.33e-05)	(2.55e-05)
Age $_{t-1}$	0.000515	0.000447	0.000629	0.000594
	(0.000511)	(0.000537)	(0.000503)	(0.000523)
Size 2 $_{t-1}$	0.00937	0.00985	0.0122	0.0122
	(0.0521)	(0.0540)	(0.0510)	(0.0525)
Expense Ratio $_t$	-0.0211	-0.0246	-0.0174	-0.0216
	(0.0199)	(0.0211)	(0.0185)	(0.0199)
R-squared	0.264	0.190	0.263	0.193
Observations	309	309	305	305
t test (Constant + B-W)	-0.0215**	-0.0338***	-0.0249**	-0.0374***
	(0.0105)	(0.0113)	(0.0103)	(0.0112)

***p<0.01, ** p<0.05, * p<0.1

Table 20b. Risk Change Models with Size 2

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	0.0140	0.0183	0.0126	0.0168
	(0.0118)	(0.0118)	(0.0119)	(0.0118)
Beta $_{t-1}$	-0.00573	-0.0153	-0.00518	-0.0139
	(0.0253)	(0.0152)	(0.0253)	(0.0154)
Jensen's Alpha Excess Ret$_{t-1}$	-0.00208		-0.00131	
	(0.0294)		(0.0300)	
4 Factor Excess Ret$_{t-1}$		0.0230		0.0216
		(0.0603)		(0.0608)
Best-Worst $_{t-1}$	0.0103*	0.00886	0.00876	0.00756
	(0.00564)	(0.00657)	(0.00552)	(0.00647)
Best-Worst x Jensen's	-0.0226**		-0.0212*	
	(0.0107)		(0.0109)	
Best-Worst x 4Factor		-0.119***		-0.116***
		(0.0387)		(0.0388)
Flow 1$_{t-1}$	0.00234	0.00252		
	(0.00268)	(0.00263)		
Flow 2$_{t-1}$			8.05e-06	6.92e-06
			(2.94e-05)	(2.96e-05)
Age $_{t-1}$	-0.000150	-7.12e-05	-2.11e-05	6.94e-05
	(0.000512)	(0.000522)	(0.000505)	(0.000513)
Size 2 $_{t-1}$	-0.0319	-0.0322	-0.0330	-0.0332
	(0.0574)	(0.0583)	(0.0533)	(0.0547)
Expense Ratio $_t$	0.00976	0.0118	0.0102	0.0122
	(0.0246)	(0.0247)	(0.0234)	(0.0233)
R-squared	0.028	0.045	0.020	0.038
Observations	309	309	305	305

***p<0.01, ** p<0.05, * p<0.1

The determinants of the risk change decision of managers are modeled in this table as follows:

$$\Delta RISK_{i,t} = a_0 + a_1 Risk_{i,t-1} + a_2 Age_{i,t-1} + a_3 Size2_{i,t-1} + a_4 Expense_{i,t}$$
$$+ a_5 Perf_{i,t-1} + a_6 Flow_{i,t-1} + a_7 Best\_Worst_{t-1} + a_8 Best\_Worst\ x\ Performanc\ e + u_{i,t}$$

Fund characteristics, namely flow, performance, age, size, risk, and expense ratio, are explanatory variables, whereas the dependent variable is the semiannual change in a fund's betas. The difference between Panel A and Panel B is the lagged risk proxies used among the explanatory variables. One period lagged risk is defined as standard deviation of daily returns in Panel A and as beta in Panel B. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns. Robust standard errors are presented in parenthesis.

Table 20b illustrates the determinants of systematic risk change decision of fund managers when the size of a fund is defined as the market value of a fund's assets as a percentage of total market value of all funds included in the sample. Results in Panel A are comparable to those obtained by using the first *Size* variable. The only difference is that *Size 2* now loses its significance in two models, although it still has a positive coefficient. Regarding the similar coefficients for variables and R^2 statistics, one may conclude that risk change decisions of managers, either in terms of total or systematic risk, are also robust to different definitions of the size variable.

The last analysis conducted with new *Size 2* variable is the spatial lag of X model for total and systematic risk change decisions of managers. The results of these estimations are shown in Tables 21a and 21b.

Table 21a. Spatial Lag of X Model of Risk Change with Size 2 Variable

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.00130	0.00344	-0.000900	0.00366*
	(0.00163)	(0.00218)	(0.00164)	(0.00219)
Std. Dev $_{t-1}$	-0.410***	-0.134	-0.417***	-0.167
	(0.151)	(0.115)	(0.151)	(0.116)
Jensen's Alpha Excess Ret$_{t-1}$	0.0156***		0.0150***	
	(0.00314)		(0.00310)	
Spatial Lag (Jensen's$_{t-1}$)	0.00367		0.00319	
	(0.00223)		(0.00217)	
4 Factor ExcessRet$_{t-1}$		0.00723**		0.00663**
		(0.00294)		(0.00289)
Spatial Lag (4Factor$_{t-1}$)		0.0199***		0.0197***
		(0.00367)		(0.00363)
Best-Worst $_{t-1}$	-0.00221***	-0.00151***	-0.00223***	-0.00140**
	(0.000667)	(0.000560)	(0.000669)	(0.000542)
Best-Worst x Jensen's	0.00145		0.00152	
	(0.00124)		(0.00126)	
Best-Worst x 4Factor		-0.00171		-0.000968
		(0.00463)		(0.00455)
Flow 1$_{t-1}$	0.000108	-0.000146		
	(0.000167)	(0.000192)		
Flow 2$_{t-1}$			-3.93e-07	5.08e-07
			(1.25e-06)	(1.51e-06)
Age $_{t-1}$	-3.20e-05	-8.87e-05	-3.28e-05	-9.83e-05
	(6.40e-05)	(6.71e-05)	(6.40e-05)	(6.80e-05)
Size 2 $_{t-1}$	-0.00397	-0.00330	-0.00354	-0.00348
	(0.00291)	(0.00252)	(0.00281)	(0.00267)
Expense Ratio $_{t}$	-0.00466*	-0.00257	-0.00492**	-0.00245
	(0.00247)	(0.00236)	(0.00243)	(0.00215)
R-squared	0.297	0.301	0.292	0.314
Observations	304	304	300	300
t test (Constant + B-W)				0.0023
				(0.0018)

***p<0.01, ** p<0.05, * p<0.1

Table 21a. Spatial Lag of X Model of Risk Change with Size 2 Variable

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.00296***	0.000244	-0.00266**	0.000375
	(0.00112)	(0.00139)	(0.00110)	(0.00138)
Beta $_{t-1}$	-0.00410**	0.00276**	-0.00412**	0.00231*
	(0.00191)	(0.00120)	(0.00189)	(0.00118)
Jensen's Alpha Excess Ret$_{t-1}$	0.0139***		0.0135***	
	(0.00222)		(0.00225)	
Spatial Lag (Jensen's$_{t-1}$)	0.00430*		0.00376	
	(0.00238)		(0.00234)	
4 Factor ExcessRet$_{t-1}$		0.00688**		0.00626**
		(0.00288)		(0.00282)
Spatial Lag (4Factor$_{t-1}$)		0.0192***		0.0189***
		(0.00369)		(0.00359)
Best-Worst $_{t-1}$	-0.00198***	-0.00120**	-0.00200***	-0.00112**
	(0.000710)	(0.000531)	(0.000711)	(0.000516)
Best-Worst x Jensen's	0.00109		0.00104	
	(0.00174)		(0.00179)	
Best-Worst x 4Factor		0.000687		0.00148
		(0.00396)		(0.00386)
Flow 1$_{t-1}$	-7.80e-07	-0.000167		
	(0.000184)	(0.000216)		
Flow 2$_{t-1}$			-1.03e-06	2.14e-07
			(1.55e-06)	(1.53e-06)
Age $_{t-1}$	1.63e-07	-6.89e-05	-1.24e-06	-7.58e-05
	(6.01e-05)	(6.07e-05)	(6.04e-05)	(6.19e-05)
Size 2 $_{t-1}$	-0.00257	-0.00151	-0.00187	-0.00147
	(0.00310)	(0.00226)	(0.00276)	(0.00233)
Expense Ratio $_t$	-0.00532*	-0.00450*	-0.00543*	-0.00432*
	(0.00294)	(0.00256)	(0.00288)	(0.00238)
R-squared	0.222	0.300	0.210	0.302
Observations	304	304	300	300

***p<0.01, ** p<0.05, * p<0.1

The findings from the spatial lag of X model are presented in Panel A and Panel B of this table. The model specification is shown below:

$$\Delta RISK_{i,t} = \psi_0 + \psi_1 Risk_{i,t-1} + \psi_2 Age_{i,t-1} + \psi_3 Size2_{i,t-1} + \psi_4 Expense_{i,t} + \psi_5 Perf_{i,t-1}$$

$$+ \tau\sum_{j=1}^{n} W_{ij} Perf_{i,t-1} + \psi_6 Flow_{i,t-1} + \psi_7 Best\_Worst_{t-1} + \psi_8 Best-Worst\ x\ Performance + \upsilon_{i,t}$$

Dependent variable is defined as the change in the semiannual standard deviation of daily returns. Fund characteristics are flow, performance, age, size, risk, and expense ratio. Fund performance is scaled by a spatial weight matrix (W) obtained from DEAs based on fund efficiencies. The fund i is accepted as neighbor to its peer group. The distance between two funds is the multiplicative inverse of fund i's inefficiency value. Models in Panel A and Panel B differ by lagged risk proxies used. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns. Robust standard errors are presented in parenthesis.

Table 21b. Spatial Lag of X Model of Risk Change with Size 2 Variable

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.0492***	-0.0495***	-0.0522***	-0.0516***
	(0.0133)	(0.0121)	(0.0132)	(0.0121)
Std. Dev $_{t-1}$	7.679***	5.100***	7.699***	5.240***
	(1.016)	(0.825)	(1.020)	(0.840)
Jensen's Alpha Excess Ret$_{t-1}$	-0.102***		-0.0998***	
	(0.0183)		(0.0185)	
Spatial Lag (Jensen's$_{t-1}$)	0.0450		0.0484*	
	(0.0274)		(0.0277)	
4 Factor ExcessRet$_{t-1}$		0.00349		0.00287
		(0.0626)		(0.0631)
Spatial Lag (4Factor$_{t-1}$)		-0.0151		-0.0127
		(0.0364)		(0.0366)
Best-Worst $_{t-1}$	0.0184***	0.0140**	0.0172***	0.0126*
	(0.00531)	(0.00666)	(0.00527)	(0.00666)
Best-Worst x Jensen's	-0.00902		-0.00708	
	(0.0103)		(0.0104)	
Best-Worst x 4Factor		-0.0654*		-0.0648*
		(0.0381)		(0.0379)
Flow 1$_{t-1}$	0.000463	0.00152		
	(0.00247)	(0.00217)		
Flow 2$_{t-1}$			1.50e-07	-1.73e-06
			(2.24e-05)	(2.55e-05)
Age $_{t-1}$	0.000459	0.000472	0.000575	0.000621
	(0.000508)	(0.000582)	(0.000498)	(0.000576)
Size 2 $_{t-1}$	0.0110	0.0116	0.0135	0.0145
	(0.0525)	(0.0543)	(0.0515)	(0.0532)
Expense Ratio $_{t}$	-0.00877	-0.0245	-0.00416	-0.0211
	(0.0197)	(0.0220)	(0.0194)	(0.0205)
R-squared	0.274	0.192	0.274	0.195
Observations	304	304	300	300
t test (Constant + B-W)	-0.0307**	-0.0354***	-0.035***	-0.039***
	(0.012)	(0.013)	(0.012)	(0.013)

***p<0.01, ** p<0.05, * p<0.1

Table 21b. Spatial Lag of X Model of Risk Change with Size 2 Variable

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	0.0120	0.0182	0.00928	0.0169
	(0.0144)	(0.0123)	(0.0144)	(0.0123)
Beta $_{t-1}$	-0.00338	-0.0154	-0.00191	-0.0141
	(0.0283)	(0.0157)	(0.0282)	(0.0158)
Jensen's Alpha Excess Ret$_{t-1}$	-0.00525		-0.00569	
	(0.0337)		(0.0343)	
Spatial Lag (Jensen's$_{t-1}$)	0.00698		0.0115	
	(0.0303)		(0.0307)	
4 Factor ExcessRet$_{t-1}$		0.0236		0.0198
		(0.0732)		(0.0739)
Spatial Lag (4Factor$_{t-1}$)		-0.000853		0.00441
		(0.0398)		(0.0395)
Best-Worst $_{t-1}$	0.0106*	0.00860	0.00931	0.00751
	(0.00610)	(0.00726)	(0.00602)	(0.00725)
Best-Worst x Jensen's	-0.0226**		-0.0212*	
	(0.0109)		(0.0112)	
Best-Worst x 4Factor		-0.120***		-0.119***
		(0.0388)		(0.0385)
Flow 1$_{t-1}$	0.00240	0.00259		
	(0.00270)	(0.00272)		
Flow 2$_{t-1}$			8.40e-06	7.18e-06
			(2.94e-05)	(2.97e-05)
Age $_{t-1}$	-0.000167	-8.04e-05	-3.50e-05	5.01e-05
	(0.000520)	(0.000571)	(0.000513)	(0.000568)
Size 2 $_{t-1}$	-0.0315	-0.0311	-0.0324	-0.0323
	(0.0579)	(0.0588)	(0.0538)	(0.0553)
Expense Ratio $_t$	0.0123	0.0146	0.0136	0.0159
	(0.0251)	(0.0247)	(0.0238)	(0.0233)
R-squared	0.028	0.045	0.021	0.038
Observations	304	304	300	300

***p<0.01, ** p<0.05, * p<0.1

The findings from the spatial lag of X model are presented in Panel A and Panel B of this table. The model specification is shown below:

$$\Delta RISK_{i,t} = \psi_0 + \psi_1 Risk_{i,t-1} + \psi_2 Age_{i,t-1} + \psi_3 Size2_{i,t-1} + \psi_4 Expense_{i,t} + \psi_5 Perf_{i,t-1}$$

$$+ \tau \sum_{j=1}^{n} W_{ij} Perf_{i,t-1} + \psi_6 Flow_{i,t-1} + \psi_7 Best\_Worst_{t-1} + \psi_8 Best - Worst\ x\ Performanc\ e \quad + \upsilon_{i,t}$$

Dependent variable is defined as the change in a fund's betas. Fund characteristics are flow, performance, age, size, risk, and expense ratio. Fund performance is scaled by a spatial weight matrix (*W*) which is obtained from DEAs based on fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is the multiplicative inverse of fund *i*'s inefficiency value. Models in Panel A and Panel B differ by the lagged risk proxies used. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns. Robust standard errors are presented in parenthesis.

Spatial lag of X models for risk change decision that are estimated with *Size 2* variable also produce comparable results with those obtained from original *Size* variable. From Table 21a, it seems that managers take into account the neighboring funds' performance when changing the total risk of their portfolios. The systematic risk change decision, on the other hand, shows slight evidence of neighboring effect since, in only one model in Panel A of Table 21b, there is a positive and significant coefficient on spatial lag. Positive coefficients for performance variables in Table 21a are not consistent with tournament behavior. The only evidence in favor of tournament hypothesis is the negative coefficient of Jensen's alpha excess return measure in Table 21b. This coefficient points out that managers may decrease the systematic risk of their portfolio in the second half of the year if the fund performs well in the first half of the year. However, as Cullen et al. (2012) has suggested, there may be reasons other than tournament behavior to alter the portfolio risk like portfolio re-balancing. Hence, stronger evidence is needed to conclude that tournament behavior do exist in Turkish mutual fund industry. So far, findings mostly indicate the opposite. However, the results are generally robust to two different definitions of the fund size variable.

5.2. Additional Control Variables

The serious economic crisis taking place in Turkey at the beginning of 2000s did not only affect banking sector, but all the financial system. In these years, the ratio of mutual funds to GDP was low in comparison to the countries with similar economic development level like Greece or Spain (Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği, 2003). In 2004, this ratio was around 5%. With the beginning of the US sub-prime mortgage crisis at the end of the 2008, prices of financial securities decreased significantly and contributed to the decline in the ratio of mutual funds to GDP as well. In 2009, the ratio of mutual funds to GDP became 3% (Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği, 2010). One can also reasonably argue that the market conditions might have changed significantly from before to after this global financial crisis.

Since, this dissertation covers a period from 2005 to 2011, to account for the effect of this global financial crisis on Turkish investors' mutual fund investment decisions and fund managers' risk altering behaviors, a Crisis Dummy variable is added to the flow and the risk models. This Crisis Dummy variable has a value of 1 for the period from 2009 to 2011 and 0 otherwise. In addition to the Crisis Dummy, to take into account the bank dominance in this industry, another dummy variable, namely *Bank Dummy* is created. This dummy variable takes a value of 1 if the fund is owned by a bank and 0 otherwise. The effect of these two variables on the flow and the risk change models are estimated and reported in the next section of this chapter.

5.2.1. Flow Models with Crisis Dummy

To examine the effects of the global financial crisis and bank ownership on the investors' mutual fund choices, one may benefit from the regression specification given below:

$$\begin{aligned} Flow_{i,t} = {} & \gamma_0 + \gamma_1 Perf_{i,t-1} + \gamma_2 Age_{i,t-1} + \gamma_3 Size_{i,t-1} + \gamma_4 Risk_{i,t-1} + \gamma_5 Expense_{i,t} \\ & + \gamma_6 Flow_{i,t-1} + \gamma_7 Semiannual\_Dummy + \gamma_8 Best\_Worst_{t-1} \\ & + \gamma_9 Best\_WorstxPerformance + \gamma_{10} Bank\_Dummy + \gamma_{11} Crisis\_Dummy + \varepsilon_{i,t} \end{aligned} \tag{9}$$

Apart from these two new variables, other dependent and independent variables remain the same. Table 2a has the explanations of these variables. To be consistent with earlier robustness analysis, these modified regressions are estimated with both size variable definitions as well.

Table 22a. Flow Models

VARIABLES	(1)	(2)	(3)	(4)
Constant	3.168**	3.609***	3.162**	3.507***
	(1.234)	(1.368)	(1.243)	(1.330)
Jensen's Alpha Excess Ret_{t-1}	-0.909**		-0.941**	
	(0.431)		(0.454)	
4 Factor Excess Ret_{t-1}		-0.922		-0.923
		(0.626)		(0.608)
Std. Dev $_{t-1}$	12.90	4.956		
	(10.67)	(11.14)		
Beta $_{t-1}$			0.596*	0.331
			(0.311)	(0.235)
$Flow_{t-1}$	-0.0434**	-0.0401**	-0.0417**	-0.0404***
	(0.0172)	(0.0155)	(0.0165)	(0.0155)
Best-Worst $_{t-1}$	0.135	-0.164	0.0850	-0.153
	(0.164)	(0.158)	(0.165)	(0.152)
Best-Worst x Jensen's	0.425*		0.295	
	(0.249)		(0.263)	
Best-Worst x 4Factor		-1.135*		-1.031*
		(0.590)		(0.579)
Semiannual Dummy	0.0239	0.00929	0.0351	0.0118
	(0.119)	(0.110)	(0.119)	(0.110)
Crisis Dummy	0.229**	0.261**	0.242**	0.264**
	(0.112)	(0.110)	(0.111)	(0.108)
Bank Dummy	-0.0162	-0.0755	-0.0303	-0.0851
	(0.132)	(0.141)	(0.132)	(0.144)
Age $_{t-1}$	-0.00746	-0.00811	-0.00797	-0.00816
	(0.0101)	(0.0101)	(0.00996)	(0.00995)
Size $_{t-1}$	-0.192***	-0.216***	-0.200***	-0.218***
	(0.0724)	(0.0795)	(0.0730)	(0.0803)
Expense Ratio $_t$	-1.785	-1.638	-1.840	-1.743
	(1.663)	(1.518)	(1.636)	(1.539)
R-squared	0.065	0.073	0.066	0.074
Observations	611	611	611	611
t test (Jensen's + B-W x Jensen's)	-0.4835			
	(0.408)			

*** p<0.01, ** p<0.05, * p<0.1

This table shows the findings from the flow model that relates the fund flow to the fund characteristics, such as performance, age, size, risk, and expense ratio as well as one period lagged flow. The formal model can be represented as follows:

$$Flow_{i,t} = \gamma_0 + \gamma_1 Perf_{i,t-1} + \gamma_2 Age_{i,t-1} + \gamma_3 Size_{i,t-1} + \gamma_4 Risk_{i,t-1} + \gamma_5 Expense_{i,t} + \gamma_6 Flow_{i,t-1} + \gamma_7 Semiannual\_Dummy + \gamma_8 Best\_Worst_{t-1} + \gamma_9 Best\_WorstxPerformance + \gamma_{10} Crisis\_Dummy + \gamma_{11} Bank\_Dummy + \varepsilon_{i,t}$$

Here, the dependent variable is the cash flow obtained from daily reports to CMB. Models presented in this Table alternate the performance proxies, namely Jensen's alpha excess returns and Four-Factor excess returns, as well as risk proxies, namely standard deviation and beta. Robust standard errors are presented in parenthesis.

Table 22b. Flow Models

VARIABLES	(1)	(2)	(3)	(4)
Constant	-181.9***	-154.7**	-186.5***	-158.4**
	(66.33)	(69.62)	(66.87)	(69.04)
Jensen's Alpha Excess Ret_{t-1}	48.38		38.13	
	(45.32)		(28.45)	
4 Factor Excess Ret_{t-1}		122.5*		119.4*
		(66.25)		(63.66)
Std. Dev $_{t-1}$	-1,142	-1,024		
	(1,740)	(1,458)		
Beta $_{t-1}$			-17.28	-20.78
			(46.36)	(28.40)
$Flow_{t-1}$	-0.0724***	-0.0703***	-0.0732***	-0.0714***
	(0.0208)	(0.0206)	(0.0210)	(0.0209)
Best-Worst $_{t-1}$	-2.960	-20.72	-0.977	-20.56
	(15.68)	(15.76)	(17.18)	(15.63)
Best-Worst x Jensen's	-18.47		-15.59	
	(28.12)		(34.03)	
Best-Worst x 4Factor		-68.69		-69.53
		(49.80)		(46.59)
Semiannual Dummy	-12.71	-11.88	-12.97	-12.47
	(11.73)	(11.70)	(11.97)	(11.50)
Crisis Dummy	-40.31***	-39.30***	-41.39***	-40.22***
	(13.81)	(13.75)	(13.28)	(13.26)
Bank Dummy	26.21***	23.78**	26.34***	24.10**
	(9.762)	(9.622)	(9.805)	(9.642)
Age $_{t-1}$	-0.679	-0.659	-0.614	-0.607
	(1.566)	(1.555)	(1.502)	(1.497)
Size $_{t-1}$	14.75***	14.39***	15.10***	14.72***
	(5.036)	(5.030)	(5.235)	(5.141)
Expense Ratio $_{t}$	38.76	45.69	37.35	47.36
	(41.62)	(44.00)	(42.28)	(44.07)
R-squared	0.056	0.059	0.056	0.059
Observations	603	603	603	603

*** p<0.01, ** p<0.05, * p<0.1

Dependent variables in this table are the change in the number of investors scaled by the previous period number of investors (number of investors $_{i,t}$/number of investors$_{i,t-1}$). The formal model can be represented as follows:

$$Flow_{i,t} = \gamma_0 + \gamma_1 Perf_{i,t-1} + \gamma_2 Age_{i,t-1} + \gamma_3 Size_{i,t-1} + \gamma_4 Risk_{i,t-1} + \gamma_5 Expense_{i,t} + \gamma_6 Flow_{i,t-1} + \gamma_7 Semiannual\_Dummy + \gamma_8 Best\_Worst_{t-1} + \gamma_9 Best\_WorstxPerformance + \gamma_{10} Crisis\_Dummy + \gamma_{11} Bank\_Dummy + \varepsilon_{i,t}$$

Models presented in this Table alternate the performance proxies, namely Jensen's alpha excess returns and Four-Factor excess returns, as well as risk proxies, namely standard deviation and beta. Robust standard errors are shown in parenthesis.

One may observe that he results presented in Tables 22a and 22b are consistent with those reported in Tables 9a and 9b. Again, it is seen that TL flow is negatively related with Jensen’s alpha measure. However, the outflow from funds is lower for the best funds, because the coefficients for *Best-Worst x Jensen’s* variable and the constant term are found to be positive. No risk aversion for fund investors can be detected. Instead, weak evidence of risk taking behavior may be observed because of positive *Beta* coefficient in one of the models. Although bank ownership has no effect on TL flows, it has a positive impact on account numbers. Investors may find it easier to make transactions with bank-owned mutual funds. Therefore the change in number of investors may be positively related with bank ownership. Crisis dummy, on the other hand, is significant in all the models. It has a positive effect on TL flows, whereas a negative impact of this variable is observed on change in number of investors. It seems that although mutual funds have attracted some cash flows after the crisis, the number of accounts have declined during that period. Because of this opposite change in number of investors and fund flows after the crisis, mutual fund market in Turkey was able to protect its ranking based on the ratio of mutual fund industry to GDP among other countries in the world (Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği, 2011, 2012).

This analysis is also repeated with Size 2 variable in order to provide comparable results. The findings are shown in Tables 23a and 23b.

Table 23a. Flow Models with Size 2

VARIABLES	(1)	(2)	(3)	(4)
Constant	0.347	0.366	0.376	0.344
	(0.227)	(0.275)	(0.269)	(0.244)
Jensen's Alpha Excess Ret_{t-1}	-0.867**		-0.661	
	(0.440)		(0.426)	
4 Factor Excess Ret_{t-1}		-0.533		-0.490
		(0.590)		(0.564)
Std. Dev $_{t-1}$	17.67	11.58		
	(11.73)	(12.53)		
Beta $_{t-1}$			0.144	0.249
			(0.330)	(0.230)
$Flow_{t-1}$	-0.0497**	-0.0464**	-0.0489**	-0.0463**
	(0.0196)	(0.0182)	(0.0192)	(0.0180)
Best-Worst $_{t-1}$	0.178	-0.0977	0.157	-0.0974
	(0.179)	(0.156)	(0.186)	(0.152)
Best-Worst x Jensen's	0.324		0.309	
	(0.240)		(0.267)	
Best-Worst x 4Factor		-0.533		-0.490
		(0.590)		(0.564)
Semiannual Dummy	0.0200	-0.00179	0.0212	0.00479
	(0.121)	(0.109)	(0.119)	(0.111)
Crisis Dummy	0.192	0.212*	0.206*	0.221*
	(0.122)	(0.122)	(0.120)	(0.119)
Bank Dummy	-0.0392	-0.0754	-0.0362	-0.0790
	(0.143)	(0.148)	(0.139)	(0.150)
Age $_{t-1}$	-0.0109	-0.0118	-0.0120	-0.0125
	(0.0105)	(0.0105)	(0.0104)	(0.0104)
Size 2 $_{t-1}$	-1.366**	-1.738***	-1.431***	-1.747***
	(0.534)	(0.631)	(0.538)	(0.630)
Expense Ratio $_{t}$	-1.099	-0.903	-1.044	-0.913
	(1.379)	(1.266)	(1.346)	(1.262)
R-squared	0.022	0.021	0.020	0.021
Observations	611	611	611	611

*** p<0.01, ** p<0.05, * p<0.1

This table shows the findings from the flow model that relates the fund flow to the fund characteristics, such as performance, age, size, risk, and expense ratio as well as one period lagged flow. The formal model can be represented as follows:

$$Flow_{i,t} = \gamma_0 + \gamma_1 Perf_{i,t-1} + \gamma_2 Age_{i,t-1} + \gamma_3 Size2_{i,t-1} + \gamma_4 Risk_{i,t-1} + \gamma_5 Expense_{i,t} + \gamma_6 Flow_{i,t-1}$$
$$+ \gamma_7 Semiannual\_Dummy + \gamma_8 Best\_Worst_{t-1} + \gamma_9 Best\_WorstxPerformance$$
$$+ \gamma_{10} Crisis\_Dummy + \gamma_{11} Bank\_Dummy + \varepsilon_{i,t}$$

Here, the dependent variable is the cash flow obtained from daily reports to CMB. Models presented in this Table alternate the performance proxies, namely Jensen's alpha excess returns and Four-Factor excess returns, as well as risk proxies, namely standard deviation and beta. Robust standard errors are presented in parenthesis.

Table 23b. Flow Models with Size 2

VARIABLES	(1)	(2)	(3)	(4)
Constant	18.24	43.07	9.049	35.23
	(20.48)	(29.08)	(25.10)	(29.49)
Jensen's Alpha Excess Ret$_{t-1}$	45.65		22.20	
	(45.99)		(28.11)	
4 Factor Excess Ret$_{t-1}$		108.0		103.5
		(66.40)		(63.49)
Std. Dev $_{t-1}$	-1,244	-1,024		
	(1,788)	(1,452)		
Beta $_{t-1}$			14.67	-4.124
			(43.48)	(26.70)
Flow$_{t-1}$	-0.0758***	-0.0748***	-0.0765***	-0.0755***
	(0.0284)	(0.0284)	(0.0285)	(0.0285)
Best-Worst $_{t-1}$	-4.560	-24.10	-4.682	-23.21
	(15.63)	(15.90)	(16.99)	(15.79)
Best-Worst x Jensen's	-7.070		-12.22	
	(28.19)		(34.05)	
Best-Worst x 4Factor		-78.74		-72.75
		(51.15)		(47.30)
Semiannual Dummy	-12.44	-11.42	-12.03	-12.02
	(11.73)	(11.65)	(11.92)	(11.47)
Crisis Dummy	-35.96***	-34.95***	-36.96***	-35.89***
	(13.01)	(12.90)	(12.40)	(12.38)
Bank Dummy	24.10***	20.83**	23.07**	20.54**
	(9.248)	(9.037)	(9.134)	(8.934)
Age $_{t-1}$	-0.0432	-0.0433	0.0496	0.0364
	(1.535)	(1.526)	(1.466)	(1.463)
Size 2 $_{t-1}$	487.6*	479.4*	491.7*	486.5*
	(280.7)	(278.8)	(281.1)	(279.9)
Expense Ratio $_t$	17.40	27.96	10.24	22.03
	(31.31)	(33.33)	(33.02)	(34.28)
R-squared	0.058	0.063	0.058	0.062
Observations	603	603	603	603

*** p<0.01, ** p<0.05, * p<0.1

Dependent variables in this table are the change in the number of investors scaled by the previous period number of investors (number of investors $_{i,t}$/number of investors$_{i,t-1}$). The formal model can be seen below:

$$Flow_{i,t} = \gamma_0 + \gamma_1 Perf_{i,t-1} + \gamma_2 Age_{i,t-1} + \gamma_3 Size2_{i,t-1} + \gamma_4 Risk_{i,t-1} + \gamma_5 Expense_{i,t} + \gamma_6 Flow_{i,t-1}$$
$$+ \gamma_7 Semiannual\_Dummy + \gamma_8 Best\_Worst_{t-1} + \gamma_9 Best\_WorstxPerformance$$
$$+ \gamma_{10} Crisis\_Dummy + \gamma_{11} Bank\_Dummy + \varepsilon_{i,t}$$

Models presented in this Table alternate the performance proxies, namely Jensen's alpha excess returns and Four-Factor excess returns, as well as risk proxies, namely standard deviation and beta. Robust standard errors are shown in parenthesis.

Tables 23a and 23b provide essentially the same results with previous flow models. More specifically, the negative and significant effect of performance variable on TL flow to the funds is exhibited in results reported in Table 23a. The crisis dummy variable still has a significant and positive coefficient, indicating and increase in TL flows to mutual funds in the period after the global financial crisis. However, change in number of investors is still negatively affected from the global financial crisis. Bank ownership is only important for the change in number of investors variable. Investors do seem to prefer bank-owned funds to create new investment accounts.

Examining flow models with different size and additional control variables, such as ownership structure and crisis dummy variables, reveal that results are robust to different specifications of the flow model. It is found that investors care mostly about prior performance of a fund. However, instead of investing more in funds with good performance in the previous 6-month period, they tend to withdraw their money and realize their net gain from these funds. There is evidence showing that best performing funds do experience lower withdrawals than worst performing funds.

Both the original flow models and models with *Size 2* variable show that investors are not affected from other funds' performances or cash flows when channeling their investments across funds. The only evidence indicating that investors may be affected from performances of other funds in their fund investment decisions comes from the spatial lag of X models for change in number of investors. These results point out that all else being equal, when neighbors/rivals of a fund show good performance, number of investor accounts for this fund decreases. This type of evidence is an example of exogenous interactions in investors' fund choices. Since no endogenous interactions or a combination of exogenous and endogenous interactions are detected previously, analyses reported above are repeated only for exogenous interactions. To do so, spatial lag of X models with new control variables are estimated and the results are reported in Tables 24a and 24b for the original size variable.

Table 24a. Spatial Lag of X Model of Flow

VARIABLES	(1)	(2)	(3)	(4)
Constant	3.756**	4.218**	3.774**	4.145***
	(1.462)	(1.637)	(1.480)	(1.600)
Spatial Lag of Perf. (Jensen's$_{t-1}$)	-0.00975		-0.0676	
	(0.420)		(0.407)	
Jensen's Alpha Excess Ret$_{t-1}$	-1.061**		-1.062**	
	(0.476)		(0.498)	
Spatial Lag of Perf. (4Factor$_{t-1}$)		0.731		0.601
		(0.655)		(0.651)
4 Factor ExcessRet$_{t-1}$		-1.303*		-1.225*
		(0.730)		(0.681)
Std. Dev $_{t-1}$	12.58	8.830		
	(12.16)	(11.83)		
Beta $_{t-1}$			0.498	0.339
			(0.340)	(0.256)
Flow 1$_{t-1}$	-0.0431*	-0.0452*	-0.0428*	-0.0455**
	(0.0225)	(0.0232)	(0.0221)	(0.0230)
Best-Worst $_{t-1}$	0.167	-0.151	0.122	-0.147
	(0.181)	(0.162)	(0.183)	(0.156)
Best-Worst x Jensen's	0.510**		0.410	
	(0.250)		(0.255)	
Best-Worst x 4Factor		-1.193		-1.060
		(0.805)		(0.796)
Semiannual Dummy	0.0157	-0.00388	0.0262	0.00286
	(0.123)	(0.113)	(0.124)	(0.114)
Crisis Dummy	0.246**	0.261**	0.261**	0.273***
	(0.105)	(0.104)	(0.103)	(0.101)
Bank Dummy	-0.0853	-0.134	-0.0977	-0.143
	(0.156)	(0.166)	(0.157)	(0.169)
Age $_{t-1}$	-0.00798	-0.00971	-0.00853	-0.00980
	(0.0109)	(0.0109)	(0.0107)	(0.0108)
Size $_{t-1}$	-0.223**	-0.253***	-0.230***	-0.255***
	(0.0878)	(0.0961)	(0.0885)	(0.0968)
Expense Ratio $_{t}$	-2.046	-1.924	-2.102	-2.014
	(1.918)	(1.753)	(1.898)	(1.780)
R-squared	0.073	0.079	0.073	0.080
Observations	554	554	554	554
t test (Jensen's + B-W x Jensen's)	-0.551			
	(0.432)			

*** p<0.01, ** p<0.05, * p<0.1

This table shows the results of spatial lag of X model for fund flow. Fund characteristics are age, size, expense ratio and risk. Dependent variable, Flow 1, is the flow computed from the daily reports of funds to CMB. One period lagged performance variables are scaled by W matrix. *W* is constructed by the aid of DEAs based on fund efficiencies. The distance between two funds is computed as the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parentheses. The formal model can be seen below:

$$Flow_{i,t} = \beta_0 + \theta\sum_{j=1}^{n} W_{ij} Perf_{i,t-1} + \beta_1 Perf_{i,t-1} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Risk_{i,t-1} + \beta_5 Expense_{i,t} + \beta_6 Semiannual\_Dummy$$

$$+ \beta_7 Best\_Worst_{t-1} + \beta_8 Best\_Worst\ x\ Performanc\ e + \beta_9 Crisis\_Dummy + \beta_{10} Bank\_Dummy + \vartheta_{i,t}$$

Table 24b. Spatial Lag of X Model of Flow

VARIABLES	(1)	(2)	(3)	(4)
Constant	-212.6***	-196.7**	-222.2***	-194.2**
	(76.49)	(84.09)	(77.54)	(83.56)
Spatial Lag of Perf. (Jensen's$_{t-1}$)	-59.36		-42.43	
	(37.33)		(31.27)	
Jensen's Alpha Excess Ret$_{t-1}$	47.54		34.48	
	(49.86)		(30.19)	
Spatial Lag of Perf. (4Factor$_{t-1}$)		18.66		32.01
		(58.65)		(58.48)
4 Factor ExcessRet$_{t-1}$		108.9		100.4
		(72.62)		(66.68)
Std. Dev $_{t-1}$	-1,639	-977.5		
	(2,064)	(1,582)		
Beta $_{t-1}$			-26.80	-27.23
			(49.38)	(31.25)
Flow 2$_{t-1}$	-0.0826***	-0.0811***	-0.0842***	-0.0824***
	(0.0247)	(0.0245)	(0.0251)	(0.0249)
Best-Worst $_{t-1}$	2.821	-16.68	6.024	-16.54
	(15.92)	(16.64)	(18.13)	(16.30)
Best-Worst x Jensen's	-25.22		-22.36	
	(27.57)		(35.06)	
Best-Worst x 4Factor		-99.12		-109.0*
		(64.87)		(64.41)
Semiannual Dummy	-16.81	-15.12	-17.21	-15.81
	(12.95)	(13.09)	(13.33)	(12.86)
Crisis Dummy	-47.09***	-46.60***	-48.98***	-47.90***
	(16.25)	(16.05)	(15.70)	(15.60)
Bank Dummy	29.18***	27.17**	29.85***	27.83**
	(11.19)	(11.08)	(11.34)	(11.15)
Age $_{t-1}$	-0.721	-0.690	-0.628	-0.667
	(1.647)	(1.634)	(1.572)	(1.579)
Size $_{t-1}$	18.43***	17.40***	18.87***	17.62***
	(6.180)	(6.201)	(6.422)	(6.290)
Expense Ratio $_t$	44.67	59.80	45.46	65.24
	(41.76)	(49.21)	(42.49)	(49.30)
R-squared	0.070	0.070	0.069	0.070
Observations	547	547	547	547

*** p<0.01, ** p<0.05, * p<0.1

The findings from the spatial lag of X model are presented in this table. The formal model can be seen below:

$$Flow_{i,t} = \beta_0 + \theta\sum_{j=1}^{n} W_{ij}Perf_{i,t-1} + \beta_1 Perf_{i,t-1} + \beta_2 Age_{i,t-1} + \beta_3 Size_{i,t-1} + \beta_4 Risk_{i,t-1} + \beta_5 Expense_{i,t} + \beta_6 Semiannual\_Dummy$$
$$+ \beta_7 Best\_Worst_{t-1} + \beta_8 Best\_Worst\ x\ Performanc\ e + \beta_9 Crisis\_Dummy + \beta_{10} Bank\_Dummy + \vartheta_{i,t}$$

Fund characteristics are age, size, expense ratio and risk. Dependent variables in all models, Flow 2, are the change in the number of investors in two subsequent periods. One period lagged performance variables are scaled by the spatial weight matrix. *W* is constructed by the aid of DEAs based on fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is computed as the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parentheses.

Consistent with the previous results, no spatial interaction can be detected in the TL flows to mutual funds. Thus, the models presented in Table 24a revert back to classical OLS models. Results in this table are generally consistent with those reported in Tables 9a and 12a. However, findings in Table 24b do not validate the existence of exogenous interactions anymore in models for change in number of investors. Although spatial lags for Jensen's alpha and Four-Factor excess return are negative as before, they are not statistically significantly different from zero. Putting it differently, previously found neighboring impacts on investor accounts cannot be verified when one includes the bank ownership and crisis dummy variables into the models. Mutual funds that are held by a bank continue to attract more investors in terms of number of accounts, but there is no difference between TL cash flows to bank and non-bank owned mutual funds. After 2009, TL cash flows do increase, but the number of accounts decreases. These models are re-estimated with the *Size 2* variable and the results are reported in Tables 25a and 25b.

Table 25a. Spatial Lag of X Model of Flow with Size 2

VARIABLES	(1)	(2)	(3)	(4)
Constant	0.550*	0.434	0.685*	0.412
	(0.288)	(0.301)	(0.353)	(0.275)
Spatial Lag of Perf. (Jensen's$_{t-1}$)	-0.348		-0.546	
	(0.391)		(0.404)	
Jensen's Alpha Excess Ret$_{t-1}$	-0.979**		-0.756	
	(0.480)		(0.461)	
Spatial Lag of Perf. (4Factor$_{t-1}$)		-0.140		-0.290
		(0.635)		(0.664)
4 Factor ExcessRet$_{t-1}$		-0.541		-0.439
		(0.630)		(0.582)
Std. Dev $_{t-1}$	14.28	11.00		
	(12.73)	(12.76)		
Beta $_{t-1}$			-0.0780	0.229
			(0.370)	(0.246)
Flow 1$_{t-1}$	-0.0537*	-0.0526*	-0.0535*	-0.0527*
	(0.0277)	(0.0272)	(0.0274)	(0.0269)
Best-Worst $_{t-1}$	0.200	-0.127	0.194	-0.131
	(0.196)	(0.166)	(0.207)	(0.160)
Best-Worst x Jensen's	0.420*		0.479*	
	(0.239)		(0.267)	
Best-Worst x 4Factor		-0.478		-0.396
		(0.791)		(0.796)
Semiannual Dummy	0.00325	-0.0182	-0.00221	-0.0111
	(0.124)	(0.112)	(0.121)	(0.113)
Crisis Dummy	0.177	0.193	0.189	0.206*
	(0.122)	(0.120)	(0.119)	(0.116)
Bank Dummy	-0.0715	-0.0919	-0.0665	-0.0956
	(0.160)	(0.162)	(0.156)	(0.165)
Age $_{t-1}$	-0.0117	-0.0129	-0.0127	-0.0133
	(0.0113)	(0.0115)	(0.0111)	(0.0113)
Size 2 $_{t-1}$	-1.328**	-1.710***	-1.364**	-1.705***
	(0.550)	(0.658)	(0.550)	(0.653)
Expense Ratio $_t$	-1.209	-1.019	-1.162	-1.038
	(1.540)	(1.421)	(1.521)	(1.429)
R-squared	0.022	0.019	0.022	0.019
Observations	554	554	554	554
t test (Jensen's + B-W x Jensen's)	-0.559			
	(0.447)			

*** p<0.01, ** p<0.05, * p<0.1

This table shows the results of spatial lag of X model for fund flow. Fund characteristics are age, size, expense ratio and risk. Dependent variable, Flow 1, is the flow computed from the daily reports of funds to CMB. One period lagged performance variables are scaled by W matrix. *W* is constructed by the aid of DEAs based on fund efficiencies. The distance between two funds is computed as the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parentheses. The formal model can be seen below:

$$Flow_{i,t} = \beta_0 + \theta\sum_{j=1}^{n} W_{ij} Perf_{i,t-1} + \beta_1 Perf_{i,t-1} + \beta_2 Age_{i,t-1} + \beta_3 Size2_{i,t-1} + \beta_4 Risk_{i,t-1} + \beta_5 Expense_{i,t} + \beta_6 Semiannual\_Dummy$$
$$+ \beta_7 Best\_Worst_{t-1} + \beta_8 Best\_Worst\ x\ Performanc\ e + \beta_9 Crisis\_Dummy + \beta_{10} Bank\_Dummy + \vartheta_{i,t}$$

Table 25b. Spatial Lag of X Model of Flow with Size 2

VARIABLES	(1)	(2)	(3)	(4)
Constant	31.34	44.05	13.80	41.16
	(24.77)	(30.93)	(25.37)	(32.46)
Spatial Lag of Perf. (Jensen's$_{t-1}$)	-26.17		-2.371	
	(34.02)		(28.77)	
Jensen's Alpha Excess Ret$_{t-1}$	41.65		15.79	
	(50.78)		(30.03)	
Spatial Lag of Perf. (4Factor$_{t-1}$)		73.10		81.75
		(56.81)		(58.99)
4 Factor ExcessRet$_{t-1}$		72.48		66.53
		(71.70)		(66.05)
Std. Dev $_{t-1}$	-1,476	-685.4		
	(2,112)	(1,534)		
Beta $_{t-1}$			16.78	-6.716
			(45.16)	(28.68)
Flow 2$_{t-1}$	-0.0815***	-0.0826***	-0.0830***	-0.0832***
	(0.0313)	(0.0314)	(0.0315)	(0.0315)
Best-Worst $_{t-1}$	2.739	-17.37	2.794	-16.72
	(15.78)	(16.70)	(17.84)	(16.35)
Best-Worst x Jensen's	-14.66		-23.08	
	(27.58)		(35.10)	
Best-Worst x 4Factor		-134.3**		-135.8**
		(67.39)		(66.84)
Semiannual Dummy	-15.99	-14.62	-15.26	-15.03
	(12.97)	(13.06)	(13.24)	(12.83)
Crisis Dummy	-40.07***	-40.86***	-41.50***	-41.64***
	(14.91)	(14.82)	(14.06)	(14.13)
Bank Dummy	24.01**	21.13**	23.39**	21.10**
	(9.957)	(9.793)	(9.861)	(9.678)
Age $_{t-1}$	0.0419	-0.0253	0.151	0.0146
	(1.612)	(1.593)	(1.530)	(1.532)
Size 2 $_{t-1}$	516.8*	504.9*	520.7*	507.5*
	(292.4)	(290.8)	(292.6)	(291.6)
Expense Ratio $_{t}$	10.55	31.79	5.067	30.02
	(25.90)	(30.71)	(27.33)	(30.99)
R-squared	0.066	0.071	0.065	0.071
Observations	547	547	547	547

*** p<0.01, ** p<0.05, * p<0.1

The findings from the spatial lag of X model are presented in this table. The formal model can be seen below:

$$Flow_{i,t} = \beta_0 + \theta\sum_{j=1}^{n} W_{ij}Perf_{i,t-1} + \beta_1 Perf_{i,t-1} + \beta_2 Age_{i,t-1} + \beta_3 Size2_{i,t-1} + \beta_4 Risk_{i,t-1} + \beta_5 Expense_{i,t} + \beta_6 Semiannual\_Dummy$$
$$+ \beta_7 Best\_Worst_{t-1} + \beta_8 Best\_Worst\ x\ Performance + \beta_9 Crisis\_Dummy + \beta_{10} Bank\_Dummy + \vartheta_{i,t}$$

Fund characteristics are age, size, expense ratio and risk. Dependent variables in all models, Flow 2, are the change in the number of investors in two subsequent periods. One period lagged performance variables are scaled by the spatial weight matrix. *W* is constructed by the aid of DEAs based on fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is computed as the multiplicative inverse of fund *i*'s inefficiency value. Robust standard errors are given in parentheses.

As in Tables 24a and 24b, spatial lags of performance variables are no longer significant when global financial crisis and bank dummy variables are included. In this sense, results reported in Tables 25a and 25b are consistent with those obtained by using the first Size definition. Since spatial lag variables are not significant, one may suggest that spatial modeling is not needed when analyzing the flow-performance relation for Turkish mutual funds. Instead, OLS would be sufficient and provide the most accurate estimations.

Overall different flow models presented in this dissertation lead to following conclusions. Investors generally take into account prior performance measured as Jensen's alpha excess return. However, contrary to the tournament hypothesis, investors' reaction to the past performance of a fund is negative. Therefore, Turkish investors seem to realize their net gains once they pass to the gaining region. However, funds with above median performance achieve to avoid some of the withdrawals. This asymmetric relation between flows and performance of best and worst performing funds could encourage fund managers to change the risk structure of their portfolios. This issue is analyzed in the next section by adding two control variables to the original risk models analyzed in the previous chapter. Furthermore, Turkish investors do not seem to consider the neighboring funds' performance or their flow when they channel their investments among funds, because no spatial lag variables have statistically significant coefficients. Akerlof (1997) has previously criticized the "rational agent" assumption in the economics, because this assumption does not take the possible spatial interactions caused by neighbors into account. In this sense, since no spatial interaction can be detected in the fund choices, Turkish mutual fund investors may be considered as rational agents in the fund market.

5.2.2. Risk Models with Crisis Dummy

The second part of this robustness check is to re-estimate the risk change models by adding two additional control variables. To do so, both the OLS models and spatial lag of X models are re-estimated for two different definitions of the size variable.

The new risk model estimated in this section is as follows:

$$\begin{aligned} \Delta RISK_{i,t} &= a_0 + a_1 Risk_{i,t-1} + a_2 Age_{i,t-1} + a_3 Size_{i,t-1} + a_4 Expense_{i,t} + a_5 Perf_{i,t-1} \\ &+ a_6 Flow_{i,t-1} + a_7 Best\_Worst_{t-1} + a_8 Best\_WorstxPerformanc\ e + a_9 Crisis\_Dummy \\ &+ a_{10} Bank\_Dummy + u_{i,t} \end{aligned} \tag{10}$$

The definitions of variables in this model are the same as before. Table 2b gives a detailed explanation of all the dependent and independent variables used in this model. As explained before, risk change models are only run for the second half of the year, because it is assumed that fund managers consider altering portfolio risk based on the fund’s risk and performance in the first 6-months of the year.

Table 26a. Risk Change Models

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-3.02e-05	0.000143	-0.000136	3.64e-05
	(0.00166)	(0.00218)	(0.00167)	(0.00230)
Std. Dev $_{t-1}$	-0.421***	-0.106	-0.424***	-0.131
	(0.148)	(0.125)	(0.148)	(0.128)
Jensen's Alpha Excess Ret$_{t-1}$	0.0163***		0.0157***	
	(0.00321)		(0.00318)	
4 Factor Excess Ret$_{t-1}$		0.0164***		0.0159***
		(0.00513)		(0.00505)
Best-Worst $_{t-1}$	-0.00242***	-0.00243***	-0.00242***	-0.00239***
	(0.000620)	(0.000797)	(0.000622)	(0.000766)
Best-Worst x Jensen's	0.00165		0.00164	
	(0.00129)		(0.00131)	
Best-Worst x 4Factor		0.00773*		0.00785*
		(0.00426)		(0.00421)
Crisis Dummy	4.45e-05	-0.000334	0.000196	-0.000241
	(0.000524)	(0.000665)	(0.000518)	(0.000644)
Bank Dummy	0.000365	0.000539	0.000297	0.000453
	(0.000444)	(0.000454)	(0.000437)	(0.000443)
Flow 1$_{t-1}$	0.000132	-1.94e-06		
	(0.000169)	(0.000200)		
Flow 2$_{t-1}$			-5.23e-07	-8.75e-07
			(1.26e-06)	(1.76e-06)
Age $_{t-1}$	-3.28e-05	-3.56e-05	-3.79e-05	-4.16e-05
	(7.51e-05)	(8.09e-05)	(7.56e-05)	(8.15e-05)
Size $_{t-1}$	-5.63e-05	0.000148	-2.99e-05	0.000171
	(0.000116)	(0.000114)	(0.000113)	(0.000111)
Expense Ratio $_t$	-0.00498**	-0.00447*	-0.00504**	-0.00427*
	(0.00222)	(0.00253)	(0.00213)	(0.00245)
R-squared	0.293	0.160	0.289	0.168
Observations	309	309	305	305

***p<0.01, ** p<0.05, * p<0.1

Table 26a. Risk Change Models

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.00214	-0.00285	-0.00226	-0.00298
	(0.00190)	(0.00180)	(0.00186)	(0.00182)
Beta $_{t-1}$	-0.0051***	0.00334**	-0.0050***	0.00286**
	(0.00191)	(0.00132)	(0.00187)	(0.00130)
Jensen's Alpha Excess Ret$_{t-1}$	0.0149***		0.0144***	
	(0.00238)		(0.00239)	
4 Factor Excess Ret$_{t-1}$		0.0158***		0.0153***
		(0.00481)		(0.00470)
Best-Worst $_{t-1}$	-0.0021***	-0.0021***	-0.0021***	-0.00206***
	(0.000673)	(0.000744)	(0.000675)	(0.000709)
Best-Worst x Jensen's	0.00155		0.00141	
	(0.00169)		(0.00175)	
Best-Worst x 4Factor		0.00957***		0.00976***
		(0.00359)		(0.00348)
Crisis Dummy	0.000141	-0.000339	0.000194	-0.000277
	(0.000592)	(0.000679)	(0.000560)	(0.000631)
Bank Dummy	0.000413	0.000404	0.000353	0.000341
	(0.000434)	(0.000430)	(0.000428)	(0.000423)
Flow 1$_{t-1}$	2.02e-06	-1.70e-05		
	(0.000202)	(0.000224)		
Flow 2$_{t-1}$			-1.18e-06	-9.74e-07
			(1.58e-06)	(1.76e-06)
Age $_{t-1}$	-3.80e-06	-1.95e-05	-7.66e-06	-2.33e-05
	(7.25e-05)	(7.45e-05)	(7.26e-05)	(7.49e-05)
Size $_{t-1}$	-5.40e-07	0.000143	2.19e-05	0.000169
	(0.000124)	(0.000119)	(0.000120)	(0.000113)
Expense Ratio $_t$	-0.00558**	-0.00645**	-0.00555**	-0.00619**
	(0.00262)	(0.00265)	(0.00255)	(0.00257)
R-squared	0.217	0.169	0.207	0.169
Observations	309	309	305	305

***p<0.01, ** p<0.05, * p<0.1

This table illustrates the findings from the risk models that associate the risk change decisions of fund managers to the fund characteristics, such as flow, performance, age, size, risk, and expense ratio. The formal model is as follows:

$$\Delta RISK_{i,t} = a_0 + a_1 Risk_{i,t-1} + a_2 Age_{i,t-1} + a_3 Size_{i,t-1} + a_4 Expense_{i,t} + a_5 Perf_{i,t-1} + a_6 Flow_{i,t-1}$$
$$+ a_7 Best\_Worst_{t-1} + a_8 Best\_Worst\ x\ Performanc\ e + a_9 Crisis\_Dummy + a_{10} Bank\_Dummy + u_{i,t}$$

Here, the dependent variable is the change in the semiannual standard deviation of daily returns. Models presented in Panel A and Panel B of this table only differ by the lagged risk proxies, namely standard deviation or beta, used as a control variable. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns. Robust standard errors are reported in parenthesis.

Panels A and B in Table 26a reflect the determinants of total risk change decisions of fund managers. The results reported in this table show that bank ownership and global financial crisis do not affect managers' decision on changing the portfolio's total risk.

Findings indicate a general tendency to have a positive change in the total risk of a portfolio when the fund has a good performance in the first 6-months of the year. Both performance variables have positive and mostly significant coefficients. As noted before, this behavior is contrary to the previously documented findings in the mutual fund literature. However, the coefficient of the *Best-Worst* variable indicates a significant difference between the risk change behavior of funds with above and below median performance. In other words, all else being equal, best performing funds have a tendency to decrease the total risk of their portfolios. The worst performing ones, on the other hand, do not change the total risk of their portfolios from the first to the second half of the year, because the intercept term is insignificant. The interaction terms for both performance definitions are mostly significant and positive. This indicates that the relation between past performance and risk change decision is stronger for best performing funds. When a fund exhibits good performance in the first half of the year, managers of these funds are willing to increase the change in portfolio risk more than the managers of worst performing funds in the second half of the year. These findings are also inconsistent with the tournament hypothesis.

Finally, coefficients of both risk measures are negative in general, indicating a mean reversion in risk. Fund managers tend to decrease the change in the total risk of their portfolios in the second period when the total risk or the systematic risk of the portfolio has been high in the first half of the year. This behavior also casts doubt on the validity of tournament behavior hypothesis for Turkish mutual fund managers.

The same analysis is repeated with change in beta as the dependent variable in order to examine the determinants of the systematic risk change decision of managers. The findings are presented in Panels A and B of Table 26b.

Table 26b Risk Change Models

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.0769***	-0.0766***	-0.0833***	-0.0826***
	(0.0232)	(0.0244)	(0.0236)	(0.0248)
Std. Dev $_{t-1}$	7.495***	5.051***	7.567***	5.227***
	(0.942)	(0.793)	(0.953)	(0.806)
Jensen's Alpha Excess Ret$_{t-1}$	-0.0984***		-0.0966***	
	(0.0178)		(0.0181)	
4 Factor Excess Ret$_{t-1}$		-0.0150		-0.0156
		(0.0514)		(0.0514)
Best-Worst $_{t-1}$	0.0185***	0.0163***	0.0172***	0.0149**
	(0.00509)	(0.00599)	(0.00508)	(0.00594)
Best-Worst x Jensen's	-0.00399		-0.00238	
	(0.0103)		(0.0102)	
Best-Worst x 4Factor		-0.0452		-0.0416
		(0.0376)		(0.0373)
Crisis Dummy	-0.0136***	-0.00998*	-0.0145***	-0.0109**
	(0.00498)	(0.00530)	(0.00484)	(0.00515)
Bank Dummy	0.00279	0.000588	0.00328	0.00122
	(0.00477)	(0.00529)	(0.00472)	(0.00522)
Flow 1$_{t-1}$	0.00122	0.00184		
	(0.00241)	(0.00212)		
Flow 2$_{t-1}$			-1.23e-05	-9.30e-06
			(2.32e-05)	(2.59e-05)
Age $_{t-1}$	0.000753	0.000612	0.000915*	0.000796
	(0.000538)	(0.000571)	(0.000536)	(0.000561)
Size $_{t-1}$	0.00273**	0.00195	0.00301**	0.00219
	(0.00131)	(0.00136)	(0.00133)	(0.00137)
Expense Ratio $_t$	-0.0119	-0.0193	-0.00801	-0.0163
	(0.0207)	(0.0216)	(0.0186)	(0.0197)
R-squared	0.290	0.203	0.292	0.208
Observations	309	309	305	305
t test (Constant + B-W)	-0.0583***	-0.0603**	-0.0661***	-0.0677***
	(0.0223)	(0.0236)	(0.0224)	(0.0238)

***p<0.01, ** p<0.05, * p<0.1

Table 26b. Risk Change Models

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.00989	-0.00787	-0.0158	-0.0129
	(0.0242)	(0.0244)	(0.0241)	(0.0245)
Beta $_{t-1}$	-0.00219	-0.0152	-0.00277	-0.0139
	(0.0253)	(0.0151)	(0.0253)	(0.0153)
Jensen's Alpha Excess Ret$_{t-1}$	-0.00976		-0.00737	
	(0.0297)		(0.0303)	
4 Factor Excess Ret$_{t-1}$		0.0115		0.0113
		(0.0600)		(0.0603)
Best-Worst $_{t-1}$	0.0117**	0.0103	0.00985*	0.00872
	(0.00561)	(0.00653)	(0.00554)	(0.00647)
Best-Worst x Jensen's	-0.0184*		-0.0172	
	(0.0104)		(0.0105)	
Best-Worst x 4Factor		-0.0910**		-0.0894**
		(0.0378)		(0.0373)
Crisis Dummy	-0.0138**	-0.0103*	-0.0132**	-0.00987*
	(0.00569)	(0.00569)	(0.00553)	(0.00542)
Bank Dummy	0.00323	0.00241	0.00353	0.00263
	(0.00573)	(0.00580)	(0.00573)	(0.00579)
Flow 1$_{t-1}$	0.00319	0.00305		
	(0.00278)	(0.00277)		
Flow 2$_{t-1}$			-3.81e-06	-2.86e-06
			(2.92e-05)	(2.94e-05)
Age $_{t-1}$	0.000156	0.000126	0.000294	0.000274
	(0.000557)	(0.000560)	(0.000558)	(0.000555)
Size $_{t-1}$	0.00158	0.00164	0.00188	0.00189
	(0.00149)	(0.00149)	(0.00148)	(0.00150)
Expense Ratio $_{t}$	0.0160	0.0195	0.0180	0.0213
	(0.0260)	(0.0250)	(0.0238)	(0.0230)
R-squared	0.049	0.056	0.041	0.049
Observations	309	309	305	305

***p<0.01, ** p<0.05, * p<0.1

The determinants of the risk change decision of managers are modeled in the table as follows:

$$\Delta RISK_{i,t} = a_0 + a_1 Risk_{i,t-1} + a_2 Age_{i,t-1} + a_3 Size_{i,t-1} + a_4 Expense_{i,t} + a_5 Perf_{i,t-1} + a_6 Flow_{i,t-1}$$
$$+ a_7 Best\_Worst_{t-1} + a_8 Best\_Worst\ x\ Performanc\ e + a_9 Crisis\_Dummy + a_{10} Bank\_Dummy + u_{i,t}$$

Fund characteristics, namely flow, performance, age, size, risk, and Fund characteristics, namely flow, performance, age, size, risk, and expense ratio, are explanatory variables, whereas the dependent variable is the semiannual change in a fund's betas. The difference between Panel A and Panel B is the lagged risk proxies used among the explanatory variables. One period lagged risk is defined as standard deviation of daily returns in Panel A and as beta in Panel B. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns. Robust standard errors are presented in parenthesis.

Consistent with the previous risk change models, Table 26b also demonstrates that Jensen's alpha excess return is the performance measure that fund managers take into account while changing their portfolio's systematic risk. In contrast to the total risk change decisions, prior past performance and change in systematic risk are inversely related indicating that as the performance of a fund enhances, managers are decreasing the change in systematic risk of their portfolios. This finding provides evidence for tournament hypothesis. The intercept terms are significant and negative in panel A of Table 26b. This negative intercept term indicates a negative change in betas of all funds from the first half to the second half of the year. However, best funds consistently have less negative intercept terms, so they begin with a smaller decline in their systematic risk because of positive and significant coefficient on *Best-Worst* dummy variable.

Coefficients of interactive variables in Table 26b show the incremental effect of performance for above median funds. These variables have significant and negative coefficients indicating that when a fund shows good performance in the first half of the year, its systematic risk change decision is inversely affected. Decreasing the portfolio risk when the fund has shown good performance is consistent with the tournament behavior. However, considering insignificant coefficients in majority of the models and the risk reversion evidence presented earlier, one may not be sure if this situation really reflects a tournament like behavior or it is caused by other incentives like portfolio re-balancing.

Different from previous models, Table 26b also shows a significant and negative impact of *Crisis Dummy* variable. It seems that fund managers are more cautious after the global financial crisis, and tend to have lower systematic risk in this period. On the other hand, no difference can be detected between the risk change decisions of funds owned by bank and those that are owned by non-bank institutions.

Results for the second definition of size variable, *Size 2*, are presented in Panels A and B of Tables 27a and 27b. Results reported in these tables indicate that the risk change-fund performance relations observed in previous versions of the model are robust to different definitions of the size variable even in the presence of additional control variables.

Table 27a. Risk Change Models with Size 2

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.000641	0.00248	-0.000394	0.00270
	(0.00134)	(0.00220)	(0.00135)	(0.00222)
Std. Dev $_{t-1}$	-0.424***	-0.112	-0.428***	-0.136
	(0.149)	(0.128)	(0.149)	(0.131)
Jensen's Alpha Excess Ret$_{t-1}$	0.0163***		0.0157***	
	(0.00322)		(0.00319)	
4 Factor Excess Ret$_{t-1}$		0.0163***		0.0159***
		(0.00511)		(0.00505)
Best-Worst $_{t-1}$	-0.00240***	-0.00242***	-0.00241***	-0.00240***
	(0.000608)	(0.000792)	(0.000608)	(0.000763)
Best-Worst x Jensen's	0.00159		0.00159	
	(0.00133)		(0.00135)	
Best-Worst x 4Factor		0.00712		0.00715
		(0.00445)		(0.00439)
Crisis Dummy	7.38e-06	-0.000295	0.000178	-0.000148
	(0.000528)	(0.000674)	(0.000530)	(0.000658)
Bank Dummy	0.000400	0.000571	0.000327	0.000472
	(0.000457)	(0.000467)	(0.000450)	(0.000457)
Flow 1$_{t-1}$	0.000129	3.34e-05		
	(0.000161)	(0.000190)		
Flow 2$_{t-1}$			-3.74e-07	-4.99e-07
			(1.22e-06)	(1.69e-06)
Age $_{t-1}$	-3.83e-05	-3.56e-05	-4.27e-05	-4.13e-05
	(7.58e-05)	(8.20e-05)	(7.70e-05)	(8.34e-05)
Size 2 $_{t-1}$	-0.00450	-0.00277	-0.00389	-0.00201
	(0.00301)	(0.00287)	(0.00294)	(0.00286)
Expense Ratio $_{t}$	-0.00511**	-0.00550*	-0.00525**	-0.00541*
	(0.00235)	(0.00289)	(0.00226)	(0.00283)
R-squared	0.295	0.158	0.291	0.164
Observations	309	309	305	305

***p<0.01, ** p<0.05, * p<0.1

Table 27a. Risk Change Models with Size 2

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.00204**	-0.000702	-0.00189**	-0.000502
	(0.000972)	(0.00137)	(0.000949)	(0.00135)
Beta $_{t-1}$	-0.00507***	0.00336**	-0.00493***	0.00292**
	(0.00191)	(0.00133)	(0.00187)	(0.00132)
Jensen's Alpha Excess Ret$_{t-1}$	0.0149***		0.0144***	
	(0.00242)		(0.00242)	
4 Factor Excess Ret$_{t-1}$		0.0157***		0.0153***
		(0.00480)		(0.00472)
Best-Worst $_{t-1}$	-0.00213***	-0.00208***	-0.00213***	-0.00207***
	(0.000651)	(0.000745)	(0.000653)	(0.000712)
Best-Worst x Jensen's	0.00147		0.00134	
	(0.00177)		(0.00182)	
Best-Worst x 4Factor		0.00910**		0.00921**
		(0.00377)		(0.00365)
Crisis Dummy	0.000129	-0.000293	0.000204	-0.000186
	(0.000600)	(0.000695)	(0.000576)	(0.000651)
Bank Dummy	0.000441	0.000418	0.000372	0.000343
	(0.000446)	(0.000441)	(0.000440)	(0.000434)
Flow 1$_{t-1}$	7.88e-06	1.31e-05		
	(0.000192)	(0.000214)		
Flow 2$_{t-1}$			-1.04e-06	-7.05e-07
			(1.51e-06)	(1.70e-06)
Age $_{t-1}$	-6.56e-06	-1.73e-05	-9.58e-06	-2.06e-05
	(7.28e-05)	(7.48e-05)	(7.36e-05)	(7.58e-05)
Size 2 $_{t-1}$	-0.00299	-0.000892	-0.00217	-4.72e-05
	(0.00315)	(0.00257)	(0.00288)	(0.00241)
Expense Ratio $_t$	-0.00586**	-0.00731**	-0.00590**	-0.00716**
	(0.00287)	(0.00302)	(0.00279)	(0.00294)
R-squared	0.219	0.167	0.207	0.165
Observations	309	309	305	305

***p<0.01, ** p<0.05, * p<0.1

This table illustrates the findings from the risk models that associate the risk change decisions of fund managers to the fund characteristics, such as flow, performance, age, size, risk, and expense ratio. The formal model is as follows:

$$\Delta RISK_{i,t} = a_0 + a_1 Risk_{i,t-1} + a_2 age_{i,t-1} + a_3 Size2_{i,t-1} + a_4 Expense_{i,t} + a_5 Perf_{i,t-1} + a_6 Flow_{i,t-1} + a_7 Best\_Worst_{t-1} + a_8 Best\_Worst\ x\ Performanc\ e + a_9 Crisis\_Dummy + a_{10} Bank\_Dummy + u_{i,t}$$

Here, the dependent variable is the change in the semiannual standard deviation of daily returns. Models presented in Panel A and Panel B of this table only differ by the lagged risk proxies, namely standard deviation or beta, used as a control variable. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns. Robust standard errors are reported in parenthesis.

Table 27b. Risk Change Models with Size 2

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.0360***	-0.0477***	-0.0386***	-0.0504***
	(0.0115)	(0.0115)	(0.0114)	(0.0115)
Std. Dev $_{t-1}$	7.391***	5.033***	7.469***	5.217***
	(0.950)	(0.801)	(0.964)	(0.815)
Jensen's Alpha Excess Ret$_{t-1}$	-0.0953***		-0.0931***	
	(0.0179)		(0.0182)	
4 Factor Excess Ret$_{t-1}$		-0.0154		-0.0157
		(0.0517)		(0.0518)
Best-Worst $_{t-1}$	0.0181***	0.0161***	0.0166***	0.0145**
	(0.00508)	(0.00600)	(0.00505)	(0.00593)
Best-Worst x Jensen's	-0.00822		-0.00694	
	(0.0104)		(0.0104)	
Best-Worst x 4Factor		-0.0512		-0.0486
		(0.0375)		(0.0372)
Crisis Dummy	-0.0128**	-0.00928*	-0.0131***	-0.00973*
	(0.00497)	(0.00524)	(0.00479)	(0.00503)
Bank Dummy	0.00286	0.000642	0.00322	0.00117
	(0.00479)	(0.00531)	(0.00474)	(0.00524)
Flow 1$_{t-1}$	0.00174	0.00223		
	(0.00242)	(0.00213)		
Flow 2$_{t-1}$			-8.19e-06	-6.43e-06
			(2.37e-05)	(2.60e-05)
Age $_{t-1}$	0.000809	0.000654	0.000973*	0.000841
	(0.000546)	(0.000576)	(0.000543)	(0.000565)
Size 2 $_{t-1}$	-0.000221	0.00585	0.00727	0.0114
	(0.0491)	(0.0520)	(0.0498)	(0.0517)
Expense Ratio $_{t}$	-0.0262	-0.0290	-0.0240	-0.0273
	(0.0247)	(0.0242)	(0.0222)	(0.0218)
R-squared	0.282	0.198	0.282	0.203
Observations	309	309	305	305
t test (Constant + B-W)	-0.0178*	-0.032***	-0.022**	-0.035***
	(0.0104)	(0.011)	(0.010)	(0.011)

***p<0.01, ** p<0.05, * p<0.1

Table 27b. Risk Change Models with Size 2

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	0.0153	0.0180	0.0137	0.0164
	(0.0126)	(0.0126)	(0.0127)	(0.0126)
Beta $_{t-1}$	-0.00259	-0.0157	-0.00295	-0.0141
	(0.0256)	(0.0154)	(0.0255)	(0.0155)
Jensen's Alpha Excess Ret$_{t-1}$	-0.00914		-0.00650	
	(0.0298)		(0.0305)	
4 Factor Excess Ret$_{t-1}$		0.00964		0.0100
		(0.0602)		(0.0605)
Best-Worst $_{t-1}$	0.0117**	0.0104	0.00977*	0.00875
	(0.00561)	(0.00653)	(0.00553)	(0.00645)
Best-Worst x Jensen's	-0.0218**		-0.0211*	
	(0.0107)		(0.0109)	
Best-Worst x 4Factor		-0.0976**		-0.0973**
		(0.0381)		(0.0378)
Crisis Dummy	-0.0136**	-0.00991*	-0.0124**	-0.00886*
	(0.00563)	(0.00562)	(0.00544)	(0.00529)
Bank Dummy	0.00363	0.00283	0.00381	0.00293
	(0.00574)	(0.00581)	(0.00576)	(0.00581)
Flow 1$_{t-1}$	0.00353	0.00344		
	(0.00277)	(0.00277)		
Flow 2$_{t-1}$			8.09e-07	1.87e-06
			(2.99e-05)	(3.01e-05)
Age $_{t-1}$	0.000161	0.000126	0.000297	0.000270
	(0.000559)	(0.000561)	(0.000560)	(0.000556)
Size 2 $_{t-1}$	-0.0420	-0.0380	-0.0381	-0.0354
	(0.0546)	(0.0561)	(0.0528)	(0.0542)
Expense Ratio $_{t}$	0.00357	0.00703	0.00356	0.00714
	(0.0286)	(0.0279)	(0.0261)	(0.0253)
R-squared	0.049	0.055	0.038	0.046
Observations	309	309	305	305

***p<0.01, ** p<0.05, * p<0.1

The determinants of the risk change decision of managers are modeled in the table as follows:

$$\Delta RISK_{i,t} = a_0 + a_1 Risk_{i,t-1} + a_2 Age_{i,t-1} + a_3 Size2_{i,t-1} + a_4 Expense_{i,t} + a_5 Perf_{i,t-1} + a_6 Flow_{i,t-1} + a_7 Best\_Worst_{t-1} + a_8 Best\_Worst \ x \ Performance + a_9 Crisis\_Dummy + a_{10} Bank\_Dummy + u_{i,t}$$

Fund characteristics, namely flow, performance, age, size, risk, and expense ratio, are explanatory variables, whereas the dependent variable is the semiannual change in a fund's betas. The difference between Panel A and Panel B is the lagged risk proxies used among the explanatory variables. One period lagged risk is defined as standard deviation of daily returns in Panel A and as beta in Panel B. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns. Robust standard errors are presented in parenthesis.

Findings reported in Tables 27a and 27b are qualitatively the same with those given in Tables 26a and 26b. Specifically, fund managers' tendency to decrease the change in their portfolio's total risk when the first period standard deviation is high, is also evident in these tables. This indicates a mean reversion in total risk of mutual fund portfolios. Overall, findings for Turkish mutual fund industry is, so far, not consistent with the tournament behavior hypothesis. Table 27a demonstrates that there is no difference in risk changing behavior of mutual funds based on their ownership status because *Bank Dummy* variable does not have a statistically significant coefficient in any of the models. The systematic risks of mutual fund portfolios are lower in the post crisis period even though there is not a statistically significant difference between total risks of these portfolios before and after global financial crisis.

Next step is to investigate the spatial lag of X models for risk change decisions when *Crisis* and *Bank Dummy* variables are included in the models. Tables 28a and 28b provides results for total risk and systematic risk change decisions of fund managers when the exogenous interactions are taken into consideration.

Table 28a. Spatial Lag of X Model of Risk Change

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.000903	0.00404*	-0.000823	0.00394*
	(0.00188)	(0.00220)	(0.00188)	(0.00232)
Std. Dev $_{t-1}$	-0.408***	-0.145	-0.415***	-0.166
	(0.152)	(0.114)	(0.153)	(0.116)
Jensen's Alpha Excess Ret$_{t-1}$	0.0154***		0.0150***	
	(0.00339)		(0.00337)	
Spatial Lag (Jensen's$_{t-1}$)	0.00417*		0.00336	
	(0.00242)		(0.00243)	
4 Factor ExcessRet$_{t-1}$		0.00117		0.00107
		(0.00342)		(0.00335)
Spatial Lag (4Factor$_{t-1}$)		0.0263***		0.0257***
		(0.00325)		(0.00325)
Best-Worst $_{t-1}$	-0.00223***	-0.000882	-0.00226***	-0.000873
	(0.000635)	(0.000611)	(0.000634)	(0.000580)
Best-Worst x Jensen's	0.00154		0.00156	
	(0.00126)		(0.00128)	
Best-Worst x 4Factor		0.000659		0.00101
		(0.00449)		(0.00440)
Crisis Dummy				
Bank Dummy				
Flow 1$_{t-1}$	0.000118	3.14e-05		
	(0.000182)	(0.000206)		
Flow 2$_{t-1}$			-5.94e-07	-6.60e-07
			(1.33e-06)	(1.47e-06)
Age $_{t-1}$	-2.75e-05	-5.16e-05	-3.25e-05	-5.65e-05
	(7.55e-05)	(7.21e-05)	(7.64e-05)	(7.30e-05)
Size $_{t-1}$	-5.66e-05	-4.21e-05	-3.18e-05	-2.32e-05
	(0.000120)	(0.000108)	(0.000118)	(0.000103)
Expense Ratio $_{t}$	-0.00445**	-0.00219	-0.00464**	-0.00224
	(0.00226)	(0.00200)	(0.00218)	(0.00192)
R-squared	0.298	0.357	0.291	0.363
Observations	304	304	300	300

***p<0.01, ** p<0.05, * p<0.1

Table 28a. Spatial Lag of X Model of Risk Change

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.00318	0.000977	-0.00316	0.000848
	(0.00207)	(0.00174)	(0.00201)	(0.00178)
Beta $_{t-1}$	-0.00431**	0.00254**	-0.00435**	0.00214**
	(0.00195)	(0.00108)	(0.00192)	(0.00106)
Jensen's Alpha Excess Ret$_{t-1}$	0.0138***		0.0135***	
	(0.00251)		(0.00253)	
Spatial Lag (Jensen's$_{t-1}$)	0.00463*		0.00390	
	(0.00248)		(0.00250)	
4 Factor ExcessRet$_{t-1}$		0.000958		0.000740
		(0.00330)		(0.00319)
Spatial Lag (4Factor$_{t-1}$)		0.00278		0.00318
		(0.00383)		(0.00369)
Best-Worst $_{t-1}$	-0.00199***	-0.000605	-0.00201***	-0.000607
	(0.000691)	(0.000595)	(0.000691)	(0.000558)
Best-Worst x Jensen's	0.00122		0.00114	
	(0.00167)		(0.00174)	
Best-Worst x 4Factor		0.00278		0.00318
		(0.00383)		(0.00369)
Crisis Dummy	-8.88e-05	-0.00231***	-1.42e-05	-0.00219***
	(0.000621)	(0.000506)	(0.000596)	(0.000471)
Bank Dummy	0.000452	0.000450	0.000390	0.000385
	(0.000441)	(0.000398)	(0.000434)	(0.000391)
Flow 1$_{t-1}$	-6.54e-06	4.51e-06		
	(0.000208)	(0.000231)		
Flow 2$_{t-1}$			-1.24e-06	-8.17e-07
			(1.63e-06)	(1.48e-06)
Age $_{t-1}$	4.85e-08	-3.29e-05	-3.59e-06	-3.60e-05
	(7.28e-05)	(6.69e-05)	(7.33e-05)	(6.77e-05)
Size $_{t-1}$	-6.00e-06	-4.07e-05	1.74e-05	-1.98e-05
	(0.000129)	(0.000115)	(0.000125)	(0.000109)
Expense Ratio $_t$	-0.00491*	-0.00430**	-0.00495*	-0.00425**
	(0.00262)	(0.00211)	(0.00254)	(0.00204)
R-squared	0.224	0.352	0.211	0.350
Observations	304	304	300	300

***p<0.01, ** p<0.05, * p<0.1

The findings from the spatial lag of X model are presented in Panel A and Panel B of this table. The model specification is shown below:

$$\Delta RISK_{i,t} = \psi_0 + \psi_1 Risk_{i,t-1} + \psi_2 Age_{i,t-1} + \psi_3 Size_{i,t-1} + \psi_4 Expense_{i,t} + \psi_5 Perf_{i,t-1} + \tau \sum_{j=1}^{n} W_{ij} Perf_{i,t-1}$$
$$+ \psi_6 Flow_{i,t-1} + \psi_7 Best\_Worst_{t-1} + \psi_8 Best-Worst\ x\ Performanc\ e + \psi_9 Crisis\_Dummy + \psi_{10} Bank\_Dummy + \upsilon_{i,t}$$

Dependent variable is defined as the change in the semiannual standard deviation of daily returns. Fund characteristics are flow, performance, age, size, risk, and expense ratio. Fund performance is scaled by a spatial weight matrix (*W*) obtained from DEAs based on fund efficiencies. The distance between two funds is the multiplicative inverse of fund *i*'s inefficiency value. Models in Panel A and Panel B differ by lagged risk proxies used. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns. Robust standard errors are presented in parenthesis.

Table 28b. Spatial Lag of X Model of Risk Change

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.0990***	-0.0808***	-0.109***	-0.0874***
	(0.0260)	(0.0276)	(0.0266)	(0.0284)
Std. Dev $_{t-1}$	7.850***	5.056***	7.958***	5.231***
	(0.963)	(0.809)	(0.975)	(0.824)
Jensen's Alpha Excess Ret$_{t-1}$	-0.115***		-0.114***	
	(0.0194)		(0.0197)	
Spatial Lag (Jensen's$_{t-1}$)	0.0745**		0.0812***	
	(0.0308)		(0.0312)	
4 Factor ExcessRet$_{t-1}$		-0.0185		-0.0212
		(0.0677)		(0.0677)
Spatial Lag (4Factor$_{t-1}$)		0.00732		0.0115
		(0.0432)		(0.0433)
Best-Worst $_{t-1}$	0.0206***	0.0163**	0.0193***	0.0150**
	(0.00517)	(0.00676)	(0.00516)	(0.00673)
Best-Worst x Jensen's	-0.00497		-0.00337	
	(0.0104)		(0.0103)	
Best-Worst x 4Factor		-0.0502		-0.0482
		(0.0377)		(0.0373)
Crisis Dummy	-0.0183***	-0.0111*	-0.0199***	-0.0125**
	(0.00549)	(0.00649)	(0.00541)	(0.00628)
Bank Dummy	0.00501	0.00131	0.00583	0.00206
	(0.00487)	(0.00537)	(0.00483)	(0.00530)
Flow 1$_{t-1}$	0.00125	0.00188		
	(0.00217)	(0.00213)		
Flow 2$_{t-1}$			-1.49e-05	-1.01e-05
			(2.18e-05)	(2.60e-05)
Age $_{t-1}$	0.000793	0.000599	0.000987*	0.000788
	(0.000528)	(0.000583)	(0.000520)	(0.000573)
Size $_{t-1}$	0.00303**	0.00220	0.00340**	0.00249
	(0.00139)	(0.00152)	(0.00142)	(0.00155)
Expense Ratio $_t$	0.0115	-0.0121	0.0175	-0.00787
	(0.0201)	(0.0212)	(0.0203)	(0.0199)
R-squared	0.312	0.206	0.318	0.212
Observations	304	304	300	300
t test (Constant + B-W)	-0.0178*	-0.031***	-0.022**	-0.036***
	(0.010)	(0.011)	(0.010)	(0.011)

***p<0.01, ** p<0.05, * p<0.1

Table 28b. Spatial Lag of X Model of Risk Change

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.0247	-0.0101	-0.0330	-0.0158
	(0.0286)	(0.0276)	(0.0287)	(0.0280)
Beta $_{t-1}$	0.00664	-0.0169	0.00656	-0.0156
	(0.0282)	(0.0153)	(0.0281)	(0.0155)
Jensen's Alpha Excess Ret$_{t-1}$	-0.0227		-0.0208	
	(0.0340)		(0.0345)	
Spatial Lag (Jensen's$_{t-1}$)	0.0378		0.0416	
	(0.0346)		(0.0348)	
4 Factor ExcessRet$_{t-1}$		-0.00394		-0.00542
		(0.0780)		(0.0788)
Spatial Lag (4Factor$_{t-1}$)		0.0279		0.0306
		(0.0462)		(0.0469)
Best-Worst $_{t-1}$	0.0134**	0.0114	0.0116*	0.00989
	(0.00606)	(0.00750)	(0.00600)	(0.00749)
Best-Worst x Jensen's	-0.0190*		-0.0179*	
	(0.0107)		(0.0107)	
Best-Worst x 4Factor		-0.101***		-0.100***
		(0.0371)		(0.0363)
Crisis Dummy	-0.0166***	-0.0132*	-0.0164***	-0.0131**
	(0.00636)	(0.00678)	(0.00624)	(0.00657)
Bank Dummy	0.00445	0.00329	0.00494	0.00361
	(0.00588)	(0.00588)	(0.00590)	(0.00586)
Flow 1$_{t-1}$	0.00329	0.00309		
	(0.00280)	(0.00281)		
Flow 2$_{t-1}$			-5.11e-06	-3.70e-06
			(2.87e-05)	(2.97e-05)
Age $_{t-1}$	0.000191	0.000104	0.000349	0.000260
	(0.000559)	(0.000570)	(0.000558)	(0.000565)
Size $_{t-1}$	0.00186	0.00186	0.00225	0.00215
	(0.00159)	(0.00164)	(0.00159)	(0.00167)
Expense Ratio $_t$	0.0287	0.0301	0.0320	0.0328
	(0.0253)	(0.0236)	(0.0241)	(0.0225)
R-squared	0.056	0.061	0.048	0.054
Observations	304	304	300	300

***p<0.01, ** p<0.05, * p<0.1

The findings from the spatial lag of X model are presented in Panel A and Panel B of this table. The model specification is shown below:

$$\Delta RISK_{i,t} = \psi_0 + \psi_1 Risk_{i,t-1} + \psi_2 Age_{i,t-1} + \psi_3 Size_{i,t-1} + \psi_4 Expense_{i,t} + \psi_5 Perf_{i,t-1} + \tau \sum_{j=1}^{n} W_{ij} Perf_{i,t-1}$$
$$+ \psi_6 Flow_{i,t-1} + \psi_7 Best\_Worst_{t-1} + \psi_8 Best-Worst\ x\ Performanc\ e + \psi_9 Crisis\_Dummy + \psi_{10} Bank\_Dummy\ + v_{i,t}$$

Dependent variable is defined as the change in a fund's betas. Fund characteristics are flow, performance, age, size, risk, and expense ratio. Fund performance is scaled by a spatial weight matrix (*W*) which is obtained from DEAs based on fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is the multiplicative inverse of fund *i*'s inefficiency value. Models in Panel A and Panel B differ by the lagged risk proxies, namely standard deviation and beta, used. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns. Robust standard errors are presented in parenthesis.

Although findings reported in Tables 28a and 28b are mostly in line with previous results, there are also some differences. As noted before, spatial lags reflecting the impact of exogenous interactions are found to be significant and positive both in Tables 28a and 28b. Putting it differently, managers are more likely to increase the change in their total and systematic risks in the second half of the year when their neighboring funds show good performance in the first half of the year. This behavior can be explained by managers' expectation of having a better performance as a result of taking on higher risk and being ranked among the winners. Funds' own performance is still important in the total risk change decisions as demonstrated in panels A and B of Table 28a, but now it has a positive sign. It means that managers increase the change in total risk of their portfolios, when their funds show a good performance in the first half of the year. As discussed before, this evidence is not consistent with the tournament behavior. *Best-Worst* variable has a negative coefficient when it is significant indicating that best performing funds have a lower intercept term than worst performers. This would be in line with managerial incentives created by tournament behavior. However, the existence of mean reversion behavior indicated by the negative coefficient of lagged standard deviation casts doubt on the validity of this evidence as discussed before.

Similar to the previous findings, bank ownership status has no effect on systematic or total risk change behavior of funds. However, Tables 28a and 28b show the negative impact of crisis dummy on risk change decisions. This indicates that Turkish mutual fund managers act more cautiously after the global financial crisis, and they tend to undertake lower total or systematic risks in this period compared to the pre-crisis period.

The existence of exogenous interactions is also examined with *Size 2* variable. Findings are presented in Tables 29a and 29b.

Table 29a. Spatial Lag of X Model of Risk Change with Size 2 Variable

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.00153	0.00364*	-0.00111	0.00380*
	(0.00153)	(0.00207)	(0.00156)	(0.00209)
Std. Dev $_{t-1}$	-0.412***	-0.151	-0.419***	-0.172
	(0.153)	(0.116)	(0.154)	(0.118)
Jensen's Alpha Excess Ret$_{t-1}$	0.0154***		0.0150***	
	(0.00340)		(0.00338)	
Spatial Lag (Jensen's$_{t-1}$)	0.00415*		0.00333	
	(0.00242)		(0.00244)	
4 Factor ExcessRet$_{t-1}$		0.00105		0.000948
		(0.00331)		(0.00326)
Spatial Lag (4Factor$_{t-1}$)		0.0264***		0.0258***
		(0.00333)		(0.00330)
Best-Worst $_{t-1}$	-0.00222***	-0.000845	-0.00226***	-0.000840
	(0.000632)	(0.000592)	(0.000629)	(0.000563)
Best-Worst x Jensen's	0.00148		0.00151	
	(0.00130)		(0.00131)	
Best-Worst x 4Factor		0.000545		0.000853
		(0.00461)		(0.00451)
Crisis Dummy	-0.000187	-0.00244***	1.14e-05	-0.00225***
	(0.000575)	(0.000483)	(0.000586)	(0.000473)
Bank Dummy	0.000444	0.000621	0.000357	0.000521
	(0.000453)	(0.000413)	(0.000445)	(0.000403)
Flow 1$_{t-1}$	0.000115	3.22e-05		
	(0.000174)	(0.000197)		
Flow 2$_{t-1}$			-4.52e-07	-4.80e-07
			(1.29e-06)	(1.43e-06)
Age $_{t-1}$	-3.27e-05	-5.69e-05	-3.72e-05	-6.15e-05
	(7.66e-05)	(7.32e-05)	(7.82e-05)	(7.48e-05)
Size 2 $_{t-1}$	-0.00438	-0.00483*	-0.00379	-0.00417
	(0.00302)	(0.00281)	(0.00295)	(0.00276)
Expense Ratio $_t$	-0.00454*	-0.00239	-0.00481**	-0.00249
	(0.00240)	(0.00191)	(0.00233)	(0.00180)
R-squared	0.300	0.360	0.293	0.365
Observations	304	304	300	300

***p<0.01, ** p<0.05, * p<0.1

Table 29a. Spatial Lag of X Model of Risk Change with Size 2 Variable

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.00315***	0.000512	-0.00283**	0.000655
	(0.00111)	(0.00128)	(0.00110)	(0.00126)
Beta $_{t-1}$	-0.00432**	0.00245**	-0.00432**	0.00208*
	(0.00194)	(0.00108)	(0.00192)	(0.00106)
Jensen’s Alpha Excess Ret$_{t-1}$	0.0138***		0.0135***	
	(0.00253)		(0.00255)	
Spatial Lag (Jensen’s$_{t-1}$)	0.00461*		0.00389	
	(0.00247)		(0.00250)	
4 Factor ExcessRet$_{t-1}$		0.000898		0.000680
		(0.00318)		(0.00310)
Spatial Lag (4Factor$_{t-1}$)		0.0254***		0.0249***
		(0.00318)		(0.00316)
Best-Worst $_{t-1}$	-0.00199***	-0.000589	-0.00201***	-0.000593
	(0.000682)	(0.000579)	(0.000681)	(0.000546)
Best-Worst x Jensen’s	0.00116		0.00108	
	(0.00175)		(0.00180)	
Best-Worst x 4Factor		0.00277		0.00313
		(0.00396)		(0.00380)
Crisis Dummy	-0.000102	-0.00234***	-4.44e-06	-0.00221***
	(0.000631)	(0.000509)	(0.000613)	(0.000478)
Bank Dummy	0.000477	0.000478	0.000404	0.000403
	(0.000447)	(0.000402)	(0.000441)	(0.000395)
Flow 1$_{t-1}$	-2.12e-06	5.92e-07		
	(0.000199)	(0.000222)		
Flow 2$_{t-1}$			-1.11e-06	-7.44e-07
			(1.57e-06)	(1.45e-06)
Age $_{t-1}$	-2.91e-06	-3.61e-05	-5.78e-06	-3.85e-05
	(7.35e-05)	(6.73e-05)	(7.46e-05)	(6.86e-05)
Size 2 $_{t-1}$	-0.00296	-0.00286	-0.00215	-0.00210
	(0.00315)	(0.00257)	(0.00286)	(0.00240)
Expense Ratio $_t$	-0.00517*	-0.00432**	-0.00529*	-0.00432**
	(0.00285)	(0.00211)	(0.00277)	(0.00202)
R-squared	0.225	0.353	0.212	0.351
Observations	304	304	300	300

***p<0.01, ** p<0.05, * p<0.1

The findings from the spatial lag of X model are presented in Panel A and Panel B of this table. The model specification is shown below:

$$\Delta RISK_{i,t} = \psi_0 + \psi_1 Risk_{i,t-1} + \psi_2 Age_{i,t-1} + \psi_3 Size2_{i,t-1} + \psi_4 Expense_{i,t} + \psi_5 Perf_{i,t-1} + \tau \sum_{j=1}^{n} W_{ij} Perf_{i,t-1}$$

$$+ \psi_6 Flow_{i,t-1} + \psi_7 Best\_Worst_{t-1} + \psi_8 Best-Worst\ x\ Performanc\ e + \psi_9 Crisis\_Dummy + \psi_{10} Bank\_Dummy + \upsilon_{i,t}$$

Dependent variable is defined as the change in the semiannual standard deviation of daily returns. Fund characteristics are flow, performance, age, size, risk, and expense ratio. Fund performance is scaled by a spatial weight matrix (*W*) obtained from DEAs based on fund efficiencies. The distance between two funds is the multiplicative inverse of fund *i*’s inefficiency value. Models in Panel A and Panel B differ by lagged risk proxies used. Lagged performance proxies are either Jensen’s alpha excess returns or Four-Factor excess returns. Robust standard errors are presented in parenthesis.

Table 29b. Spatial Lag of X Model of Risk Change with Size 2 Variable

Panel A

VARIABLES	(1)	(2)	(3)	(4)
Constant	-0.0532***	-0.0477***	-0.0579***	-0.0503***
	(0.0137)	(0.0121)	(0.0135)	(0.0121)
Std. Dev $_{t-1}$	7.747***	5.034***	7.861***	5.216***
	(0.976)	(0.820)	(0.992)	(0.837)
Jensen's Alpha Excess Ret$_{t-1}$	-0.112***		-0.111***	
	(0.0196)		(0.0199)	
Spatial Lag (Jensen's$_{t-1}$)	0.0742**		0.0807**	
	(0.0310)		(0.0315)	
4 Factor ExcessRet$_{t-1}$		-0.0232		-0.0261
		(0.0675)		(0.0676)
Spatial Lag (4Factor$_{t-1}$)		0.0132		0.0183
		(0.0427)		(0.0427)
Best-Worst $_{t-1}$	0.0203***	0.0167**	0.0189***	0.0153**
	(0.00518)	(0.00678)	(0.00516)	(0.00675)
Best-Worst x Jensen's	-0.00916		-0.00797	
	(0.0106)		(0.0105)	
Best-Worst x 4Factor		-0.0570		-0.0563
		(0.0378)		(0.0374)
Crisis Dummy	-0.0172***	-0.0107	-0.0181***	-0.0116*
	(0.00543)	(0.00649)	(0.00529)	(0.00624)
Bank Dummy	0.00470	0.00114	0.00533	0.00174
	(0.00490)	(0.00540)	(0.00485)	(0.00532)
Flow 1$_{t-1}$	0.00184	0.00232		
	(0.00218)	(0.00215)		
Flow 2$_{t-1}$			-1.01e-05	-6.65e-06
			(2.23e-05)	(2.62e-05)
Age $_{t-1}$	0.000843	0.000631	0.00104*	0.000821
	(0.000537)	(0.000590)	(0.000529)	(0.000579)
Size 2 $_{t-1}$	0.000128	0.00602	0.00856	0.0115
	(0.0491)	(0.0526)	(0.0505)	(0.0524)
Expense Ratio $_{t}$	-0.00647	-0.0239	-0.00300	-0.0215
	(0.0207)	(0.0233)	(0.0184)	(0.0209)
R-squared	0.304	0.201	0.307	0.206
Observations	304	304	300	300
t test (Constant + B-W)	-0.0178*	-0.031***	-0.022**	-0.036***
	(0.010)	(0.011)	(0.010)	(0.011)

***p<0.01, ** p<0.05, * p<0.1

Table 29b. Spatial Lag of X Model of Risk Change with Size 2 Variable

Panel B

VARIABLES	(1)	(2)	(3)	(4)
Constant	0.00458	0.0193	0.00175	0.0178
	(0.0159)	(0.0131)	(0.0158)	(0.0131)
Beta $_{t-1}$	0.00701	-0.0174	0.00731	-0.0158
	(0.0285)	(0.0156)	(0.0283)	(0.0157)
Jensen's Alpha Excess Ret$_{t-1}$	-0.0227		-0.0207	
	(0.0341)		(0.0347)	
Spatial Lag (Jensen's$_{t-1}$)	0.0383		0.0421	
	(0.0347)		(0.0350)	
4 Factor ExcessRet$_{t-1}$		-0.0103		-0.0118
		(0.0777)		(0.0784)
Spatial Lag (4Factor$_{t-1}$)		0.0341		0.0378
		(0.0458)		(0.0464)
Best-Worst $_{t-1}$	0.0136**	0.0121	0.0117*	0.0106
	(0.00609)	(0.00751)	(0.00603)	(0.00749)
Best-Worst x Jensen's	-0.0225**		-0.0219*	
	(0.0110)		(0.0112)	
Best-Worst x 4Factor		-0.108***		-0.109***
		(0.0377)		(0.0371)
Crisis Dummy	-0.0162**	-0.0131*	-0.0153**	-0.0124*
	(0.00624)	(0.00676)	(0.00605)	(0.00652)
Bank Dummy	0.00458	0.00350	0.00489	0.00365
	(0.00589)	(0.00588)	(0.00592)	(0.00586)
Flow 1$_{t-1}$	0.00369	0.00353		
	(0.00279)	(0.00281)		
Flow 2$_{t-1}$			1.31e-07	1.56e-06
			(2.94e-05)	(3.05e-05)
Age $_{t-1}$	0.000195	9.37e-05	0.000348	0.000243
	(0.000564)	(0.000575)	(0.000562)	(0.000568)
Size 2 $_{t-1}$	-0.0413	-0.0393	-0.0370	-0.0368
	(0.0551)	(0.0564)	(0.0537)	(0.0546)
Expense Ratio $_t$	0.0134	0.0157	0.0139	0.0162
	(0.0269)	(0.0258)	(0.0242)	(0.0234)
R-squared	0.054	0.059	0.045	0.051
Observations	304	304	300	300

***p<0.01, ** p<0.05, * p<0.1

The specification of models in Panel A and B is shown below:

$$\Delta RISK_{i,t} = \psi_0 + \psi_1 Risk_{i,t-1} + \psi_2 Age_{i,t-1} + \psi_3 Size2_{i,t-1} + \psi_4 Expense_{i,t} + \psi_5 Perf_{i,t-1} + \tau \sum_{j=1}^{n} W_{ij} Perf_{i,t-1}$$
$$+ \psi_6 Flow_{i,t-1} + \psi_7 Best\_Worst_{t-1} + \psi_8 Best - Worst\ x\ Performanc\ e + \psi_9 Crisis\_Dummy + \psi_{10} Bank\_Dummy + \upsilon_{i,t}$$

Dependent variable is defined as the change in a fund's betas. Fund characteristics are flow, performance, age, size, risk, and expense ratio. Fund performance is scaled by a spatial weight matrix (*W*) which is obtained from DEAs based on fund efficiencies. The fund *i* is accepted as neighbor to its peer group. The distance between two funds is the multiplicative inverse of fund *i*'s inefficiency value. Models in Panel A and Panel B differ by the lagged risk proxies, namely standard deviation and beta, used. Lagged performance proxies are either Jensen's alpha excess returns or Four-Factor excess returns. Robust standard errors are presented in parenthesis.

As mentioned before, findings are robust to different definitions of the size variable. Hence, findings presented in Tables 29a and 29b are the same as those reported in Tables 28a and 28b for models with the first size variable. Essentially, Tables 29a and 29b indicate the presence of spatial interactions for performance variables. Co efficient of spatial lag of performance variables are positive when they are significant. This positive coefficient indicates the willingness of portfolio managers to increase their portfolios' total or systematic risk level when neighboring or rival funds have a good performance in the first half of the year in order to have a higher chance of being among the winners and attract more cash flow to their funds. However, the positive coefficients on funds' own performance variable contradicts findings in the existing tournament behavior literature. Ownership structure is not influential on the risk altering decisions of managers. However, it seems that in the post crisis period fund managers tend to decrease the change in portfolio risk. This tendency is stronger for the systematic risk decisions, because crisis dummy has a significant coefficient in all the models.

Overall, one may conclude that risk change decisions of managers are mostly affected from prior performance of either the fund itself or its neighbors. The existence of exogenous interactions makes spatial specifications necessary for risk change models. Last but not least, it is possible to say that results are robust to different size definitions and addition of some control variables.

CHAPTER 6

CONCLUSION

Prior literature often states that individual investors respond strongly to the fund performance, even though this response is asymmetric in shape. Investors quickly channel their money into the best performers, but they are late to withdraw when the fund performance is bad. By applying different empirical methods, Brown, et al. (1996); Chevalier and Ellison (1997) and Sirri and Tufano (1998) find strong evidence for this convex flow – performance relation. They also indicate that this association creates a tournament like behavior and incentives for fund managers to alter portfolio risk which is not in the best interest of fund investors. Del Guercio and Tkac (2002) demonstrate that this situation is unique for mutual funds and it is not observed for pension funds. Ferreira et al. (2012b) confirm this relation for many countries, although the reaction is not the same. They note that as the investor sophistication increases and the participation costs fall, the convexity of flow-performance relation is reduced. Following the methodology of Brown et al. (1996), Öztürkkal and Erdem (2012) also demonstrate such a relation for Turkish mutual fund industry. Specifically, they compare the volatility ratios of above median funds to those of below median funds and find that losers increase their risk while best performers tend to decrease it. However, their data and sample selection cast doubt on the validity of their results.

Contradictory evidence on this issue is also available in the literature. Busse (2001) and Goriaev et al. (2005) explicitly state that this convex relation is a spurious outcome of cross correlation and the autocorrelation in the data. Therefore, there is no incentive generating tournament like behavior in the mutual fund industry.

In fact, all the studies mentioned above note the existence of auto- or cross correlation in mutual fund flows. They also state that relative performance also matters when engaging in such a tournament game. Specifically, Brown et al. (1996) indicate that the amount of compensation to funds when they win the tournament highly depends on their performance relative to the others. Similarly, Li and Tiwari (2006) point out that entering in such a tournament is only sensible for funds when they believe that the performance gap between the leader and themselves can be closed. In other words, the distance between the funds in terms of their performance is important and the results would be biased unless this contiguity is not addressed correctly. Hence, the primary aim of this dissertation is to investigate the determinants of fund flow and risk change decisions for Turkish mutual fund managers by using a spatial modeling. In this dissertation, data from equity, variable and mixed funds which are more prone to a tournament like behavior are analyzed.

First the determinants of Turkish mutual fund flows are investigated. It is argued that besides the serial correlation, there might also be a spatial correlation between fund flows due to a fund’s location in the risk-return space relative to its competitors. To account for this type of correlation, three types of spatial regressions are employed in analyzing the incentive creating tournament behavior. Although many studies note the importance of relative position of funds, to my knowledge, this is the first study that accounts for location directly in the modeling. Hence, use of spatial modeling in this context is one of the major contributions of this dissertation.

The second novelty of this dissertation is the flow data used. Following Sirri and Tufano (1998), literature mainly obtains fund flow as the net percentage growth in a fund's assets by employing two assumptions: i) All the dividends are reinvested. ii) All new fund flow occurs at the end of the period. Yet, in this dissertation, the exact net cash flows are computed by using the dataset obtained from the CMB. Working with the actual flow data might allow me to investigate the flow-performance association more precisely.

The last unique point of this study is the estimation of fund locations. The distances between funds are computed by the aid of data envelopment analysis. Besides ranking decision making units while considering various factors at the same time, DEA also gives the radial distances from an efficient frontier and the best groups. This ranking based nature of DEA permits creation of an abstract notion of space according to fund efficiencies. That is, I use a non-geographical but Euclidian concept of distance while determining the neighboring funds.

Apart from the flow determinants, this dissertation also examines whether the mutual fund managers' risk change decisions are affected from the performance of the fund itself and its peers. To do so, both a classical regression with OLS estimations and a spatial lag of X model are constructed. The same spatial weight matrix used in the flow analyses is also employed in these models. These analyses aim to provide insights for risk changing decisions of fund managers.

Findings indicate that individuals allocate their money across various mutual funds independently from other funds' positions on the risk and return space, because no spatial interactions are detected. Only contrary evidence is found while explaining the change in the number of investors, another flow measure used in this dissertation. It is found that the performance increase in the neighboring funds induce a decline in the fund's own number of investors as expected. However, the TL flows to a fund are not influenced from performances of neighboring funds. Based on these findings, one may conclude that individual investors are not under the influence of exogenous or endogenous interactions, since only a weak indication of exogenous interactions on number of investors is observed. As a result, OLS becomes the most efficient estimation method. Findings of this dissertation indicate that Turkish investors mostly value the prior performance of funds while allocating their cash flows. However, contrary to the evidence in the tournament behavior literature, the relation between fund flows and past performance is negative in the Turkish mutual fund industry. Furthermore, findings show that withdrawals are less from the best performing funds. The asymmetric withdrawals from best and worst performing funds may still create incentives to change the portfolio risk. The constant negative relation between fund flow and performance can be explained by the unique nature of Turkish mutual fund industry. The heavy consequences of the crises at the beginning of the 2000s discourage investors to hold an investment for a long period of time. Instead, the general findings of this dissertation show that Turkish fund investors seem to sell their holdings in mutual funds when they have a gain on their investments in the previous period.

Furthermore, funds' age is not a factor that affects flows to a fund, whereas size of the fund is an important determinant of fund flows. Contrary to the expectations, smaller funds draw more cash flow than larger ones. This finding would be related to the ownership structure of funds in Turkey. Larger funds in Turkey are usually bank related. Investors may find it easier to withdraw their money from bank owned funds when they need cash. Öztürkkal and Erdem (2012) note that banks may force their funds to take higher risks.

This could be another reason why investors prefer to invest in smaller funds. However, examination of risk-flow relation shows that individuals are not affected from the past period's total or systematic risk when allocating their money across different funds. Therefore, the ease of withdrawing money from bank related large funds seems to be the only explanation for the negative association between fund size and flow.

The insignificant relation between fund risk and flow can be caused by risk attitudes of investors holding these funds. By definition, funds analyzed in this dissertation invest heavily in equity which is a risky investment alternative. The investors holding these funds might have higher risk tolerance to begin with. Therefore, in allocating their money across these funds, they may not pay much attention to differences in risk of these funds.

Investigating the number of investors as another flow proxy demonstrates that the only variable that has an effect on fund flows is the size of the funds. As the size of the fund increases, the number of investors of a fund increases as well. This could again be a result of the ownership of larger funds by banks. It may be easier to have an account in the bank owned funds. However, analysis of these two flow measures indicate that an increase in number of investors may not necessarily result in higher TL flows.

Robustness of findings in this dissertation is also tested by using a second size definition and two control variables. The original Size variable is the natural logarithm of funds' total net asset. Since new cash flows to the funds are also scaled by total net assets, a spurious negative relation between fund flows and size might be created. To check whether the variable definition is the cause of the negative relation between fund flows and size, all the flow models are re-estimated by another size variable, *Size 2*, defined as the ratio of a fund's assets to the total net assets of all the funds included in the sample of this dissertation. However, estimations by *Size 2* results in essentially the same conclusions as the original size variable indicating that findings of this dissertation are not driven by variable definitions and are robust to different definitions of size variable.

Second, to account for dominance of the banks in the Turkish financial system, *Bank Dummy* variable is added to the models. This variable shows the differences in behavior of bank owned and non-bank owned funds. Besides the ownership status, the effect of the global financial crisis is also controlled for by adding a crisis dummy variable. However, findings do not change significantly when these two control variables are added to the models. Additionally, bank ownership does not seem to have any effect on TL cash flows of funds, but it has a positive effect on change in number of investors. This positive effect on change in number of investors may be due to the ease of making transactions with bank rather than non-bank owned mutual funds. Crisis dummy, on the other hand, has a positive effect on TL cash flows and a negative effect on change in number of accounts. These findings indicate an increase in TL cash flows but a decrease in number of accounts for Turkish funds in the post crisis period.

The second part of this dissertation, as mentioned before, deals with the fund managers' risk change decisions. The change in total and systematic risk of funds are examined separately. The most prominent finding regarding this issue is that Turkish fund managers pay attention to their relative position among other funds in making their risk change decisions. The positive coefficient for spatial lag of performance indicates that fund managers increase the total risk of their portfolios in the second half of the year when their neighboring funds exhibit a good performance in the first interim. One possible explanation is that managers try to protect their relative position or close the performance gap between their peer group and the fund itself by changing the total risk as discussed in Li and Tiwari (2006). Since there are significant exogenous interactions as defined in Manski (1993) in this model, spatial techniques become essential for the modeling of risk change decisions. Moreover, the basic argument of this dissertation, that managers act according to their positions in the risk – return space, is verified.

However, spatial interactions are not one of the determinants of systematic risk change decisions of funds. Managers do not take into account the performance of neighboring funds while deciding on how much to change their systematic risk. In this sense, OLS estimations would be appropriate for modeling systematic risk change decisions of funds.

There is also a positive relation between prior performance, either defined as Jensen's alpha excess return or Four-Factor excess return, and total risk change decision in the Turkish mutual fund industry. This result is in line with the contrary evidence in Busse (2001) and Goriaev et al. (2005) regarding the tournament hypothesis. This positive relation may be attributed to the desire of fund managers to protect their current location as discussed in Taylor (2003).

The negative coefficient on lagged risk variables indicates a mean reversion in risk change decisions of managers. If a fund's total or systematic risk in the first half of the year is high, managers tend to decrease their change in total risk in the second half of the year. Interestingly, when changing the systematic risk of the portfolio, managers only take into account the change in total risk of their portfolio in the first half of the year, but ignore the change in their portfolios beta during that time period. As suggested by Li and Tiwari (2006), managers may think that they can close the performance gap between the fund itself and the leaders by only changing the unique risk since all funds carry mostly the same systematic risk. One may observe that Turkish fund managers are mostly risk averse, since they do not prefer a high total risk level.

It is also found that managers do not pay attention to either the age or the size of the fund when making total risk change decisions. However, there is some evidence indicating that in older and larger funds, managers are willing to change the systematic risk of the portfolio more.

As in the flow models, the risk change decision of fund managers is also investigated by using an alternative *Size* variable and adding two control variables, *Bank* and *Crisis Dummy* variables. Models with *Size 2* variable yield essentially the same results with the original size variable proving that basic conclusions of this dissertation are robust to different size definitions. Interestingly, there is no difference in risk change decisions of bank and non-bank owned mutual funds. However, as in investors' flow channeling decisions, fund managers act differently before and after the global financial crisis. It seems that managers tend to be more cautious after the crisis period. In particular, they are more reluctant to change the systematic risk of their portfolios positively.

In conclusion, this dissertation shows that Turkish individual investors are not under the influence of exogenous or endogenous interactions caused by other funds' location in the risk-return space while allocating their money across a set of type-A mutual funds. In this sense, they decide independently. A less amount of outflow is observed from the best performing funds, which may create tournament like incentives for Turkish fund managers. However, the change in risk models cannot detect any evidence supporting such a behavior. Instead, the findings are consistent with the contradictory evidence. In this sense, I cannot verify the prior findings of Öztürkkal and Erdem (2012) in which worst funds alter their portfolio risk to attract more cash flow while best ones try to lock-in their positions. This disagreement can be explained by the sample selection of their study and differences in methodologies used. By using a more precisely determined flow data and a spatial model that accounts for exogenous and/or endogenous interactions, this dissertation re-examines the flow – performance relation in the Turkish mutual fund industry and shows the existence of exogenous interactions in the risk change decision of managers. In other words, it is shown that performance of neighboring funds does matter when managers change the portfolio risk. On the other hand, these exogenous and endogenous interactions do not have any effect on performance–flow relation. Overall, use of spatial modeling allows a more detailed assessment of tournament behavior for the Turkish mutual fund industry.

REFERENCES

Akerlof, G. (1970). The market for “lemons”: Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, *84*(3), 488–500. Retrieved from http://www.jstor.org/stable/10.2307/1879431

Akerlof, G. (1997). Social distance and social decisions. *Econometrica*, *65*(5), 1005–1027. Retrieved from http://www.jstor.org/stable/10.2307/2171877

Anselin, L. (1986). Some Further Notes on Spatial Models and Regional Science. *Journal of Regional Science*, *26*(4), 799–802. http://doi.org/10.1111/j.1467-9787.1986.tb01077.x

Anselin, L. (1988). *Spatial Econometrics: Methods and Models* (First Edit). Dordrecht: Kluwer Academic Publishers.

Anselin, L. (1992). *Spatial data analysis with GIS: an introduction to application in the social sciences*. Retrieved from http://repository.topoi.org/BACP-BIB/Anselin1992/Anselin1992.pdf

Anselin, L. (1999). The Future of Spatial Analysis in the Social Sciences. *Annals of GIS*, *5*(2), 67–76. Retrieved from http://www.tandfonline.com/doi/abs/10.1080/10824009909480516

Anselin, L. (2003). Spatial Externalities, Spatial Multipliers, And Spatial Econometrics. *International Regional Science Review*, *26*(2), 153–166. http://doi.org/10.1177/0160017602250972

Anselin, L. (2006). Spatial Econometrics. In T. C. Mills & K. Patterson (Eds.), *Palgrave Handbook of Econometrics Vol. 1 Econometric Theory* (pp. 901–969). New York: Palgrave Macmillan.

Anselin, L. (2010). Thirty years of spatial econometrics. *Papers in Regional Science*, *89*(1), 3–26. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.1435-5957.2010.00279.x/full

Anselin, L., Gallo, J. Le, & Jayet, H. (2008). Spatial Panel Econometrics. In L. Matyas & P. Sevestre (Eds.), *The*

Econometrics of Panel Data Advanced Studies in Theoretical and Applied Econometrics (Third Edit, pp. 625 – 660). Verlag - Berlin - Heidelberg: Springer. http://doi.org/0.1007/978-3-540-75892-1_19

Anselin, L., & Griffith, D. A. (1988). Do spatial effects really matter in regression analysis? *Papers in Regional Science*, *65*(1), 11–34. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.1435-5597.1988.tb01155.x/abstract

Arbia, G. (2006). *Spatial Econometrics* (First Edit). New York: Springer Berlin Heidelberg.

Banker, R. D., Cooper, W. W., Seiford, L. M., Thrall, R. M., & Zhu, J. (2004). Returns to scale in different DEA models. *European Journal of Operational Research*, *154*(2), 345–362. http://doi.org/10.1016/S0377-2217(03)00174-7

Basso, A., & Funari, S. (2001). A data envelopment analysis approach to measure the mutual fund performance. *European Journal of Operational Research*, *135*(3), 477–492. http://doi.org/10.1016/S0377-2217(00)00311-8

Beck, N., Gleditsch, K. S., & Beardsley, K. (2006). Space is more than geography: Using spatial econometrics in the study of political economy. *International Studies Quarterly*, *50*(1), 27–44. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.1468-2478.2006.00391.x/full

Brown, K. C., Harlow, W. V., & Starks, L. T. (1996). Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry. *Journal of Finance*, *51*(1), 85–110. Retrieved from http://www.jstor.org/stable/10.2307/2329303

Busse, J. A. (2001). Another look at mutual fund tournaments. *Journal of Financial and Quantitative Analysis*, *36*(1), 53–73. Retrieved from http://journals.cambridge.org/abstract_S002210900000939X

Chen, H., & Pennacchi, G. G. (2009). Does Prior Performance Affect a Mutual Fund's Choice of Risk? Theory and Further Empirical Evidence. *Journal of Financial and Quantitative Analysis*, *44*(04), 745–775. http://doi.org/10.1017/S002210900999010X

Chevalier, J., & Ellison, G. (1997). Risk Taking by Mutual Funds as a Response to Incentives. *Journal of Political Economy*, *105*(6), 1167–1200.

Choi, Y. K., & Murthi, B. P. S. (2001). Relative Performance Evaluation of Mutual Funds: A Non-Parametric Approach. *Journal of Business Finance & Accounting*, *28*(7&8), 853–876. http://doi.org/10.1111/1468-5957.00396

Conley, T. G. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics*, *92*(1), 1–45. Retrieved from http://www.sciencedirect.com/science/article/pii/S0304407698000840

Conley, T. G., & Dupor, B. (2003). A spatial analysis of sectoral complementarity. *Journal of Political Economy*, *111*(2), 311–352. Retrieved from http://www.jstor.org/stable/10.1086/367681

Conley, T. G., & Topa, G. (2002). Socio-economic distance and spatial patterns in unemployment. *Journal of Applied Econometrics*, *17*(4), 303–327. http://doi.org/10.1002/jae.670

Cooper, W. W., Seiford, L. M., & Tone, K. (2006). *Introduction to Data Envelopment Analysis and Its Uses. Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software*. New York: Springer. Retrieved from http://www.springerlink.com/index/d21w3x3883v56j0v.pdf

Cullen, G., Gasbarro, D., Monroe, G. S., & Zumwalt, J. K. (2012). Changes to mutual fund risk: Intentional or mean reverting? *Journal of Banking & Finance*, *36*(1), 112–120. http://doi.org/10.1016/j.jbankfin.2011.06.011

Danışoğlu, S. (2013). *A Test of Multi-Index Asset Pricing Models: The Case of Borsa Istanbul*.

Das, S. R., & Sundaram, R. K. (2002). Fee Speech: Signaling, Risk Sharing, and the Impact of Fee Structures on Investor Welfare. *Review of Financial Studies*, *15*(5), 1465–1497. Retrieved from http://rfs.oxfordjournals.org/content/15/5/1465.short

Del Guercio, D., & Tkac, P. A. (2002). The Determinants of the Flow of Funds of Managed Portfolios: Mutual Funds vs. Pension Funds. *The Journal of Financial and Quantitative Analysis*, *37*(4), 523–557.

Dow, M. M., Burton, M. L., White, D. R., & Reitz, K. P. (1984). Galton's problem as network autocorrelation. *American Ethnologist*, *11*(4), 754–770. Retrieved from http://onlinelibrary.wiley.com/doi/10.1525/ae.1984.11.4.02a00080/abstract

Elhorst, J. P. (2010). Applied Spatial Econometrics: Raising the Bar. *Spatial Economic Analysis*, *5*(1), 9–28. http://doi.org/10.1080/17421770903541772

Elton, E. J., Gruber, M. J., & Blake, C. R. (2003). Incentive fees and mutual funds. *The Journal of Finance*, *58*(2), 779–804. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/1540-6261.00545/abstract

Ferreira, M. A., Keswani, A., Miguel, A. F., & Ramos, S. B. (2012a). The Determinants of Mutual Fund Performance: A Cross-Country Study. *Review of Finance*, *17*(2), 483–525. http://doi.org/10.1093/rof/rfs013

Ferreira, M. A., Keswani, A., Miguel, A. F., & Ramos, S. B. (2012b). The flow-performance relationship around the world. *Journal of Banking & Finance*, *36*(6), 1759–1780. http://doi.org/10.1016/j.jbankfin.2012.01.019

Florax, R. J. G. M., & Van Der Vlist, A. J. (2003). Spatial Econometric Data Analysis: Moving Beyond Traditional Models. *International Regional Science Review*, *26*(3), 223–243. http://doi.org/10.1177/0160017603254937

Getis, A. (2010). Spatial Autocorrelation. In M. M. Fischer & A. Getis (Eds.), *Handbook of Applied Spatial Analysis* (First, Vol. 3, pp. 255–278). Heidelberg: Springer. http://doi.org/10.1007/978-3-642-03647-7

Goriaev, A., Nijman, T. E., & Werker, B. J. M. (2005). Yet another look at mutual fund tournaments. *Journal of Empirical Finance*, *12*(1), 127–137. http://doi.org/10.1016/j.jempfin.2003.11.001

Gökgöz, F. (2009). *Veri Zarflama Analizi ve Finans Alanına Uygulanması*. Ankara: Ankara Üniversitesi Siyasal Bilgiler Fakültesi Yayın No: 597.

Holly, S., Pesaran, M. H., & Yamagata, T. (2010). A spatio-temporal model of house prices in the USA. *Journal of Econometrics*, *158*(1), 160–173. http://doi.org/10.1016/j.jeconom.2010.03.040

Huang, J., Sialm, C., & Zhang, H. (2011). Risk Shifting and Mutual Fund Performance. *Review of Financial Studies*, *24*(8), 2575–2616. http://doi.org/10.1093/rfs/hhr001

Huang, J., Wei, K. D., & Yan, H. (2007). Participation costs and the sensitivity of fund flows to past performance. *The Journal of Finance*, *62*(3), 1273–1311. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.1540-6261.2007.01236.x/full

Ippolito, R. A. (1992). Consumer reaction to measures of poor quality: Evidence from the mutual fund industry. *Journal of Law and Economics*, *35*(1), 45–70. Retrieved from http://www.jstor.org/stable/10.2307/725554

James, C. (1987). Some evidence on the uniqueness of bank loans. *Journal of Financial Economics*, *19*(2), 217–235. Retrieved from http://www.sciencedirect.com/science/article/pii/0304405X87900031

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, *47*(2), 263–292. Retrieved from http://www.jstor.org/stable/10.2307/1914185

Keiler, S., & Eder, A. (2013). *CDS Spreads and Systemic Risk: A Spatial Econometric Approach*.

Kelejian, H. H., & Piras, G. (2014). Estimation of spatial models with endogenous weighting matrices, and an application to a demand model for cigarettes. *Regional Science and Urban Economics*, *46*, 140–149. http://doi.org/10.1016/j.regsciurbeco.2014.03.001

Kempf, A., & Ruenzi, S. (2008). Tournaments in mutual-fund families. *Review of Financial Studies*, *21*(2), 1013–1036. http://doi.org/10.1093/rfs/hhm057

Koski, J. L., & Pontiff, J. (1999). How Are Derivatives Used? Evidence from the Mutual Fund Industry. *The Journal of Finance*, *54*(2), 791–816. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/0022-1082.00126/abstract

Leenders, R. T. A. J. (2002). Modeling social influence through network autocorrelation: constructing the weight matrix. *Social Networks*, *24*(1), 21–47. http://doi.org/10.1016/S0378-8733(01)00049-1

LeSage, J. P. (1997). Regression analysis of spatial data. *Journal of Regional Analysis and Policy*, *27*(2), 83–94. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.1461-0248.2009.01422.x/full

LeSage, J. P. (1999). *The theory and practice of spatial econometrics. University of Toledo. Toledo, Ohio*. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.111.4233&rep=rep1&type=pdf

LeSage, J. P., & Pace, R. K. (2009). *Introduction to Spatial Econometrics*. Florida: Chapman and Hall.

Li, W., & Tiwari, A. (2006). *On the consequences of mutual fund tournaments. Available at SSRN 687123*. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=687123

Lin, T.-M., Wu, C.-E., & Lee, F.-Y. (2006). "Neighborhood" Influence on the Formation of National Identity in Taiwan: Spatial Regression with Disjoint Neighborhoods. *Political Research Quarterly*, *59*(1), 35–46. http://doi.org/10.1177/106591290605900104

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies*, *60*(3), 531–542. Retrieved from http://restud.oxfordjournals.org/content/60/3/531.short

Manski, C. F. (2000). Economic Analysis of Social Interactions. *Journal of Economic Perspectives*, *14*(3), 115–136. http://doi.org/10.1257/jep.14.3.115

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*(1), 77–91. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.1540-6261.1952.tb01525.x/full

Murthi, B. P. S., Choi, Y. K., & Desai, P. (1997). Efficiency of mutual funds and portfolio performance measurement: A non-parametric approach. *European Journal of Operational Research*, *98*(2), 408–418. http://doi.org/10.1016/S0377-2217(96)00356-6

O'Loughlin, J. (1986). Spatial Models of International Conflicts: Extending Current Theories of War Behavior. *Annals of the Association of American Geographers*, *76*(1), 63–80. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.1467-8306.1986.tb00104.x/abstract

O'Loughlin, J., Ward, M. D., Lofdahl, C. L., Cohen, J. S., Brown, D. S., Reilly, D., … Shin, M. (1998). The Diffusion of Democracy, 1946–1994. *Annals of the Association of American Geographers*, *88*(4), 545–574. http://doi.org/10.1111/0004-5608.00112

Öztürkkal, B., & Erdem, O. (2012). A Tournament Analysis of Mutual Funds in Turkey. *İktisat İşletme ve Finans*, *27*(321), 39–56. http://doi.org/10.3484/iif.2012.321.3354

Pinkse, J., & Slade, M. (2004). Mergers, brand competition, and the price of a pint. *European Economic Review*, *48*(3), 617–643. http://doi.org/10.1016/S0014-2921(02)00328-8

Pinkse, J., Slade, M., & Brett, C. (2002). Spatial price competition: a semiparametric approach. *Econometrica*, *70*(3), 1111–1153. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/1468-0262.00320/abstract

Qu, X., & Lee, L. (2015). Estimating a spatial autoregressive model with an endogenous spatial weight matrix. *Journal of Econometrics*, *184*(2), 209–232. http://doi.org/10.1016/j.jeconom.2014.08.008

Rey, S. J., & Montouri, B. D. (1999). US regional income convergence: a spatial econometric perspective. *Regional Studies*, *33*(2), 143–156. Retrieved from http://www.tandfonline.com/doi/abs/10.1080/00343409950122945

Schwarz, C. G. (2011). Mutual Fund Tournaments: The Sorting Bias and New Evidence. *Review of Financial Studies*, *25*(3), 913–936. http://doi.org/10.1093/rfs/hhr091

Simmons, B. A., & Elkins, Z. (2004). The globalization of liberalization: Policy diffusion in the international political economy. *American Political Science Review*, *98*(1), 171–189. Retrieved from http://works.bepress.com/cgi/viewcontent.cgi?article=1011&context=zachary_elkins

Sirri, E. R., & Tufano, P. (1998). Costly search and mutual fund flows. *The Journal of Finance*, *53*(5), 1589–1622. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/0022-1082.00066/abstract

SPK Yatırımcı Bilgilendirme Kitapçıkları. (2010). *Yatırım Fonları*.

Tarım, S. A., & Karan, M. B. (2001). Investment Fund Performance Measurement Using Weight-Restricted Data Envelopment Analysis: An Application to the Turkish Capital Market. *Russian and East European Finance and Trade*, *37*(5), 64–84. Retrieved from http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Investment+Fund+Performance+Measurement+Using+Weight-Restricted+Data+Envelopment+Analysis+An+Application+to+the+Turkish+Capital+Market#0

Taylor, J. (2003). Risk-taking behavior in mutual fund tournaments. *Journal of Economic Behavior & Organization*, *50*(3), 373–383. http://doi.org/10.1016/S0167-2681(02)00028-8

Tirtiroglu, D., Tanyeri, B., Tirtiroglu, E., & Daniels, K. N. (2011). *Banking Geography and Cross - Fertilization in the Productivity Growth of US Commercial Banks*.

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography*, *46*(Supplement: Proceedings), 234–240. Retrieved from http://www.jstor.org/stable/10.2307/143141

Türkiye Kurumsal Yatırımcılar Derneği. (n.d.). Fon Türleri Nelerdir? Retrieved from http://www.tkyd.org.tr/t/yatirim_fonlari_k.aspx

Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği. (2003). *Türkiye Sermaye Piyasası 2002*. İstanbul.

Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği. (2004). *Türkiye Sermaye Piyasası 2003*. İstanbul.

Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği. (2005). *Türkiye Sermaye Piyasası 2004*. İstanbul.

Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği. (2006). *Türkiye Sermaye Piyasası 2005*. İstanbul.

Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği. (2007). *Türkiye Sermaye Piyasası 2006*. İstanbul.

Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği. (2008). *Türkiye Sermaye Piyasası 2007*. İstanbul.

Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği. (2009). *Türkiye Sermaye Piyasası 2008*. İstanbul.

Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği. (2010). *Türkiye Sermaye Piyasası 2009*. İstanbul.

Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği. (2011). *Türkiye Sermaye Piyasası 2010*. İstanbul.

Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği. (2012). *Fînansal Piyasalar*.

Viton, P. A. (2010). *Notes on Spatial Econometric Models*. *City and Regional Planning*. Retrieved from http://facweb.knowlton.ohio-state.edu/pviton/courses2/crp8703/spatial.pdf

Ward, M. D., & Gleditsch, K. S. (2007). *An introduction to spatial regression models in the social sciences. Manuscript at http:// www. faculty. washington. edu/ mdw …*. Retrieved from http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:An+Introduction+to+Spatial+Regression+Models+in+the+Social+Sciences#6

White, D. R., Burton, M. L., & Dow, M. M. (1981). Sexual Division of Labor in African Agriculture: a Network Autocorrelation Analysis. *American Anthropologist*, *83*(4), 824–849. Retrieved from http://onlinelibrary.wiley.com/doi/10.1525/aa.1981.83.4.02a00040/abstract

Yatırım Fonlarına İlişkin Esaslar Tebliği Seri: III No.52.1 (2013). Capital Markets Board of Turkey.

Yatırım Fonlarına İlişkin Esaslar Tebliği Seri:VIII, No:10 (1996). Capital Markets Board of Turkey.

Yıldırım, J., Öcal, N., & Özyıldırım, S. (2009). Income Inequality and Economic Convergence in Turkey: A Spatial Effect Analysis. *International Regional Science Review*, *32*(2), 221–254. http://doi.org/10.1177/0160017608331250

Yıldız, A. (2006). Yatırım Fonları Performanslarının Veri Zarflama Analizi Yöntemiyle Değerlendirilmesi. *Ankara Üniversitesi SBF Dergisi*, *61*(2), 211–234.

Zheng, L. (2008). The Behavior of Mutual Fund Investors. In A. V. Thakor & A. W. A. Boot (Eds.), *Handbook of Financial Intermediation and Banking* (pp. 259–283). Amsterdam: North Holland. http://doi.org/10.1016/B978-0-444-51558-2.50014-3

APPENDICES

APPENDIX A. FUNDS INCLUDED INTO THE SAMPLE

Fund's Ticker Symbol	Fund's Name
AAK	Ata Yatırım Menkul Kıymetler A.Ş. A Tipi Karma Fon
ACD	Acar Yatırım Menkul Değerler A.Ş. A Tipi Değişken Fonu
ACK	Acar Yatırım Menkul Değerler A.Ş. A Tipi Karma Fon
ADD	Anadolubank A.Ş. A Tipi Değişken Fon
AK3	Akbank T.A.Ş. A Tipi Şemsiye Fonu'na Bağlı Hisse Senedi Alt Fonu(Hisse Senedi Yoğun Fon) (Birinci Alt Fon)
AN1	Alternatifbank A.Ş. A Tipi Değişken Yatırım Fonu
ASA	Alternatifbank A.Ş. A Tipi Hisse Senedi Fonu
BAT	Başkent Menkul Değerler A.Ş. A Tipi Değişken Fon
DAH	Denizbank A.Ş. A Tipi Hisse Senedi Fonu(Hisse Senedi Yoğun Fon)
DTD	Delta Menkul Değerler A.Ş. A Tipi Değişken Fonu(Hisse Senedi Yoğun Fon)
DZA	Denizbank A.Ş. A Tipi Değişken Fon
DZK	Denizbank A.Ş. A Tipi Afili Bankacılık Karma Fon
EC2	Eczacıbaşı Menkul Değerler A.Ş. A Tipi Değişken Aktif Fonu (Hisse Senedi Yoğun Fon)
ECA	Eczacıbaşı Menkul Değerler A.Ş. A Tipi Değişken Analiz Fonu
ECH	Eczacıbaşı Menkul Değerler A.Ş. A Tipi Hisse Senedi Fonu(Hisse Senedi Yoğun Fon)
EID	Ergo Sigorta A.Ş. Dinamik A Tipi Değişken Fon
FAF	Finansbank A.Ş. A Tipi Hisse Senedi Fonu(Hisse Senedi Yoğun Fon)
FI2	Finansbank A.Ş. A Tipi Değişken Fon(Hisse Senedi Yoğun Fon)
FYD	Finans Yatırım Menkul Değerler A.Ş. A Tipi Değişken Fonu(Hisse Senedi Yoğun Fon)
GAD	T. Garanti Bankası A.Ş. Özel Bankacılık Ve Portföy Yönetimi A Tipi Değişken Fonu (Hisse Senedi Yoğun Fon)
GAF	Gedik Yatırım Menkul Değerler A.Ş. A Tipi Hisse Senedi Fonu(Hisse Senedi Yoğun Fon)
GAK	Gedik Yatırım Menkul Değerler A.Ş. A Tipi Karma Fon
GBK	Global Menkul Değerler A.Ş. A Tipi Karma Fon

Table A1 (Cont'd). Funds Included into the Sample

Fund's Ticker Symbol	**Fund's Name**
GHS	T. Garanti Bankası A.Ş. A Tipi Hisse Senedi Fonu(Hisse Senedi Yoğun Fon)
GL1	Global Menkul Değerler A.Ş. A Tipi Değişken Yatırım Fonu
GMA	Global Menkul Değerler A.Ş. A Tipi Karma Aktif Strateji Fonu
HAF	T. Halk Bankası A.Ş. A Tipi Değişken Fonu
HLK	T. Halk Bankası A.Ş. A Tipi Karma Fon
HVS	HSBC Bank A.Ş. A Tipi Hisse Senedi Fonu (Hisse Senedi Yoğun Fon)
IAA	Ashmore İş Yatırım A Tipi Değişken Fon (Hisse Senedi Yoğun Fon)
IGD	ING Bank A.Ş. A Tipi Değişken Yatırım Fonu
IGH	ING Bank A.Ş. A Tipi Hisse Senedi Yatırım Fonu(Hisse Senedi Yoğun Fon)
IYD	İş Yatırım Menkul Değerler A.Ş. A Tipi Değişken Fonu(Hisse Senedi Yoğun Fon)
KA2	Türkiye Kalkınma Bankası A.Ş. A Tipi Değişken Fon
KYA	Kare Yatırım Menkul Değerler A.Ş. A Tipi Değişken Fonu
MAD	Meksa Yatırım Menkul Değerler A.Ş. A Tipi Değişken Fon
OKD	Oyak Yatırım Menkul Değerler A.Ş. A Tipi Değişken Fon(Hisse Senedi Yoğun Fon)
SMA	Sanko Menkul Değerler A.Ş. A Tipi Değişken Yatırım Fonu
ST1	Strateji Menkul Değerler A.Ş. A Tipi Değişken Fon(Hisse Senedi Yoğun Fon)
STH	Strateji Menkul Değerler A.Ş. A Tipi Risk Yönetimi Hisse Senedi Fonu(Hisse Senedi Yoğun Fon)
SUA	Ünlü Menkul Değerler A.Ş. A Tipi Değişken Fonu
TAH	Tekstil Bankası A.Ş. A Tipi Hisse Senedi Fonu
TAP	Türkiye İş Bankası A.Ş. A Tipi Privia Değişken Yatırım Fonu(Hisse Senedi Yoğun Fon)
TCD	Tacirler Menkul Değerler A.Ş. A Tipi Değişken Fon
TE3	Türk Ekonomi Bankası A.Ş. A Tipi Karma Fon
TGA	T. Garanti Bankası A.Ş. A Tipi Değişken Fonu
TI2	Türkiye İş Bankası A.Ş. A Tipi Hisse Senedi Fonu (Hisse Senedi Yoğun Fon)
TI7	Türkiye İş Bankası A.Ş. A Tipi Değişken Fonu
TKF	Tacirler Menkul Değerler A.Ş. A Tipi Karma Fon
TKK	Türkiye İş Bankası A.Ş. A Tipi Karma Kumbara Fonu
TMD	Tekstil Menkul Değerler A.Ş. A Tipi Değişken Fonu

Table A1 (Cont'd). Funds Included into the Sample

Fund's Ticker Symbol	Fund's Name
TUD	Turkish Yatırım A.Ş. A Tipi Değişken Fonu
TYH	TEB Yatırım Menkul Değerler A.Ş. A Tipi Hisse Senedi Fonu (Hisse Senedi Yoğun Fon)
TZD	Ziraat Yatırım Menkul Değerler A.Ş. A Tipi Değişken Fon
TZF	T.C. Ziraat Bankası A.Ş. A Tipi Şemsiye Fonu'na Bağlı Değişken Başak Alt Fonu (2.Alt Fon)
TZK	T.C. Ziraat Bankası A.Ş. A Tipi Şemsiye Fonu'na Bağlı Karma Alt Fonu (3.Alt Fon)
VAF	Türkiye Vakıflar Bankası T.A.O. A Tipi Değişken Fonu
YAD	Yatırım Finansman Menkul Değerler A.Ş. A Tipi Değişken Fon
YAF	Yapı Kredi Yatırım Menkul Değerler A.Ş. A Tipi Şemsiye Fonu'na Bağlı Değişken Alt Fonu(1.Alt Fon)
YAK	Yapı ve Kredi Bankası A.Ş. A Tipi Şemsiye Fonu'na Bağlı Karma Alt Fonu (3. Alt Fon)
YHS	Yapı ve Kredi Bankası A.Ş. A Tipi Şemsiye Fonu'na Bağlı Hisse Senedi Alt Fonu (Hisse Senedi Yoğun Fon)(2.Alt Fon)
ZBA	T.C. Ziraat Bankası A.Ş. A Tipi Şemsiye Fonu'na Bağlı Değişken Değer Alt Fonu (4.Alt Fon)

APPENDIX B. MORAN SCATTER PLOTS

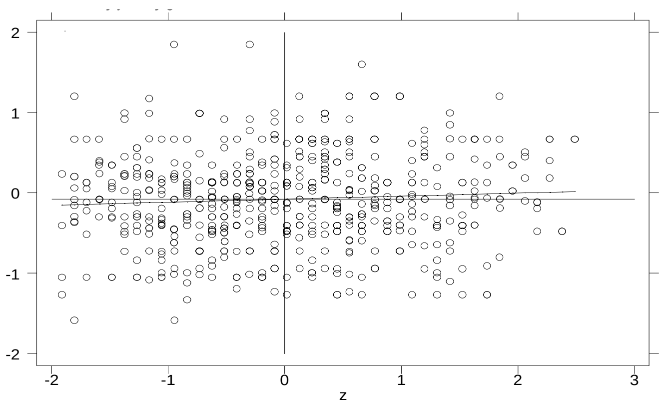


Figure 1. Moran scatter plots for fund age

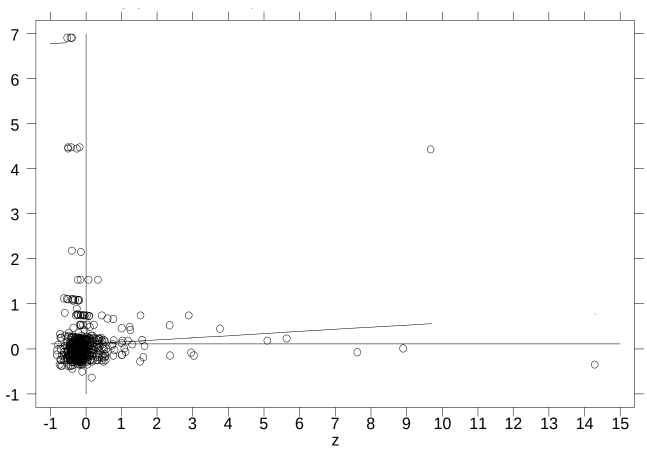


Figure 2. Moran scatter plots for flow from financial statements

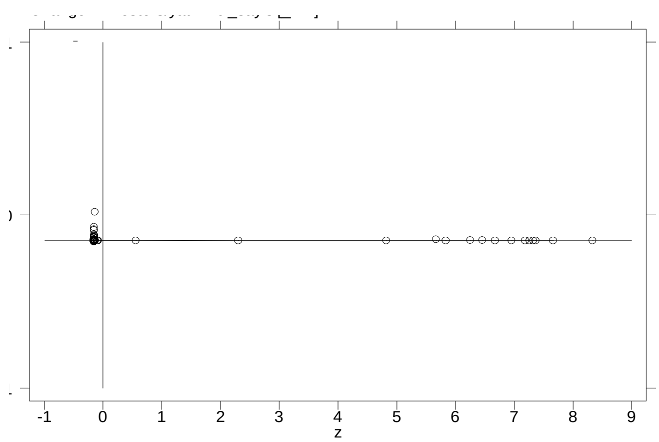


Figure 3. Moran scatter plots for change in number of investors

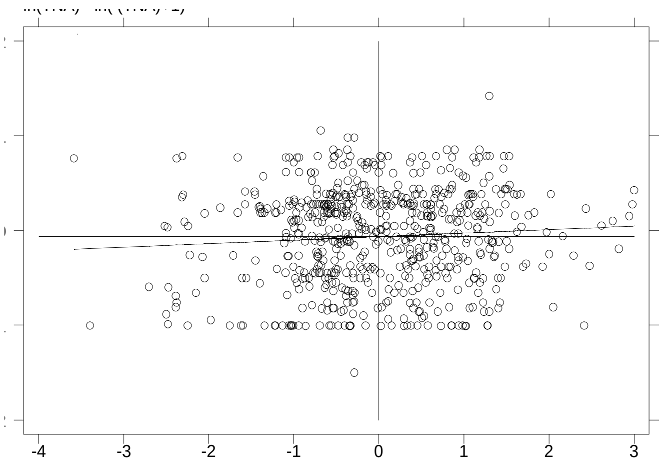


Figure 4. Moran scatter plots for size

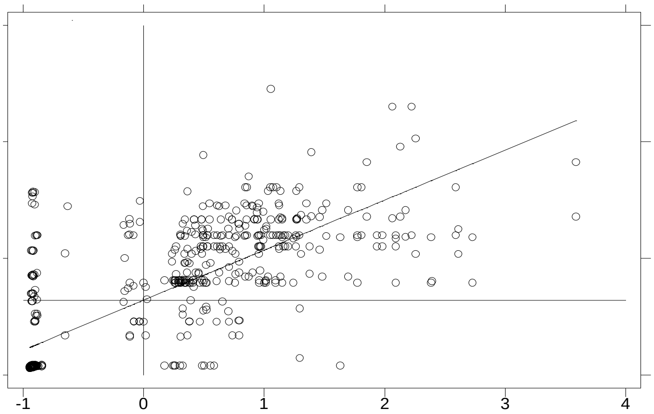


Figure 5. Moran scatter plots for expense ratio

APPENDIX C. CURRICULUM VITAE

PERSONAL INFORMATION

Surname, Name: Tuzcu, Sevgi Eda
Nationality: Turkish (TC)
Date and Place of Birth: 13 September 1984, Ankara
Marital Status: Married
Phone: +90 312 595 13 64
Fax: +90 312 319 77 36
e-mail: stuzcu@politics.ankara.edu.tr

EDUCATION

Degree	**Institution**	**Year of Graduation**
MBA	Ankara Univ. Graduate School of Social Sciences Business Administration	2008
BS	Ankara Univ. Faculty of Political Sciences Business Administration	2005
High School	Fethiye Kemal Mumcu Anadolu High School, Ankara	2001

WORK EXPERIENCE

Year	**Place**	**Enrollment**
2009 - Present	Ankara University SBF	Research Assistant
2005-2009	Gazi University	Research Assistant

FOREIGN LANGUAGES

Advanced English, Fluent Spanish, Intermediate French

PUBLICATIONS

Tuzcu, Sevgi Eda, "Spatial Modeling of Mutual Fund Tournament Hypothesis", *35th Annual Meeting of Middle East Economical Association*, January 3-6th, 2015, Boston, USA

Tuzcu, Sevgi Eda and Arcan Tuzcu, "Renewable Energy and Proven Oil Reserves Relation: Evidence from OPEC Members", *Çankırı Karatekin Üniversitesi İİBF Dergisi*, Vol.4 (2), 2014

Çınar Yetkin, Sevgi Eda Tuzcu and Gökçe Gürsel, "Türkiye'deki Ticari Bankaların Kredi Notlarının Geri Beslemeli Yapay Sinir Ağları ile

Tahmini”, *Yöneylem Araştırması ve Endüstri Mühendisliği 34. Ulusal Kongresi*, 2014, Bursa, Türkiye

Tuzcu, Sevgi Eda “The Effect of Derivatives Activity on Bank Profitability before and During the Subprime Mortgage Crisis: Evidence from Turkey”, *Ankara Üniversitesi Sosyal Bilimler Dergisi*, Vol.6(1), 2015

Tuzcu, Sevgi Eda “Does Lunacy Increase Investor Pessimism? Lunar Phases and Short Selling Relation in Istanbul Stock Exchange” *Global Business and Technology Association Fourteenth Annual International Conference*, July 10-14th, 2012, New York City, New York, USA

APPENDIX D. TURKISH SUMMARY

Finans literatüründe en çok tartışılan konulardan biri, fon yöneticilerinin aktif yönetimleri sonucunda elde ettikleri performansın, yönetim ücretlerini sürekli bir biçimde karşılayıp karşılayamadığıdır. Bu konunun ayrıntılı bir biçimde incelenmesi fona gelen yeni nakit akışları ile fonun geçmiş performansı arasındaki ilginç bir durumu ortaya çıkarmıştır. Literatürdeki pek çok çalışma, yatırım fonunu tercih eden yatırımcıların, geçmiş fon performansına bakarak yatırım kararlarını şekillendirdiklerini; ancak gösterdikleri tepkinin simetrik olmadığını ortaya koymaktadır (Brown, Harlow, & Starks, 1996; Chevalier & Ellison, 1997; Ippolito, 1992; Sirri & Tufano, 1998). Başka bir ifadeyle, fona gelen nakit akım ve fon performansı arasındaki ilişkiyi doğrusal değil de dışbükey olarak nitelendirmek mümkündür. Bu durum, yüksek performans gösteren, bir başka deyişle, kazanan fonların yeni nakit akışı anlamında ödüllendirilmesi; ancak kaybeden – performansı düşük olan- fonların aynı miktarda nakit çıkışı ile cezalandırılmaması anlamına gelmektedir (Sirri & Tufano, 1998). Literatürde farklı çalışmalar ile gösterildiği üzere, fon yöneticileri yılı yüksek performans ile kapatabilmek için bu dışbükey ilişkiyi kendi lehlerine kullanabileceklerdir. Bir başka anlatımla, fon yöneticileri, başarılı oldukları takdirde daha çok net nakit akışı kazanacakları, dolayısıyla fon büyüklüğünü ve kendi gelirlerini arttıracağı umuduyla portföy riskini arttırmayı seçebilirler. Çünkü başarısız olmaları halinde, kaybedecekleri nakit akışı, tersi durumdakine göre oldukça küçüktür. Ne var ki, bu görüşün tersini savunan çalışmalar da mevcuttur. Busse (2001) ve Goriaev, Nijman, ve Werker (2005), geçmiş çalışmalarda kullanılan günlük veride yüksek miktarda otokorelasyon bulunduğunu, bu durumun da sapmalı sonuçlara neden olabileceğini belirtmektedir. Karşıt görüşteki çalışmalara göre, aslında net nakit akışı ve fon performansı arasında dışbükey bir ilişki bulunmamaktadır. Bu çerçevede, bu tezin amacı, söz konusu dışbükey ilişkinin varlığını yeni bir dizi teknik yardımıyla Türkiye yatırım fonu sektörü için tekrar araştırmaktır. Böylelikle, daha önceki çalışmalarda bahsedilen çapraz kesit korelasyonun yanı sıra yatırım fonu sektöründe bulunması muhtemel mekânsal bağımlılık da dikkate alınmaya çalışılacaktır. Şimdiye kadar, yatırım fonu sektöründeki olası mekânsal bağımlılığı; fonlara olan nakit akışı ve fon performansı ilişkisine etki eden bir faktör olarak ele alan bir çalışmaya rastlanmamıştır.

Yatırım fonları piyasasında görülen turnuva hipotezine dair literatürde pek çok çalışma bulunmaktadır. Ancak bunların ilki olarak Ippolito (1992) çalışmasına yer verilebilir. Ippolito (1992)'nin asıl amacı, Akerlof (1970)'te bahsedilen asimetrik bilgi problemini bir de yatırım fonları açısından incelemektir. Buna göre, Ippolito (1992), fon yöneticilerinin gerçek yetenekleri bilinemediğinden, düşük kaliteli fonların da yüksek kaliteli olanlarla aynı şekilde davranabileceğini savunmaktadır. Yatırımcılar, bir fonun kalitesini geçmiş performansına bakarak değerlendirmektedirler. Bu nedenle, söz konusu çalışmada riske göre düzeltilmiş getirisi daha yüksek olan fonlar, kalitesi daha yüksek olan fon olarak kabul edilmiştir. Ippolito (1992)'nin, fon büyümesi ile fon performansı arasındaki ilişkiyi incelediği bu çalışmasının sonuçlarına göre, yatırımcıların kazanan (daha yüksek performans gösteren) ve kaybeden (daha düşük performansı olan) fonlara karşı tutumu aynı değildir. Bir başka deyişle, yatırımcılar, beklenenin üstünde performans gösteren fonlara daha çok yönelirken, kötü performans gösteren fonlardan nakitlerini aynı oranda çekmemektedirler.

Yatırımcıların kazanan ve kaybeden fonlara değin bu asimetrik tepkilerinin yatırım fonu yöneticileri üzerinde nasıl bir etki yarattığı ise Brown vd. (1996) tarafından incelenmiştir. Bir fonun piyasada performans açısından kazanıp kazanmadığı, bir başka deyişle yüksek performans gösteren fonlar arasında yer alıp almadığı, rakipleri olan diğer fonlara göre konumuna bağlı olarak belirlenir. Bu nedenle, Brown vd. (1996) rekabetçi bir yapıda olan yatırım fonları piyasasını spor turnuvalarına benzetmektedir. Bir başka anlatımla, yatırımcıları daha iyi performansı daha kötü olana tercih ettiklerinden, yöneticiler de daha yüksek nakit akışını fona çekebilmek için birbirleriyle mücadele etmek zorundadırlar. Brown vd. (1996)2ya göre, yatırım fonu piyasasındaki bu performansa göre sıralama sistemi, sektörde "çok dönemli, çok oyunlu bir turnuvaya" neden olmaktadır. Bu çalışma ayrıca, yatırım fonu yöneticilerinin elde ettiği kişisel getiri, fonun toplam net varlıklarının bir oranı olduğu sürece, yöneticilerin daha çok nakit akışını fona çekmek isteyeceklerini ifade etmektedir. Nakit akışlarındaki bu artış ise, ancak yılın son döneminde fonun rakiplerine göre daha iyi bir performans sergilemesi ile mümkün olacaktır. Sonuç olarak, fon yöneticileri daha iyi bir performans ve daha yüksek bir nakit akışı beklentisi ile portföyün daha fazla risk üstlenmesine izin verecek ve bu durum da "alım opsiyonu benzeri" bir sonuç yaratacaktır. Bu durumda fon yöneticileri, seneyi diğer fonlara göre daha yüksek bir performans ile bitirebilmek için portföy riskini değiştirecektir. Literatürde ilk kez olarak, Brown vd. (1996), söz konusu portföy değişikliğinin yatırımcıların faydası için olmayabileceğine; dolayısıyla yatırımcılar ve yöneticiler arasında bir temsil problemine yola açabileceğine değinmiştir.

Türkiye yatırım fonu piyasasında Brown vd. (1996) ile ortaya konan turnuva benzeri bir davranışın varlığını araştıran ilk çalışma ise Öztürkkal ve Erdem (2012) tarafından gerçekleştirilmiştir. Aslında Öztürkkal ve Erdem (2012)'nin çalışması, Brown vd. (1966)'nın yönteminin gelişmekte olan bir ülke piyasası için yeniden uygulanması şeklindedir. Bu amaçla, Türkiye'de faaliyet gösteren A tipi fonların tamamı için 2002 ile 2007 yılları arasındaki aylık veriyi kullanmışlardır. Çalışmanın ele aldığı veri, yatırım fonu portföylerinin sadece hisse senedi kısmı için portföy içeriğini aylık olarak sunmaktadır. Söz konusu veri Sermaye Piyasası Kurulu tarafından sağlanmış olmakla birlikte kamuya açık bir veri değildir. Önceki çalışmanın izinden giderek, Öztürkkal ve Erdem (2012) de, öncelikle fonlar için getiri hesaplaması yapmış, daha sonra ise bu getirinin volatilitesini medyandan yüksek performans gösteren ve medyandan düşük performans gösteren fonlar için kıyaslamıştır. Öztürkkal ve Erdem (2012)'nin bulguları Türkiye için de turnuva hipotezinin var olduğunu gösterir niteliktedir. Bir başka deyişle, Türkiye'de haziran ve temmuz aylarında, kaybeden grupta yer alan fon yöneticileri portföy risklerini yılın ikinci yarısı için arttırma eğilimindeyken, kazanan fonlar risklerini azaltma eğilimindedirler. Öztürkkal ve Erdem (2012), benzer şekilde, portföy riskini değiştiren fonların toplam fonlar içindeki payını da dikkate alarak, risk değiştirme eğiliminin kaybeden fonlar arasında yaygın olduğu sonucuna da varmıştır. Geçmiş çalışmalarda olduğu gibi, Türkiye'de görülen bu davranış da, yöneticinin yılsonundaki performans değerlendirme sürecinde iyi bir sıralama alma isteğiyle açıklanabilir. Brown vd. (1996)'ya göre, yatırım fonu yöneticilerinin bu tutumu tamamen, kaybeden fonların nakit akışlarındaki çıkış bakımından daha az cezalandırılması sebebiyle ortaya çıkan bir kumar ya da fazla risk alma eğiliminin bir sonucudur. Öztürkkal ve Erdem (2012) ise, Türkiye'deki yatırım fonu turnuva hipotezinin sadece yatırım fonu yöneticisinin risk iştahı ile açıklanamayacağını savunmaktadır. Buna göre, gelişmekte olan bir ülke örneği olarak Türkiye'de, yatırım fonu yöneticileri arasındaki devir hızı yüksektir. Bu da, yatırım fonu yöneticilerinin tek başına baskın bir rol üstlenmesine imkân vermemektedir. Aslında, pek çok yatırım fonu şirketi, başka finansal aracılarla veya bankalarla yakından ilişkilidir. Bankaların bizzat kendisi de, yeni yatırımcıları çekmek için daha fazla risk alma davranışını destekliyor olabilir. Öztürkkal ve Erdem (2012)'ye göre, yılın ikinci altı ayında risk arttırma davranışı içine giren fonlar, aslında fona yeni nakit akışı çekme baskının bir sonucudur.

Öztürkkal ve Erdem (2012)'nin yukarıda kısaca değinilen çalışması aslında bu tez için son derece önemlidir. Söz konusu çalışma, Türkiye için yatırım fonu turnuva hipotezinin varlığını araştıran ilk çalışma olma özelliğini taşımaktadır. Gelişmekte olan bir ülkede, kamuya açık olmayan bir veri ile analiz yaparak, literatürün genellikle ABD gibi gelişmiş ülkeler için sonuçlara değindiği bir alana gerçekten katkı yapmışlardır. Ancak, bu çalışmanın bazı eksik bıraktığı noktalar bulunmaktadır.

Öncelikle, daha önce de belirtildiği gibi, veri yokluğu sebebiyle, Öztürkkal ve Erdem (2012), yatırım fonu portföylerinin sadece hisse senedine ilişkin kısmına ait detaylı bilgiye sahiptir. Elde ettikleri sonuçları da fona gelen yeni nakit akışları ile ilişkilendirmişlerdir. Eğer bir portföyün riskini değiştirmek için tek yol, hisse senedi yatırımlarını değiştirmek olsaydı, söz konusu analiz doğru bir sonuca varmış olacaktı. Ne var ki, bir fon tahvil piyasasındaki yatırımlarını çekerek, elde ettiği nakdi hisse senedi piyasasında değerlendirmeyi seçebilir. Hisse senedi piyasasından geri çektiği yatırımlarını ise tahvil piyasasında değerlendirebileceği gibi bir süre nakit tutmayı da tercih edebilir. Bu koşullar altında, portföyde tutulan tüm varlıkların ayrıntısı bilinmeden, hisse senedi yatırım için kullanılan yeni nakdin yeni fon yatırımcılarından mı yoksa diğer yatırım seçeneklerinden mi geldiğini kimse bilemez. Risk üstlenme davranışını incelemek için daha iyi bir yol olarak Schwarz (2011)'in önerisini dikkate almak söz konusu olabilir. Bu amaçla, portföy riskini azaltmak (arttırmak) için, fon yöneticileri daha ziyade en yüksek (düşük) riskli yatırım seçeneğini elden çıkarmayı ve bunu en düşük (yüksek) riskli alternatifle yer değiştirmeyi tercih edecektir.

Ancak, bir portföyün sadece hisse senedine ilişkin kısmını incelemek böyle bir analize izin vermeyecektir.

Öztürkkal ve Erdem (2012)'nin çalışmasına yapılabilecek ikinci eleştiri, çalışmadaki örneklem seçimine yöneltilebilir. Söz konusu örneklem, piyasada o tarihler arasında yer alan tüm A tipi fonları ele alarak hazırlanmıştır. Ne var ki, A tipi ve B tipi fonlar arasındaki temel farklılıklara ek olarak, A tipi fonların kendisi de portföy yapılarına göre ayrı bir sınıflandırılmaya tabi tutulmaktadır. Türkiye Sermaye Piyasası Kurulunun 2010 yılındaki raporuna göre, Türkiye'de A tipi yatırım fonları 17 ayrı sınıfta ele alınabilmektedir (SPK Yatırımcı Bilgilendirme Kitapçıkları, 2010). Türk Kurumsal Yatırımcı Yöneticileri Derneği'ne göre, para piyasası fonu, tahvil ve bono fonu ile yabancı kıymet menkul kıymet fonu dışındaki tüm fonlar A tipi veya B tipi olabilir. Bu yukarıda sayılan fonlar ise sadece B tipi olarak düzenlenebilir. Her ne kadar, 2012 yılı itibariyle A ve B tipi ayrımı yatırım fonları için ortadan kalmış olsa ve fon tipleri temelde 20 ayrı şekilde sınıflandırılsa da, Öztürkkal ve Erdem (2012)'nin çalışması bu yeni düzenlemeden önce yapıldığı için daha önceki sınıflandırmayı esas almak daha doğru olacaktır. Görüldüğü gibi, A tipi olarak ele alınan fonlar geniş bir grubu kapsamakta ve sektör veya endeks fonları gibi fon tiplerinin yanı sıra, hisse senedi yoğun fonları da içermektedir. Ne var ki, Öztürkkal ve Erdem (2012) çalışmalarında, tüm bu fonları bir sepete koymuş ve turnuva hipotezinin varlığını hepsi üzerinden test etmiştir. Önceki literatür ise bu hipotezin ortaya çıkabileceği büyüme amaçlı fonlar gibi belli başlı fonları örneklem olarak ele almıştır. Özellikle sektör ve değerli maden fonları gibi fonların da Öztürkkal ve Erdem (2012)'in örneklemi içerisinde yer alması, sonuçların geçerliliğine gölge düşürmektedir. Bu tezde ise, önceki literatür ile uyumlu olarak, yalnızca hisse senedine yoğun bir biçimde yatırım amacı taşıyan karma, hisse senedi yoğun ve değişken fonlar ele alınmıştır.

Önceki dönem fon performansı ile fona gelen yeni nakit akışları arasındaki ilişkiyi araştıran önceki çalışmalar, konunun hem yatırım fonuna yatırım yapan bireyler hem de yatırım fonu yöneticileri için özellikle gelişmekte olan ülkelerde ne kadar önemli olduğunu göstermektedir. Bu tez ise, söz konusu ilişkiyi ve fon yöneticileri arasında turnuva hipotezinin varlığını araştıran modellere mekânsal etkilerin eklenmesi ile bir katkıda bulunmayı amaçlamaktadır. Yatırım fonu piyasasında söz konusu olabilen turnuva hipotezi, fon gelen nakit akışlarının geçmiş dönem fon performansı ile doğrusal olmayan bir biçimde ilişkili olabileceğini ve bu ilişkinin de fonun göreli konumundan kaynaklanabileceğini göstermektedir. Bu göreli konumun ise mekânsal etkilere yol açması oldukça muhtemeldir. Şimdiye kadar incelenen pek çok çalışma, söz konusu ilişkinin modellenmesinde otokorelasyonun ve çapraz kesit korelasyonun önemine değinmektedir. Ne var ki, incelendiği kadarıyla, fonların kendi içerisindeki sıralamasının neden olabileceği mekânsal etkiler şimdiye kadar dikkate alınmamıştır. Bu tez ile ele alınan farklı mekânsal modeller sayesinde, gerek nakit akışı ile geçmiş dönem fon performansı arasındaki ilişkinin, gerekse fon yöneticilerinin fazladan risk alma eğilimini ortaya çıkaran durumların daha ayrıntılı bir biçimde incelenmesi sağlanmaktadır.

Fon performansı ve nakit akışlarını inceleyen literatür, aslında geçmişte mekânsal ilişkinin varlığına değinmiştir. Çalışmalar öncelikle fon yöneticilerinin yatırımcıları kendine çekebilmek için diğer fonlarla rekabet içerisinde olmaları ve kazananlar arasında olması gerekmektedir. Örneğin, Brown vd. (1996), yatırım fonu sektöründeki turnuva benzeri durumu, piyasadaki sürekli olan sıralamaya bağlamaktadır. Bu durum, çalışmalarında şu şekilde ifade edilmektedir: “Bir fonun turnuvayı kazanması sonucu sağlayacağı gelir, fonun diğerlerine göre performansına dayanmaktadır.” (Brown vd., 1996: 85). Benzer bir biçimde, Del

Guercio ve Tkac (2002) yatırım fonlarının nakit akışları arasında yüksek düzeydeki otokorelasyona işaret etmektedir. Del Guercio ve Tkac (2002)'ye göre bu otokorelasyonun sebebi, bazı fonların diğerlerine göre daha fazla nakit çekmesi ve bunu gelecekte de sürdürebilmesidir. Başka bir deyişle, sektördeki bir yatırım fonu "kazanan" olarak adlandırılması ve daha yüksek bir getiri/ nakit akışı sağlaması ancak rakiplerinden iyi bir performans sağlamasına bağlıdır. Yatırım fonu sektöründeki yüksek otokorelasyon nedeniyle, geçen dönemin kazanan fonları, gelecek dönemde de kazanan olmayı sürdürecektir. Del Guercio ve Tkac (2002)' e göre, bu otokorelasyon, belirli fonlar etrafındaki toplanma davranışı ile açıklanabilir.

Busse (2001) ve Goriaev vd. (2005), çalışmalarında, nakit akışı ve risk arasındaki otokorelasyonu dikkate almıştır. Bu tezde ise, yatırım fonu sektöründeki turnuvanın kazanının, fonun diğer fonlara göre uzayda nerede olduğu ile ilgili olduğu savunulmaktadır. Buna göre, söz konusu konumun önemi nedeniyle mekânsal bağımlılık ortaya çıkabilir. Çünkü yatırım fonunun, rakiplerine göre konumu yatırımcıların değerlendirmelerini etkilemektedir. Konumun sözü edilen bu etkisi, şimdiye kadar nakit akışlarının yapısını ve fon yöneticilerinin davranışlarını inceleyen çalışmalar tarafından çoğunlukla göz ardı edilmiştir. Bu tez ise, yatırım fonları sektöründeki yöneticiler arasında görülen turnuva benzeri davranışı açıklamakta mekânsal etkileri de dikkate almaktadır.

Bu tezin, literatürden bir diğer farkı ise analizlerde kullandığı nakit akışı ile ilgili veridir. Şimdiye kadarki çalışmalar, fonlara nakit akışı – fon performansı ilişkisini değerlendirirken, tahmini bir nakit giriş çıkışı kullanmaktadır. Bunun için kullanılan temel tahmin yöntemi, Sirri ve Tufano (1998) tarafından fonun net yüzde büyümesi olarak önerilmektedir. Bu sırada, iki temel varsayımda bulunulmaktadır: Bunlardan ilki, bütün temettü ödemelerinin yeniden yatırıldığı, ikincisi ise yeni nakit akışlarının dönem sonunda gerçekleştiği varsayımıdır. Bu tahmin yöntemi, literatürdeki Chevalier ve Ellison (1997); Huang, Wei, ve Yan (2007); Huang, Sialm, ve Zhang (2011); Ferreira, Keswani, Miguel ve Ramos (2012b)'un çalışmalarında da olduğu gibi yaygın bir kullanım alanı bulmaktadır. Del Guercio ve Tkac (2002) ise bu tahmin yönteminin yanı sıra, yatırımcı sayısındaki değişmeyi de bir başka ölçüt olarak kullanmıştır. Türkiye'deki yatırım fonlarına ait veri ise Sermaye Piyasası Kurulu tarafından toplanmakta ve yayınlanmaktadır. Bu veride, bir fonun kaç adet payı olduğu ve pay başına toplam varlıkları bulunmaktadır. Bu iki veriden yola çıkarak fona net nakit akışını hesaplamak mümkün olmaktadır. Hesaplanan bu nakit akışının doğruluğu için, fonların yıllık bilançolarındaki katılım sertifikası hesabı kullanılmıştır. Bilançolar geçen yıl ile karşılaştırmalı olarak hazırlanmaktadır. Söz konusu hesabın iki yıl arasındaki farkı, o yıl fona sağlanan net nakit akışını vermektedir. Ancak bu veri sadece yıllık olarak bulunmaktadır. Bu tezde geliştirilen ve katılım sertifikası hesaplarının farkı ile kıyaslanan nakit akışı hesaplama yöntemi ise günlük veriden yola çıkılması sebebiyle her tür zaman sıklığına göre elde edilebilir. Gerçek net nakit akışına bu şekilde ulaşılabilmesi, fon nakit akışı – fon performansı arasındaki ilişkinin tahmin hatalarından ve varsayımlardan uzak bir biçimde değerlendirilmesine izin vermekte ve bu sayede literatüre katkı sunmaktadır.

Mekânsal ekonometri, standart ekonometrik tekniklerin kullanılmasına izin vermeyen konumdan kaynaklanan etkileri inceleyen ekonometri dalıdır (Anselin, 1988). Bu mekânsal etkiler ya da ilişkiler, araştırma biriminin uzaydaki diğer birimlere göre konumundan kaynaklanmaktadır. Temelde, bu etkilerin tümü mekânsal bağımlılık ve mekânsal heterojenlik olarak ikiye ayrılmaktadır. Bu tez ise, yatırım fonu yöneticilerinin kendi getirilerini maksimize etmek için portföyün risk- getiri yapısını göreli konumlarına göre değiştirdikleri; bu nedenle analizlerde dikkate alınması gereken bir mekânsal bağımlılığın ortaya çıkabileceği tartışılmaktadır. Aslında, söz konusu argüman, Busse (2001) ve Goriaev vd. (2005)'in bulduğu sonuçlarla da paralellik göstermektedir. Bu çalışmalar, temelde fon verilerindeki otokorelasyonu dikkate almadan nakit akışı- fonun gerçek performansı arasındaki ilişkinin tam olarak belirlenemeyeceğini belirtmektedir. Ancak bu çalışmalarda sonuçların doğruluğunu etkileyen otokorelasyonun bir zaman periyodu çerçevesinde tek yönlü bir ilişki olduğunu unutmamak gerekir. Busse (2001) ve Goriaev vd. (2005)'e göre bir dönemde fona gelen nakit akışları, gelecek dönemi de etkilemektedir. Bir başka deyişle, geçmişten bugüne olacak şekilde zaman çizelgesine dayalı bir bağımlılık söz konusudur. Ne var ki, nakit akışı – fon performansındaki olası bir mekânsal etkide, bağımlılık sonsuz yönlüdür. Uzayda her yöne doğru olan bu bağımlılık ise çapraz kesit bir çalışmada gözden kaçırılmaktadır. Bu tezde ise, şimdiye kadar ele alınmamış bu mekânsal etkiler de fonun getiri – risk uzayındaki konumuna göre ele alınmıştır. Bu şekilde, yatırım fonu sektöründe olduğu belirtilen turnuva hipotezinin daha farklı bir biçimde açıklanması mümkün olacaktır.

Her ne kadar finans literatüründeki uygulaması daha sınırlı olsa da, mekânsal ekonometri pek çok alanda, özellikle coğrafi uzaklıkların mekânsal ölçüt olarak kullanıldığı bölgesel çalışmalarda, sıklıkla kullanılmaktadır. Örneğin, bölgelerin ekonomik olarak birbirine yakınsaması (Rey ve Montouri, 1999) veya ev fiyatlarının belirlenmesi (Holly, Pesaran ve Yamagata, 2010), mekânsal tekniklerin kullanılmasını gerektiren alanlardır. Bölgesel çalışmaların yanı sıra, mekânsal modellemeye açık olan başka çalışma alanları da mevcuttur. Tırtıroglu vd. (2011), örneğin, ABD bankalarının performansını ölçerken mekânsal tekniklerden yararlanmıştır.

Mekânsal ekonometrinin, literatürdeki tipik kullanımından farklı olarak, bu tezde yatırım fonuna gelen nakit akışı – geçmiş fon performansı arasındaki ilişki, soyut bir uzay kavramı kullanılarak, bir başka deyişle, analitik düzlem üzerindeki fon performanslarına göre bir uzaklık tanımlayarak, modellenmeye çalışılmıştır. Aslında, uzayın ve/veya uzaklığın gelenekselden farklı bir biçimde tanımlanması, literatürde sık ele alınan bir konudur. Pek çok çalışma, özellikle sosyal bilimler alanında, soyut uzaklık kavramlarına ve mekânsal modellemeye ihtiyaç olduğunu vurgulamaktadır (Akerlof, 1997; Anselin, 1988; Dow, Burton, White, & Reitz, 1984). Ancak, az sayıda çalışma, Öklid tanımından farklı bir uzaklık kavramı kullanmıştır. Coğrafik olmayan uzaklık kavramları arasında, dil benzerliği (Dow vd., 1984), ulaşım maliyetleri (Conley, 1999), sosyal ağlar (Conley ve Topa, 2002), ikili ticari ilişkiler (Beck, Gleditsch, & Beardsley, 2006; Simmons & Elkins, 2004) sayılabilir. Bu tezde ise, uzaklık kavramı, yatırım fonlarının performans sıralamasına bağlı olarak analitik düzlem üzerinde düşünülmüştür. Bu açıdan bakıldığında, benzer risk – performans yapısına sahip olan fonlar birbirine yakın kabul edilmektedir.

Fonların analitik düzlemdeki konumlarını ve aralarındaki uzaklıkları hesaplamak için ise veri zarflama analizinden (VZA) yararlanılmaktadır. Aslında VZA, daha önce de fon performanslarının değerlendirilmesi amacıyla kullanılmıştır (Basso & Funari, 2001; Choi & Murthi, 2001; Murthi, Choi, & Desai, 1997). Ancak bu çalışmalar genellikle, aynı anda pek çok kriteri ele alabilen VZA'nın bir performans değerlendirme aracı olarak yatırım fonu sektörüne uygulanmasına odaklanmaktadır. Bu açıdan bakıldığında, VZA, bir kıyas noktasına gerek duymadan yatırım fonlarının etkinliğine göre göreli bir sıralama veren bir araçtır

(Murthi vd., 1997). Söz konusu çalışmalardan farklı olarak bu tezde ise VZA'nın performans değerlemesinden elde edilen bilgi; fon performansı ile nakit akışları arasındaki ilişkiyi analiz eden mekânsal regresyonlardaki mekânsal ağırlık olarak kullanılmaktadır. VZA, analiz edilen birimin etkin sınıra olan uzaklığını radyal ve Öklid mesafelere göre hesapladığı için, bu tezin de Anselin (1988)'de ifade edildiği üzere "soyut" bir uzaklık kavramı kullandığı söylenebilir. Bu uzaklık, her ne kadar hala Öklid tanımından yaralansa da, artık coğrafi olmayan bir biçimde hesaplanmaktadır. VZA'dan elde edilen bilgiler ışığında, tezdeki mekânsal regresyonlarda kullanılmak üzere genelleştirilmiş bir mekânsal ağırlık matrisi oluşturulmuştur. Daha açık bir ifadeyle, bu matrisin elemanları, fonların etkinsizlik derecelerinin çarpmaya göre tersi olarak alınmıştır ve birbirinin "referans kümesinde" olan fonlar, birbirine komşu kabul edilmiştir. Bu referans set ise, fonlar arasındaki minimum radyal uzaklığa göre VZA tarafından belirlenmiştir. Ayrıca, VZA'nın çalışma prensibi olarak göreli bir değerlendirme yapması, mekânsal ekonometri için gerekli olan konumun hesaplanması için özellikle uygundur.

Kısaca, bu tezin literatüre üç ayrı katkısı olduğundan söz edilebilir: Öncelikle, bu çalışma, Türkiye'deki yatırım fonlarının nakit akışı – performans yapısını mekânsal otokorelasyon ve heterojenliği de dikkate alarak yeniden incelemektedir. Buna göre, söz konusu ilişkiyi daha doğru bir biçimde modellemeyi amaçlayan mekânsal tekniklerden yararlanmaktadır. Ayrıca, Ferreira vd. (2012b), fonlara nakit akışı ve geçmiş performans arasındaki ilişki için önceki çalışmalarda bahsedilen dışbükeyliğin ülkelerin gelişmişlik düzeyine göre farklılık gösterdiğini belirtmektedir. Söz konusu çalışma, ülkelerin gelişmişlik düzeyleri ile dışbükeylik derecesi arasında ters yönlü bir ilişki olduğunu göstermektedir. Bu açıdan bakıldığında, Türkiye yatırım fonu piyasasında fona nakit akışları ve geçmiş performans arasındaki ilişkinin daha yüksek bir dışbükeylik göstermesi beklenebilir. Türkiye'deki veri setinin özelliğinden dolayı, fona günlük nakit akımlarının tam olarak hesaplanması ise çalışmanın literatüre bir başka katkısı olacaktır. Bu sayede, yapılan hesaplamalar, tahmin hatalarından bağımsız olabilecektir. Son olarak, mekânsal ekonometride klasik olarak kullanılan uzaklık kavramlarına ek olarak, bu tez ile soyut bir uzaklık kavramının oluşturulması için çalışılmıştır. Böylelikle, hem fon performansı ve nakit akışları arasındaki literatüre; hem de yeni bir uzaklık tanımı ile mekânsal ekonometri alanına katkıda bulunmak amaçlanmaktadır.

Çalışmanın dayandığı literatür ve amaçları doğrultusunda ilk olarak Türkiye'deki yatırım fonlarına gelen nakit akışının belirleyicileri saptanmaya çalışılmıştır. Daha önce de açıklandığı gibi, nakit akışlarına ait veride otokorelasyonun yanı sıra, fonun risk-getiri uzayındaki konumuna göre mekânsal korelasyonun da olması muhtemeldir. Bu tip bir etkiyi de dikkate almak için, yatırım fonları sektöründeki turnuva hipotezinin açıklanmasında üç ayrı tip mekânsal regresyon analizi yapılmıştır. Göreli konumun veya sektördeki sıralamanın yatırım fonları açısından önemi pek çok çalışmada belirtilse de, bu tez modelleme sırasında bu etkiyi doğrudan ele alan ilk çalışma olma özelliğine sahiptir. Bu açıdan mekânsal modelleme, tezin güçlü noktalarından birini oluşturmaktadır.

Söz konusu çalışmanın ikinci aşaması ise yatırım fonu yöneticilerinin portföy riskini değiştirme kararlarını nasıl verdiklerini ve fona gelen nakit akışları ile komşu fonların durumuna göre bu kararı değiştirip değiştirmediklerini incelemektir. Bu amaçla, öncelikle en küçük kareler yöntemiyle tahminde bulunan klasik bir regresyondan, daha sonra ise mekânsal gecikmeli X modelinden yararlanılmaktadır. Nakit akışlarının analizinde kullanılan aynı mekânsal ağırlık matrisinden risk modelleme sürecinde de kullanılmıştır. Böylelikle, yatırım fonu yöneticilerinin hangi koşullar altında portföy riskinde değişikliğe gittiğine ışık tutmak istenmektedir.

Çalışmanın bulguları, yatırımcıların, çeşitli yatırım fonları içerisinden seçim yaparken, diğer fonların pozisyonlarından bağımsız bir şekilde karar verdiklerini göstermektedir. Çünkü hiçbir modelde, mekânsal etkiye rastlanamamıştır. Bu yöndeki tek bulgu, yatırımcı sayısındaki değişmenin açıklanması sırasında ortaya çıkmıştır. Buna göre, komşu fonlardaki bir performans artışı, fonun kendi yatırımcılarının sayısında bir azalma ile sonuçlanmaktadır. Ne var ki, aynı etki Türk Lirası cinsinden hesaplanan nakit akışları için bulunamamıştır. Bir başka ifadeyle, Türk Lirası cinsinden nakit akışları, fonun komşularından etkilenmemektedir. Bu bulgular ışığında, genel olarak bireysel yatırımcılarının içsel ve dışsal etkiler altında kalmadan yatırım fonu hakkındaki kararlarını verdikleri söylenebilir. Bu durumun tek istinası, dışsal etkilerin varlığının zayıf bir biçimde tespit edildiği yatırımcı sayısındaki değişme cinsinden nakit akışı olabilir. Sonuç olarak, en küçük kareler yöntemi, nakit akışlarının açıklanması sırasında kullanılan tahmin yöntemleri arasında en etkin olma özelliğini sürdürmektedir. Sonuçlar, aynı zamanda, yatırımcıların nakit akışlarının yönüne karar verirken en çok dikkat ettikleri değişkenin fon performansı olduğuna işaret etmektedir. Ancak, turnuva hipotezi doğrultusunda beklenenin tersine, analizlerde kullanılan bütün performans değişkenleri için bu ilişki pozitif değil, negatif bulunmuştur. Bir başka ifadeyle, bir dönem önce iyi performans gösteren fonlardan nakit çıkışı gözlemlenmektedir. Yine de, bulgular, performansı daha iyi olan fonların kaybettiği nakdin, performansı düşük olanlara göre daha az olduğunu ortaya koymaktadır. Bu durumda, yöneticilerin kendi lehlerine ve yatırımcıların aleyhine portföy riskini değiştirmeleri hala mümkündür. Türkiye yatırım fonu piyasasındaki nakit akışları ve fonların geçmiş performansı arasındaki sürekli gözlemlenen ters yönlü ilişkinin ise sektörün kendine özgü özellikleri ile açıklanması mümkündür. 2000'li yılların başında yaşanan ağır ekonomik krizler, yatırımcıların uzun dönemli bir elde tutma süresi geliştirmesine engel olmuştur. Bunun yerine, Türk yatırım fonu yatırımcılarının, başa baş noktasını geçer geçmez, yatırımlarını nakde çevirme eğiliminde olduğu görülmektedir.

Fon karakteristiklerinin incelenmesi ise, öncelikle yatırımcıların kararlarında fonun yaşını dikkate almadığını göstermektedir. Ancak, fonun büyüklüğü yatırım kararları üzerinde etkili görünmektedir. Bulgular, daha küçük fonların büyük olanlara göre daha fazla nakit akışını çektiğini göstermektedir. Bu sonuç, fonların sahiplik yapısı ile de ilgili olabilir. Türkiye'de daha büyük fonlar, genellikle bankalar ile ilişkilidir. Yatırımcılar, bankalar ile işlem yapmayı ve gerektiğinde banka hesaplarından para çekmeyi daha kolay buluyor olabilirler. Yatırım fonlarına olan nakit akışlarını incelerken ortaya çıkan bir diğer ilginç bulgu da, risk-nakit akışı ilişkisidir. Sonuçlar, yatırımcıların nakit akışlarını fonlar arasında paylaştırırken, fonun geçmiş dönemde üstlendiği toplam veya sistematik risk düzeyinden etkilenmediğini ortaya koymaktadır. Çünkü ne toplam ne sistematik risk düzeylerine ilişkin değişkenler incelenen modellerde istatistiksel olarak anlamlı olarak bulunabilmiştir.

Risk değişkenlerinin genel olarak anlamsız olarak bulunması çalışma için seçilen örneklemin yapısı ile açıklanabilir. Çalışmanın örneklemi, karma, değişken ve hisse senedi yoğun fonlardan oluşmaktadır; çünkü bu üç tip fonun yöneticileri turnuva davranışına en açık olabilecek gruptur. Öte yandan, bu fonların yatırımcıları da, fonların portföy yapısı gereği hisse senedine ağırlık vermesi sebebiyle, risk almaya en istekli gruptur. Yatırımcıların bu özelliği kendisini riskten kaçınmanın ortaya çıkmaması ile gösteriyor olması mümkündür.

Yatırımcı sayılarının değişmesini bir diğer nakit akışı göstergesi olarak incelemek ise, bu değişken üzerindeki en etkili fon özelliğinin büyüklük olduğunu göstermektedir. Buna göre, fon büyüklüğü yatırımcı sayısını pozitif yönde etkilemektedir. Bu durum yine büyük fonların sahiplik yapısı ile açıklanabilir. Bankalarla ilişkili fonlarda hesap açtırmak yatırımcılar için daha kolay olabilir. Ancak, bu tezdeki analizler, yatırımcı sayısının her zaman Türk Lirası nakit akışı ile aynı olmadığını göstermektedir.

Çalışmanın bulgularının sağlamlığı, ikinci bir büyüklük değişkeni ve iki ayrı yapısal değişken ile yeniden test edilmiştir. Fon büyüklüğü, tanım gereği, fon toplam net varlıklarının doğal logaritması olarak ele alınmıştır. Öte yandan fona gelen yeni nakit akışları da fonun toplam net varlıklarına bölünerek, büyüklüğün etkisinden arındırılmaya çalışılmıştır. Bu açıdan bakıldığında, Türk Lirası cinsinden nakit akışı ile fon büyüklüğü arasındaki sürekli bulunan ters yönlü ilişkinin bir başka büyüklük değişkeni ile test edilmesi ihtiyacı doğmuştur. Bu amaçla, fon toplam net varlıklarının örneklemdeki toplam net varlıklara bölünmesi ile bulunan ikinci bir fon büyüklüğü değişkeni tanımlanmıştır. Bu yeni değişken de, nakit akışlarının belirleyicilerinin ortaya konduğu regresyonlarda temelde aynı sonuçları vermiştir. Bu nedenle, sonuçların farklı büyüklük tanımlarına karşı güçlü olduğu söylenebilir.

İkinci olarak, bankaların Türk finansal sistemindeki ağırlığını dikkate almak amacıyla banka kukla değişkeni modellere eklenmiştir. Bu kukla değişken ile bankalarla ilişkili olan ve olmayan fonlar arasındaki farklılık ortaya konmaya çalışılmıştır. Sahiplik yapısının yanı sıra, ABD'deki konut kredisi krizinin etkilerini dikkate almaya yönelik ikinci bir kukla değişken tanımlanmıştır. Kriz kuklası adı verilen bu değişken, 2009 ve sonrası dönemler için “1” değerini almakta, öncesinde ise “0” olmaktadır. Bu iki yeni değişkenin eklenmesi ile elde edilen sonuçlar, ilk bulgular ile temel olarak aynı durumu ifade etmektedir. Daha ayrıntılı olarak incelendiğinde ise, banka sahipliğinin Türk Lirası cinsinden hesaplanan nakit akışı üzerinde etkisi olmamasına rağmen, yatırımcı sayıları üzerinde olumlu yönde bir etki ettiği görülmektedir. Bu pozitif yönlü etki, önceden de belirtildiği gibi, yatırımcıların bankalarla ilişkili fonlar ile daha kolay işlem yapabildiğini göstermektedir. Öte yandan, kriz kuklası, Türk Lirası cinsinden hesaplanan nakit akışları üzerinde pozitif bir etkiye sahipken, yatırımcı sayıları üzerinde ters yönlü bir etki göstermektedir. Bu sonuç, kriz sonrası dönemde yatırımcı sayısında görülen bir azalmanın Türk Lirası nakit akışı ile desteklendiği ve toplamın sabit kaldığı şeklinde yorumlanabilir. Aslında benzer bir çıkarım, Türkiye Sermaye Piyasası Aracı Kuruluşları Birliği (2011 ve 2012) raporları tarafından da ortaya konmuştur. Bu raporlara göre, kriz sonrası dönemlerde yatırım fonlarının gayri safi yurtiçi hasılaya oranı sabit kalmaktadır.

Bu çalışmanın ikinci bölümü, daha önce de belirtildiği üzere, yatırım fonu yöneticilerinin portföy riskini değiştirme davranışlarını incelemektedir. Bu amaçla, üstlenilen toplam portföy riski ve sistematik risk kararı ayrı ayrı incelenmiştir. Bu konudaki en çok öne çıkan bulgu, Türkiye’deki fon yöneticilerinin, risk değişikliği kararını verirken, komşu fonlar içerisindeki göreli konumuna önem verdiğini işaret etmektedir. Mekânsal gecikmeli X modelinden elde edilen performansın mekânsal gecikmesinin pozitif bir katsayıya sahip olması, komşularının yılın ilk altı ayında iyi performans göstermesi üzerine, fon yöneticilerinin ikinci altı ayda portföyün toplam riskini arttırma eğiliminde olduğunu göstermektedir. Fon yöneticilerinin, komşulara göre daha fazla risk üstlenme eğilimini şu şekilde açıklamak mümkündür: Li ve Tiwari (2006)’ nın çalışmasında da bahsedildiği üzere, fon yöneticileri portföylerinin toplam riskini arttırmak suretiyle daha iyi bir performans ile seneyi kapatmayı, böylelikle de sektör içerisindeki mevcut konumlarını korumayı ya da rakip fon grubu ve fonun kendisi arasındaki performans açığını kapatmayı umuyor olabilir. Toplam riskin değişmesi kararında Manski (1993) tarafından tanımlanan dışsal etkilerin yoğun olarak bulunduğu tespit edildiğinden, bu kararın modellenmesinde mekânsal tekniklerden yararlanmak gereklidir. Ayrıca, bu tezin temel argümanı olan risk- getiri uzayındaki konuma göre hareket etme eğilimi de bu sayede doğrulanmış olmaktadır.

Ancak, sistematik risk değişikliği kararı incelendiğinde, mekânsal etkilerin varlığı çok zayıf kalmıştır. İncelenen sekiz ayrı modelin yalnızca birinde, mekânsal etkilerin varlığına rastlanmıştır. Bu açıdan bakıldığında yatırım fonu yöneticilerinin, sistematik risk değişikliğine ilişkin kararlarını verirken, başka fonlara ait pozisyonlardan etkilenmedikleri söylenebilir. Bu nedenle, söz konusu ilişkinin tahmini için kullanılan en küçük kareler yöntemi etkinliğini sürdürecektir.

Bulgular ayrıca, ister Jensen alfası isterse dört faktöre göre hesaplanmış aşırı getirilere dayalı performans değişkeninin, Türkiye yatırım fonu piyasası için toplam portföy riskini pozitif yönlü etkilediğini ortaya koymaktadır. Bu açıdan sonuçların, daha önce turnuva hipotezine karşıt görüşler sunan Busse (20019 ve Goriaev vd. (2005) ile uyum içerisinde bulunduğu söylenebilir. İlişkinin pozitif yönlü olması, Taylor (2003)'te de tartışıldığı gibi fonun mevcut konumunu koruması isteği ile açıklanabilir.

Yılın ilk altı ayındaki portföy riskine bakıldığında ise toplam risk değişikliği kararında bir ortalamaya dönme davranışının söz konusu olduğu söylenebilir. Eğer fon ilk altı ayda yüksek düzeyde toplam veya sistematik risk üstlenmişse, yılın ikinci yarısında, yöneticiler portföylerinin toplam riskini düşürme eğiliminde olduğu görülmektedir. Öte yandan, ilginç bir biçimde, yöneticilerin portföyün sistematik riskini değiştirme kararını verirken, sadece ilk altı aydaki toplam risk düzeyini dikkate aldıkları ama bu dönemdeki sistematik riski göz ardı ettikleri ortaya çıkmıştır. Li ve Tiwari (2006), daha önce fon yöneticilerinin, yatırım fonunun kendisi ile lider grup arasındaki performans açığını ancak sistematik olmayan riski değiştirerek kapatabileceklerini, çünkü aynı piyasadaki fonların az çok aynı sistematik risk düzeyine maruz kaldıklarını vurgulamıştır. Portföyün toplam riskini oluşturan faktörler açısından bakıldığında, Türkiye'deki yatırım fonu yöneticilerinin yüksek bir risk düzeyini tercih etmedikleri, bu anlamda riskten kaçınan bir davranış sergiledikleri görülebilir.

Çalışmada bulunan bir diğer sonuç ise, yatırım fonu yöneticilerinin toplam portföy riskini değiştirme kararlarında, fonun yaşını veya büyüklüğünü dikkate almadıkları yönündedir. Ne var ki, daha yaşlı ve büyük fonlarda, yöneticilerin portföyün sistematik riskini değiştirme konusunda daha istekli oldukları görülebilir.

Yatırımcıların nakit akışlarını nasıl yönlendirdiğini inceleyen nakit akışı modellerinde olduğu gibi, risk değişim modellerinde de bulguların sağlamlığı ikinci bir fon büyüklüğü değişkeni ve daha önce sözü edilen yapısal kukla değişkenler ile test edilmiştir. Risk modelleri, öncelikle, fon büyüklüğünün, fonun toplam net varlıklarının örneklemin toplamına bölünmesi ile hesaplandığı şekliyle tekrar gözden geçirilmiştir. Bu haliyle yeni hesaplanan modellerin ilk büyüklük tanımı ile hesaplananlarla temelde aynı sonuçları vermiş olması, bulguların fon büyüklüğü tanımından etkilenmediğini göstermektedir. Öte yandan, banka ile ilişkili fonlar için risk değişikliği üzerinde anlamlı bir etki bulunamamıştır. Bir başka deyişle, yatırım fonlarının yöneticileri, portföy riskini değiştirme kararı alırken, bankaların bir etkisi olmamaktadır. Ancak, ABD'de yaşanan konut kredisi krizinin etkisini inceleyen kriz kuklasının yatırımcıların nakit akışlarını yönlendirmesi üzerinde olduğu gibi, fon yöneticilerinin risk alma davranışları üzerinde de etkili olduğu görülmektedir. Yöneticilerin, kriz sonrası dönemde, risk almaya karşı daha dikkatli bir tutum sergiledikleri gözlemlenebilir. Daha açık bir ifadeyle, bu dönemde, portföylerinin sistematik riskini pozitif yönde değiştirmek konusunda daha gönülsüz davranmaktadırlar.

Sonuç olarak, bu tez, Türkiye'deki yatırım fonu yatırımcılarının, bir grup A tipi yatırım fonu içerisinden seçim yaparken fonların risk-getiri uzayındaki konumlarından kaynaklanan içsel ve dışsal etkilerden bağımsız karar verdiklerini göstermektedir. Bu açıdan bakıldığında, fon yatırımcıları Akerlof (1997)'nin tanımladığı biçimiyle bağımsız ve rasyonel bireylerdir. İncelenen dönemde, fon yatırımlarından sürekli bir çıkış olduğu gözlemlenmiş olsa da, bu çıkış eğilimi yüksek performans gösteren fonlar açısından daha düşüktür. Bir başka deyişle, daha iyi performans gösteren fonlar, bir dereceye kadar fondan nakit çıkışlarını engelleyebilmektedir. Performansa bağlı olan bu tutum, yine de yatırım fonu yöneticilerinin turnuva hipotezine benzer bir davranış içerisine girmelerine neden olabilir. Bu nedenle, yöneticilerin portföy riskini nasıl değiştirdikleri ile ayrıca incelenmiştir. Ancak, bu modellerde de, turnuva hipotezini ortaya koyacak bir bulguya rastlanamamıştır. Tersine, sonuçlar genel olarak bu hipotezi desteklemeyen literatür ile uyumludur. Bu açıdan bakıldığında, Öztürkkal ve Erdem (2012)'nin, performansı düşük olan fonların daha fazla nakit akışı çekebilmek için portföy riskini arttırdığı; performansı yüksek olanların ise göreli pozisyonlarını korumak yönünde davrandığı bulgusu doğrulanamamıştır. İki çalışma arasındaki bu fark, Öztürkkal ve Erdem (2012)'nin çalışmalarında ele aldığı örneklem ile açıklanabilir. Öte yandan, bu tezin sahip olduğu nakit akışı verisi sayesinde, Türkiye'deki yatırım fonu sektöründeki performans nakit akışı ilişkisi bir kez daha ele alınabilmektedir. Daha önemlisi, bu çalışma, portföy riskinin modellenmesinde dışsal etkilerin de varlığını göstermiş olmaktadır. Çalışmanın sonuçları, komşu fonların performansının, yönetimin kendi fonunun riski üzerinde karar verirken etkili olduğunu göstermektedir. Bu nedenle, dışsal etkilerin dikkate alınmaması, sonuçlarda bazı sapmalara neden olabilir. Bir bütün olarak ele alındığında, mekânsal modellemenin kullanılması, Türkiye'deki yatırım fonu piyasasının turnuva hipotezi açısından daha detaylı bir biçimde modellenmesini sağlamıştır denebilir.

APPENDIX E. TEZ FOTOKOPİSİ İZİN FORMU

ENSTİTÜ

Fen Bilimleri Enstitüsü	
Sosyal Bilimler Enstitüsü	X
Uygulamalı Matematik Enstitüsü	
Enformatik Enstitüsü	
Deniz Bilimleri Enstitüsü	

YAZARIN

Soyadı: Tuzcu
Adı: Sevgi Eda
Bölümü: İşletme

TEZİN ADI: A New Look at Mutual Fund Tournament Hypothesis Using Spatial Modeling

TEZİN TÜRÜ: Yüksek Lisans [ ] Doktora [X]

1. Tezimin tamamından kaynak gösterilmek şartıyla fotokopi alınabilir. [ ]

2. Tezimin içindekiler sayfası, özet, indeks sayfalarından ve/veya bir bölümünden kaynak gösterilmek şartıyla fotokopi alınabilir. [ ]

3. Tezimden bir (1) yıl süreyle fotokopi alınamaz. [X]

TEZİN KÜTÜPHANEYE TESLİM TARİHİ: