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Three Essays in Macroeconomics and Financial Economics

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Three Essays in Macroeconomics and Financial Economics

by

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Dedication

To my beloved and my family.

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Three Essays in Macroeconomics and Financial Economics

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In the first chapter, I analyze the question that whether the elasticity of intertemporal substitution or risk aversion is more important determinant of precautionary savings. This is an important question since a significant fraction of the capital accumulation is due to precautionary savings according to studies. Thus, knowing the important determinant of precautionary savings will be helpful to understand the capital accumulation mechanism. I look into the effects of the elasticity of intertemporal substitution and risk aversion on precautionary savings separately by performing simulations in order to obtain numerical results. I find that the elasticity of intertemporal substitution is more important determinant than risk aversion.

In the second chapter, I study the impact of the introduction of futures trading on the volatility of the underlying spot market for Turkish Istanbul Stock Exchange (ISE).The economic literature intensified the debate on the negative or positive impact of futures trading on the stock market volatility. Although there are empirical studies for different countries with mixed results, most of them focus on developed countries. There

are a few empirical researches on emerging markets. Analyzing the data, following results are obtained for ISE. First, the results suggest that the introduction of futures trading has decreased the volatility of ISE. Second, the results show that futures trading increases the speed at which information is impounded into spot market prices. Third, the asymmetric responses of volatility to the arrival of news for ISE have increased after the introduction of futures trading.

In the third chapter, I investigate the presence of calendar anomalies in ISE by using GARCH models. The presence of calendar anomalies and their persistence presence since their first discovery still remains a puzzle to be solved. On the other hand, there are some claims that general anomalies are much less pronounced after they became known to the public. Most of the studies have examined the developed financial markets. However, it is important to test the calendar effects in data sets that are different from those in which they are originally discovered and so ISE is a good case to test the calendar effects for a developing country.

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1.1 Introduction

The main question that this paper tries to answer is whether the elasticity of intertemporal substitution (EIS), the percentage change in intertemporal consumption in response to a given percentage change in the intertemporal price, or risk aversion is more important determinant of precautionary savings. This is an important question since a significant fraction of the capital accumulation that occurs in the United States is due to precautionary savings according to Zeldes (1989a), Skinner (1988) and Caballero (1990). Thus, knowing the important determinant of precautionary savings will be helpful to understand the capital accumulation mechanism in the U.S.

Zeldes (1989a) calculates the optimal amount of precautionary savings under uncertain income environment for the agents who have constant relative risk aversion utility. He finds that agents optimally choose to save more in an uncertain environment than they would have done in a certain environment when there is no borrowing or lending constraints. He uses numerical methods to closely approximate the optimal saving. In Deaton (1991)'s paper, the agents are restricted in their ability to borrow to finance consumption. However, nothing prevents these agents from saving and accumulating assets in order to smooth their consumption in bad states. In this environment, he shows that the behavior of saving and asset accumulation is quite sensitive to what agents believe about the stochastic process generating their income.

Aiyagari (1994) modifies the standard growth model of Brock and Mirman (1972) to include a role for uninsured idiosyncratic risk and borrowing constraints. In his model, there are a large number of agents who receive idiosyncratic labor endowment shocks that are uninsured. He analyzes its qualitative and quantitative implications for the contribution of precautionary saving to aggregate saving, importance of asset trading, and income and wealth distributions. He shows that aggregate saving is larger under idiosyncratic risk than certainty. Therefore, he demonstrates that two household with identical preferences over present and future consumption will under certainty save the same, but this does not necessarily imply that these two households will save the same in uncertain environments. In a recent work, Guvenen (2006) shows that aggregate investment is mostly determined by wealthy people who have high EIS and aggregate consumption is mostly determined by non-wealthy people who have low EIS. In his model, there are two different types of agents who differ in elasticity of intertemporal substitution and limited participation in the stock market. Limited participation is only used to create substantial wealth inequality similar to the data. Thus, difference in the elasticities is an important factor for determining savings.

My paper is an extension of Weil (1993)' paper where the determinants of precautionary savings can be studied analytically by assuming exponential risk utility function in Epstein-Zin (1989) preferences. This assumption makes the problem analytically solvable. Weil (1993) shows that savings increase in each of these cases:

- when persistence of income shocks increases
- when the coefficient of risk aversion increases
- when EIS increases

However, Weil does not rank the importance of these determinants in saving decisions.

The purpose of this paper is to understand the effects of the elasticity of intertemporal substitution (EIS) and risk aversion on savings separately and determine which coefficient is more important factor for precautionary savings. The numerical calculations are performed for the more general form of the Epstein-Zin utility function in order to calculate savings for different EIS and risk aversion, RA, coefficients to see which one is the more important determinant of precautionary savings. In this paper, I first look at the savings for different values of EIS by keeping the risk aversion coefficient constant. Then, savings are calculated by changing the risk aversion coefficients and keeping EIS constant. As a result, I obtained graph of savings for different EIS and risk aversion coefficients.

According to Chatterjee, Giuliano and Turnovsky (2004), most of the existing literature assumes that the preferences of the representative agent are represented by a constant elasticity utility function. While this specification of preferences is convenient, it is also restrictive in that two key parameters, the elasticity of intertemporal substitution and the coefficient of relative risk aversion, become directly linked to one another and cannot vary independently. This is a significant limitation and one that can lead to seriously misleading impressions of the effects that each parameter plays in determining the precautionary savings.

Arrow (1965) and Pratt (1964) introduced the concept of the coefficient of relative risk aversion and it is well defined in the absence of any intertemporal dimension. Hall (1978, 1988) and Mankiw, Rotemberg, and Summers (1985) established the concept of the elasticity of intertemporal substitution and it is well defined in the absence of risk. The standard constant elasticity utility function has the property that both parameters EIS and RA are constant, though it imposes the restriction EIS*RA = 1 with the widely employed logarithmic utility function corresponding to EIS=RA=1. Thus it is important to realize that in imposing this constraint the constant elasticity utility function is also invoking these separability assumptions according to Giuliano and Turnovsky (2003).

Although there are empirical studies about the value of the elasticity of intertemporal substitution, the results are different from each other. Hall (1988) and Campbell and Mankiw (1989) estimate EIS 0.1 based on macro data. Epstein and Zin (1991) provide estimates spanning the range 0.05 to 1, with clusters around 0.25 and 0.7. Attanasio and Weber (1993, 1995) find that their estimate of EIS is 0.3 using aggregate data and is 0.8 using cohort data. They propose that the aggregation implicit in the macro data may cause a significant downward bias in the estimate of EIS. Beaudry and van Wincoop (1995) estimate EIS near 1. More recent estimates by Ogaki and Reinhart (1999) suggest values of around 0.4. Moreover, Atkeson and Ogaki (1996) and Ogaki and Atkeson (1997) find evidence to suggest that the EIS increases with household wealth. As a result of these findings, the variation of EIS from 0.04 to 0.99 is used in the numerical calculations.

Similar to the elasticity of intertemporal substitution, the value the coefficient of risk aversion shows a discrepancy in the literature. Epstein and Zin (1991) conclude that their estimate of RA is near 1. In contrast, Kandel and Stambaugh (1991) take RA as 30 and Obstfeld (1994a) takes RA as 18. More recent study by Constantinides, Donaldson, and Mehra (2002) present that empirical evidence suggests that RA is most plausibly around 5. According to these findings, the variation of RA from 1.01 to 25 is used in the numerical calculations.

Zeldes (1989a), Deaton (1991) and Aiyagari (1994) use expected value of a discounted sum of time-additive utilities in the model, thus the motion of risk aversion and EIS is confused. As a result, it is not possible to look at the effects of EIS and risk aversion separately. According to Giuliano and Turnovsky (2003), this is important for two reasons. First, conceptually, EIS and RA impinge on the economy in quite independent, and in often conflicting ways. They therefore need to be decoupled if the true effects of each are to be determined. Risk aversion impinges on the equilibrium through the portfolio allocation process, and thus through the equilibrium risk that the economy is willing to sustain. It also determines the discounting of risk in deriving the certainty equivalent level of income. The intertemporal elasticity of substitution then determines the allocation of this certainty equivalent income between current consumption and future consumption. Second, the biases introduced by imposing the compatibility condition EIS*RA=1 for the constant elasticity utility function can be quite large, even for relatively weak violations of this relationship. According to Chatterjee, Giuliano and Turnovsky (2004), while one certainly cannot rule out using the constant elasticity utility function, as a practical matter, their results suggest that it should be employed with caution, recognizing that if the condition for its valid use is not met, very different implications may be drawn.

This paper follows Weil (1993) by using an Epstein-Zin utility function that permits risk attitudes to be disentangled from the degree of intertemporal substitutability. This facilitates the study of the effects of EIS and risk aversion separately. It is shown saving increases as EIS increases. Similarly, saving increases as the coefficient of risk aversion increases. More importantly, it is observed that EIS is a more important factor for precautionary savings than risk aversion because saving is more responsive to changes in EIS than changes in risk aversion. For example, starting from the benchmark preference parameters RA= 5 and EIS = 0.2, the constant elasticity utility function implies that doubling RA to 10 (and thus simultaneously halving EIS to 0.1 so that EIS*RA=1) would reduce the savings to 0.9148 when the savings in benchmark case is normalized to 1. On the other hand, when the EIS is doubled to 0.4 and RA is halved to 2.5, the savings increases to 1.4074. In the unrestricted utility function, if RA increases two times, RA=10, and EIS stays the same, the savings become 1.3838 whereas if EIS increases twice, EIS=0.4, and RA stays the same, the savings become 1.9083. Thus, the change in savings is much less sensitive to the degree of risk aversion than to the intertemporal elasticity of substitution.

The paper is structured as follows. Section 1.2 describes the model, by explaining the preferences and the optimization problem faced by individuals in the economy. The numerical results are presented and discussed in Section 1.3. Section 1.4 concludes the paper by outlining some directions for future research. Section 1.5 describes the numerical solution of the model.

1.2 Model

Our model is the standard problem of a representative agent who lives for many periods and chooses optimal current consumption and next period's bond holding in order to maximize the utility function. The source of uncertainty considered is in exogenous future income and there exist no markets in which agents can insure against this uncertainty. Although agents can save by holding bonds, they are not able to borrow, i.e. there is a borrowing constraint.

1.2.1 Preferences

Following Weil's (1993) terminology, a representative agent whose preferences over deterministic consumption stream exhibit a constant elasticity of intertemporal substitution:

$$\mathrm{W}(\mathrm{c_t}, \mathrm{c_{t+1}}, \mathrm{c_{t+2}}, \ldots) = \left[(1-\beta)\sum_{s=0}^{l} \beta^s \, c_{t+s}^{\varphi}\right]^{\frac{1}{\varphi}} \tag{1.1}$$

where $\rho = \dfrac{1}{(1-\varphi)} > 0$ is the elasticity of intertemporal substitution, EIS, and $\beta \in (0,1)$ is the constant exogenous discount factor. These preferences can be represented recursively as:

$$\mathrm{W}(\mathrm{c_t}, \mathrm{c_{t+1}}, \mathrm{c_{t+2}}, \ldots) = U[\mathrm{c_t}, \mathrm{W}(\mathrm{c_{t+1}}, \mathrm{c_{t+2}}, \mathrm{c_{t+3}}, \ldots)] \tag{1.2}$$

$$= \left[(1-\beta)c_t^{\varphi} + \beta\,\{\mathrm{W}(\mathrm{c_{t+1}}, \mathrm{c_{t+2}}, \mathrm{c_{t+3}}, \ldots)\}^{\varphi}\right]^{\frac{1}{\varphi}} \tag{1.3}$$

where U(.,.) is an aggregator function. Behavior towards risk is summarized by a constant coefficient of risk aversion, denoted by the parameter α >1.

$$\widehat{W} = (EW'^{1-\alpha})^{\frac{1}{1-\alpha}} \tag{1.4}$$

Equation 1.4 defines the utility certainty equivalent of a lottery yielding a random utility level W' is $\widehat{W}$ for the representative agent where E is expectation operator. $\widehat{\mathrm{W}}(\widetilde{\mathrm{c_{t+1}}}, \widetilde{\mathrm{c_{t+2}}}, \widetilde{\mathrm{c_{t+3}}}, \ldots)$ represents the certainty equivalent, conditional on time t information, of time t+1 utility. It is assumed that preferences over random consumption lotteries have the recursive representation with the aggregator function. Therefore, current utility becomes the aggregate of current consumption and the certainty equivalent of future utility as seen in Equation 1.5.

$$\mathrm{W}(\mathrm{c_t}, \widetilde{\mathrm{c_{t+1}}}, \widetilde{\mathrm{c_{t+2}}}, \ldots) = U[\mathrm{c_t}, \widehat{\mathrm{W}}(\widetilde{\mathrm{c_{t+1}}}, \widetilde{\mathrm{c_{t+2}}}, \widetilde{\mathrm{c_{t+3}}}, \ldots)] \tag{1.5}$$

This utility function has both a constant elasticity of intertemporal substitution, $\rho = \frac{1}{(1-\varphi)}$, and a constant coefficient of risk aversion, α. This utility function distinguishes EIS and RA explicitly. This facilitates the study of the effects of EIS and risk aversion separately.

1.2.2 Utility Function

This utility function is used to calculate the determinants of precautionary savings:

$$U_t = [(1-\beta)(C_t)^{\varphi} + \beta\,(E_t(U_{t+1})^{1-\alpha})^{\frac{\varphi}{1-\alpha}}]^{\frac{1}{\varphi}}$$

where β is time discount factor, C_t is consumption today, $\rho = \frac{1}{(1-\varphi)}$ is the EIS and α is the coefficient of risk aversion. This type of utility preference allows us to disentangle the EIS and the risk aversion and examine their effects independently. Also, being third derivative of utility function is positive, $U''' > 0$, introduces prudence into the decisions of the consumer.

Weil (1993) assumes the exponential risk utility function in Epstein-Zin (1989) preferences and so the determinants of precautionary savings can be studied analytically. In other words, this assumption makes the problem analytically solvable.

However, in my model, the exponential risk utility function is not assumed in order to look at more general model. Thus, the problem is not analytically solvable anymore. Instead, the problem is solved numerically for the model that is more general than the model of Weil (1993).

1.2.3 Budget Set

When y denotes today's income, b denotes today's bond holding, C denotes today's consumption, b' tomorrow's bond holding and R denotes the interest rate, the budget constraint of the representative agent for each period becomes as seen in Equation 1.6 below.

$$C + b' \leq Rb + y \tag{1.6}$$

1.2.4 Household Dynamic Decision Problem

The agent solves her problem recursively in a given state. The optimal solution to this problem is characterized most simply in terms of a value function, V(y,b). The agent knows today's income, y, and bond holding, b, and chooses today's consumption, c, and tomorrow's bond holding, b', in order to maximize the utility function as a dynamic programming problem:

$$V(y,b) = \max_{C,b'} [(1-\beta)(C)^{\varphi} + \beta(E(V(y',b')\mid y)^{\frac{\varphi}{1-\alpha}}]^{\frac{1}{\varphi}}$$

s.t

$$C + b' \leq Rb + y \tag{1.7}$$

$$y' = \Gamma(y) \tag{1.8}$$

$$b' \geq 0 \tag{1.9}$$

$$\mathrm{C} \geq 0 \tag{1.10}$$

where E denotes the mathematical expectation operator conditional on information available today. As said earlier, Equation 1.7 is the budget constraint. Equation 1.8 is the law of motion for income and it is a Markov Process getting two different income values, income low and income high, in the numerical calculations. Equation 1.9 shows the borrowing constraint and shows that asset holding or saving cannot be negative. Equation 1.10 shows that consumption cannot be negative. The time discount factor, β is chosen smaller than 1/R in order to prevent agents to save infinitely which is proved in Aiyagari (1994) that if β is larger than 1/R, agents save infinitely. Furthermore, the coefficient of risk aversion, α, is greater than 1 and the coefficient of EIS, $\rho = \frac{1}{(1-\varphi)}$, is between 0.04 and 0.99.

1.3 Results

In the model, the law of motion for income is a Markov Process in which agents can get only two different amounts of exogenous income, income low and income high. There is an assignment of the probability of getting the same income that defines the persistence of income shocks. As discussed in the introduction section, the EIS varies from 0.04 to 0.99 and the risk aversion (RA) varies from 1.01 to 25 as according to the estimates of these coefficients in the literature.

The model is simulated for 1000 periods in order to make the bond holdings converge to a stochastic steady state. Then, the agent's savings are summed from period

300 to 1000 and divided by 701. As a result, the findings are the average savings of the agent. The numerical solution of the model is explained explicitly in the Section 1.5.

For the time discount factor, β = 0.955 and the probability of getting the same income, persistence of income shocks, is 0.7, the savings are shown in Table 1.1 below:

Table 1.1: Savings when persistence is 0.7

Persistence=0.7			**EIS**			
	0.05	0.1	0.2	0.4	0.8	0.99
Risk Aversion						
20	0.8795	1.1607	1.6916	2.7664	5.8416	9.7270
10	0.4863	0.9148	1.3838	2.3787	5.2578	9.0545
5	0.4057	0.8258	1.0000	1.9083	4.6570	8.2933
2.5	0.2903	0.4699	0.6960	1.4074	4.0172	7.4701
1.25	0.2279	0.3220	0.5079	1.0249	3.3490	6.5828
1.01	0.2010	0.2839	0.4476	0.8789	3.0111	6.2032

The benchmark preference parameters are RA= 5, EIS = 0.2 and the probability of getting the same income is 0.7. The savings in benchmark case is normalized to 1 and the savings for various parameters are proportions to the savings of benchmark case. For instance, if RA is doubled to 10 by implying the constant elasticity utility function (thus simultaneously halving EIS to 0.1 so that EIS*RA=1), the savings reduces to 0.9148. On the other hand, when the EIS is doubled to 0.4 and RA is halved to 2.5, the savings increases to 1.4074. In the unrestricted utility function, if RA increases two times, RA=10, and EIS stays the same, the savings become 1.3838 whereas if EIS increases twice, EIS=0.4, and RA stays the same, the savings become 1.9083. Thus, the change in savings is much less sensitive to the degree of risk aversion than to the intertemporal elasticity of substitution.

The three dimensional graph of savings according to different parameters of the elasticity of intertemporal substitution and risk averse is depicted in Figure 1.1. The figure demonstrates that, as similar to the results in the Weil(1993)'s paper , saving increases when the parameter of EIS increases by keeping risk aversion constant because an increase in the elasticity of intertemporal substitution increases the propensity to consume out of wealth and out of current income. Also, saving increases when the parameter of risk aversion increases by keeping EIS constant as expected since the more risk averse the agent is, the stronger his precautionary saving motive. More prominently, I observe that EIS is more important in precautionary saving decision than risk aversion since saving is more responsive to changes in EIS than changes in risk aversion as portrayed in Figure 1.2 and Figure 1.3.

Figure 1.1: 3-D graph of savings when persistence is 0.7

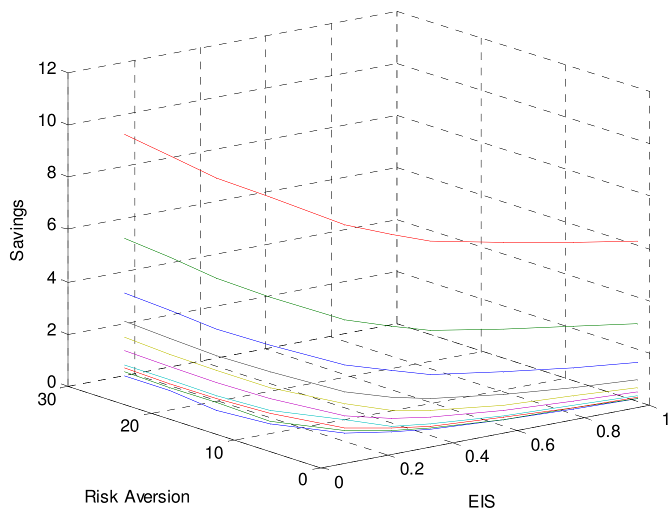


Figure 1.2: Savings when keeping EIS constant and when persistence is 0.7

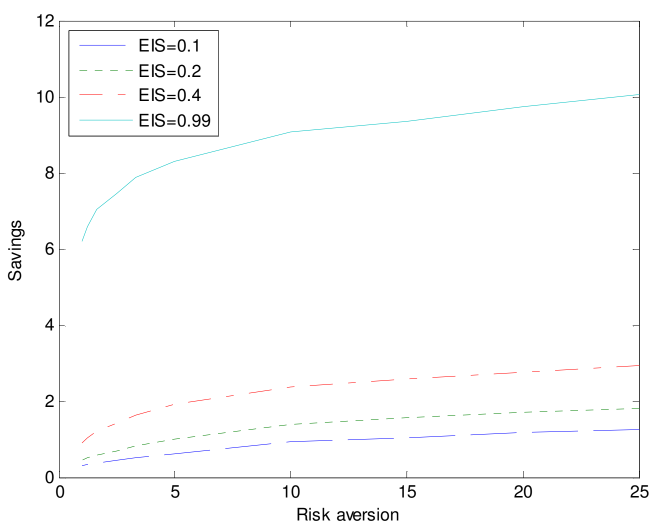
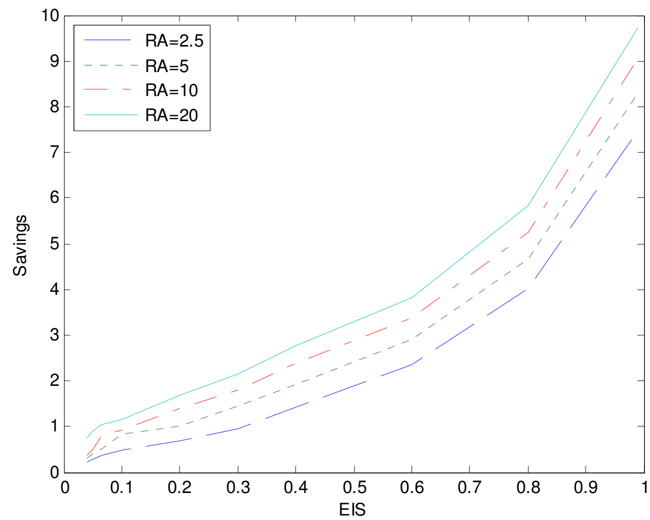


Figure 1.3: Savings when keeping RA constant and when persistence is 0.7



Also one can ask whether saving increases as if the persistence of income shocks increases as shown in the Weil(1993)'s paper. This is examined by increasing the probability of getting the same income. If the persistence of income shocks is increased to 0.8, savings are tabulated in Table 1.2.

Table 1.2: Savings when persistence is 0.8

Persistence=0.8			**EIS**			
	0.05	0.1	0.2	0.4	0.8	0.99
Risk Aversion						
20	1.1238	1.5943	2.3077	3.6695	7.6213	12.5308
10	0.6277	1.1794	1.8532	3.0868	6.7874	11.6185
5	0.5128	0.8944	1.2281	2.3364	5.7818	10.4551
2.5	0.3268	0.5706	0.7397	1.5477	5.8636	9.0654

1.25	0.2195	0.3768	0.5013	1.0132	3.5628	7.4995
1.01	0.1911	0.2767	0.4350	0.8577	3.0529	6.7754

For the parameters RA=5 and EIS=0.2, the savings is 1.2281. It means there is about 22.8 % increase if the persistence increases from 0.7 to 0.8 since the savings in the benchmark case is normalized to 1 and in the benchmark case preference parameters are RA= 5, EIS = 0.2 and the probability of getting the same income is 0.7. In the constant elasticity utility function, if RA is multiplied by 4 and RA becomes 20 (thus simultaneously halving EIS to 0.05 so that EIS*RA=1), the savings reduces to 1.1238 from 1.2281. The percentage reduction is 8.5 %. On the other hand, when the EIS is multiplied by 4 to make EIS=0.8 and RA becomes to 1.25, the savings increases to 3.5628 and the percentage raise is 190.1 %. In the unrestricted utility function, if RA increases four times, RA=20, and EIS stays the same, the savings become 2.3077 whereas if EIS increases four times, EIS=0.8, and RA stays the same, the savings become 5.7818. As seen from percentages, it is clear that saving is much more responsive to changes in EIS than to changes in risk aversion.

The persistence of income shocks is a determinant of the strength of precautionary savings motive. The more persistent the income process, the more responsive current consumption to fluctuations in current income. Therefore, the more persistence in income shocks leads to a stronger precautionary savings motive as seen in Table 1.2.

The three dimensional graph of savings according to different parameters of the elasticity of intertemporal substitution and risk aversion when the persistence of income shocks is 0.8 is depicted in Figure 1.4 below. Also, the savings when keeping EIS constant and when keeping RA constant portrayed in Figure 1.5 and Figure 1.6 respectively.

Figure 1.4: 3-D graph of savings when persistence is 0.8

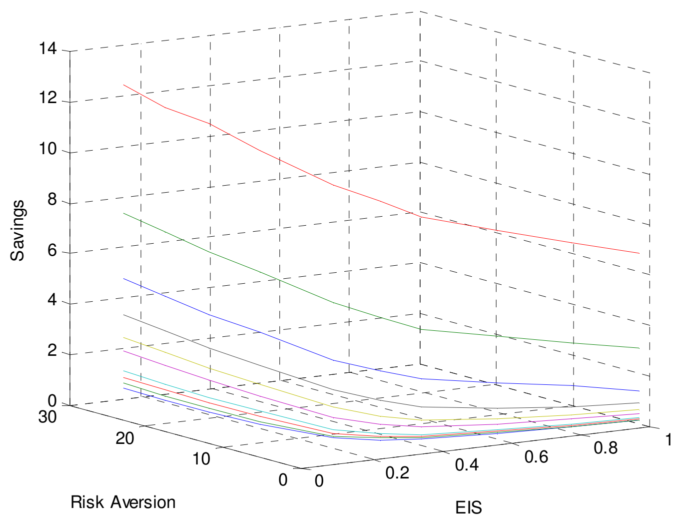


Figure 1.5: Savings when keeping EIS constant and when persistence is 0.8

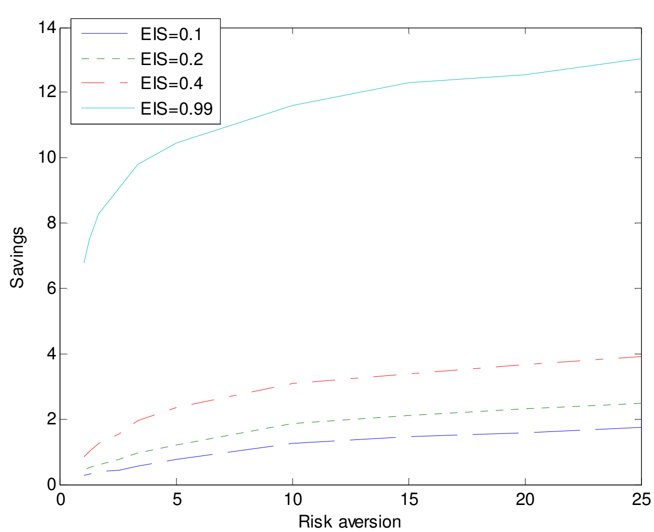
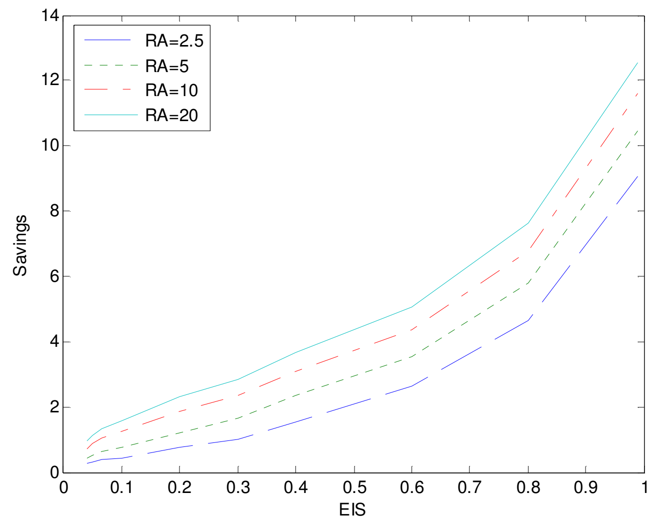


Figure 1.6: Savings when keeping RA constant and when persistence is 0.8



It is explained that savings increase when persistence of income shocks increases in Weil(1993)'s paper. It is shown in the figures below that the savings when probability is 0.8 is larger than the savings when probability is 0.7. It is also observed the same result that EIS is a more significant determinant of savings than risk aversion for each probability.

Figure 1.7: Savings when EIS=0.2 for persistence 0.7 and 0.8

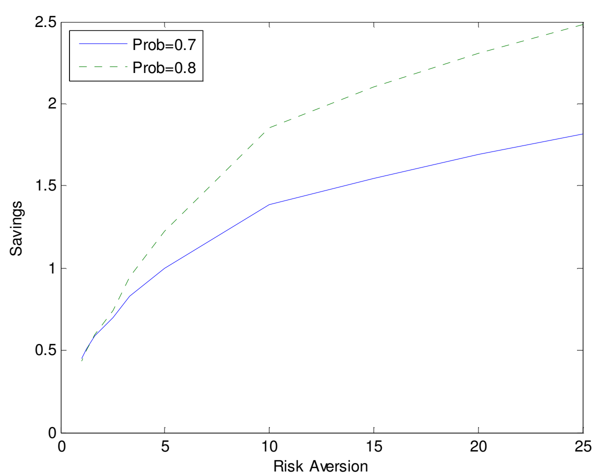
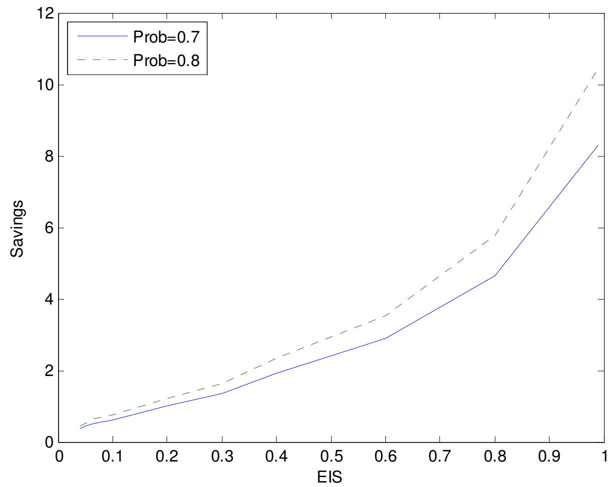


Figure 1.8: Savings when Risk Aversion=5 for persistence 0.7 and 0.8



The savings are calculated also when persistence of income shock is 0.5. When the persistence is 0.5, the savings for the benchmark parameters, EIS=5 and RA=1, is 0.55 and so there is 45 % decrease if the persistence decreases from 0.7 to 0.5. In the constant elasticity utility function, if RA is multiplied by 5 and RA becomes 25 (thus simultaneously halving EIS to 0.04 so that EIS*RA=1), the savings reduces to 0.41 from 0.55 and so the percentage reduction becomes 25 %. On the other hand, when the EIS is multiplied by 5 to make EIS=0.99 and RA becomes to 1.01, the savings increases to 4.26 and the percentage raise is 675 %. The similar results are obtained that EIS is more important determinant of precautionary savings as shown in the figures below.

Figure 1.9: Savings when keeping EIS constant and when persistence is 0.5

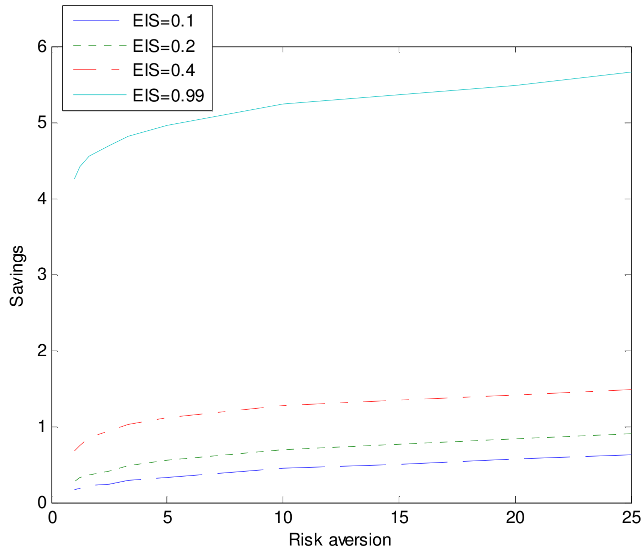
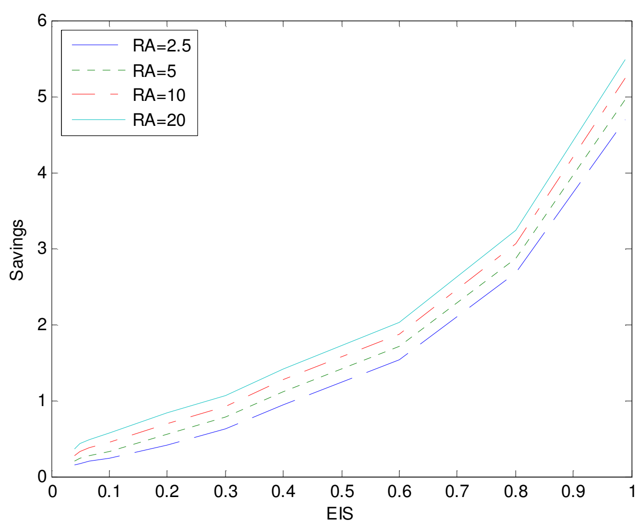


Figure 1.10: Savings when keeping RA constant and when persistence is 0.5



If the persistence decreases from 0.7 to 0.6, there is 31 % decrease in the savings for the benchmark parameters since the savings 0.69 in this case. In the constant elasticity utility function, if EIS is multiplied by 2 and EIS becomes 0.4 (thus simultaneously halving RA to 2.5 so that EIS*RA=1), the savings rise to 1.02 from 0.69 and so the percentage raise becomes 48 %. On the other hand, when the RA is multiplied by 2 to make RA= 10 and EIS becomes to 0.1, the savings shrinks to 0.62 and the percentage reduction is 10 %. In the unrestricted utility function, if EIS increases two times, EIS=0.4, and RA stays the same, the savings become 1.35 whereas if RA increases two times, RA=10, and EIS stays the same, the savings become 0.95. The increase is 96 % in the first case and 38 % in the second case. As seen from percentages, it is clear that saving is much more responsive to changes in EIS than to changes in risk aversion. The results are as portrayed in the Figure 1.11 and Figure 1.12 below.

Figure 1.11: Savings when keeping EIS constant and when persistence is 0.6

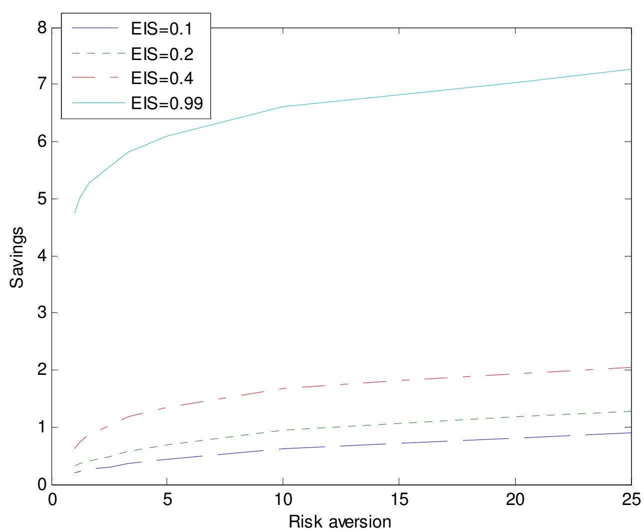
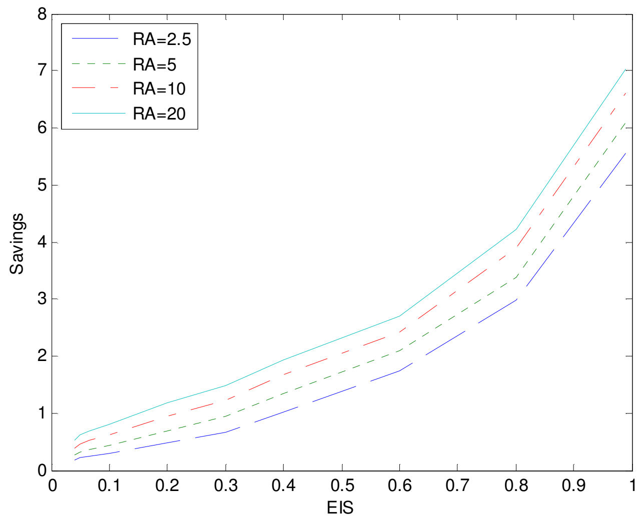


Figure 1.12: Savings when keeping RA constant and when persistence is 0.6



As mentioned earlier, the persistence of income shocks is a determinant of the strength of precautionary savings motive. The more persistence in income shocks leads to a stronger precautionary savings. It is shown in the Figure 1.13 and Figure 1.14 below that the savings when the persistence of income shocks is 0.6 is larger than the savings when persistence is 0.5. The ratio of the savings when persistence is 0.5 to the savings when persistence is 0.6 ranges from 0.70 to 0.89 by comparing the savings with the same parameter values for the coefficients of elasticity of intertemporal substitution and risk aversion. The range is wider when keeping the EIS=0.2 constant and changing the coefficient of risk aversion than when keeping the RA=5 constant and changing the coefficient of elasticity of intertemporal substitution as seen in Figure 1.13 and Figure 1.14 below.

Moreover, it is also observed the same result that EIS is a more crucial determinant of savings than risk aversion for each persistence of income shocks since saving is more sensitive to changes in EIS than in risk aversion.

Figure 1.13: Savings when EIS=0.2 for persistence 0.5 and 0.6

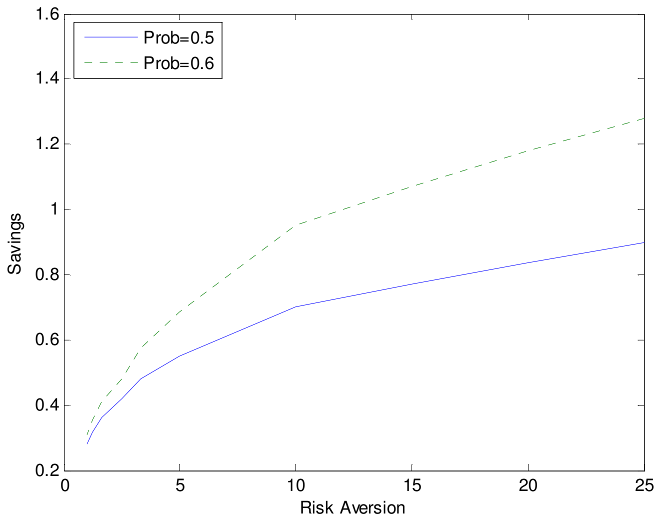
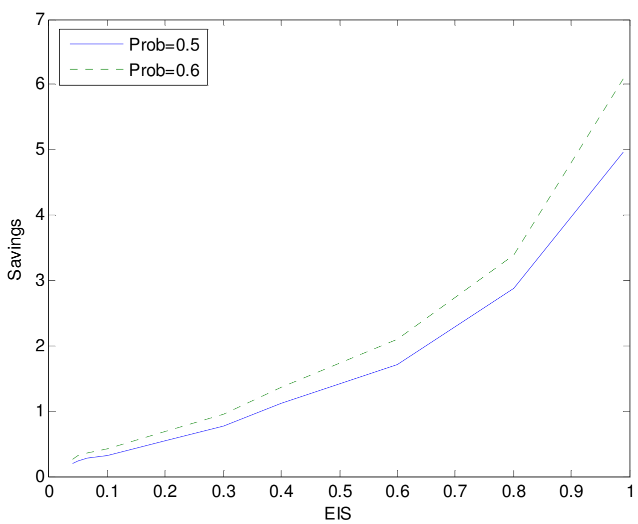


Figure 1.14: Savings when Risk Aversion=5 for persistence 0.5 and 0.6



1.4 Conclusion and Discussion

In this paper, I attempt to determine the important factors of precautionary saving. Saving under temporal risk aversion and intertemporal substitution usually exceeds the certainty-equivalent level of saving and this type of prudent behavior is called the precautionary motive for saving. Precautionary saving arises when consumers are risk averse and have elastic intertemporal preferences and so hedge against unanticipated future declines in income. The precautionary motive induces individuals to save in order to provide insurance against future periods in which their incomes are low or their needs are high according to Van der Ploeg (1993). I look at the effects of EIS and risk aversion to savings separately by using Epstein-Zin (1989) recursive utility function. I use Epstein-Zin (1989) utility since this utility permit risk attitudes to be disentangled from the degree of intertemporal substitutability and provides a motive for precautionary saving.

According to Chatterjee, Giuliano and Turnovsky (2004), most of the existing literature assumes that the preferences of the representative agent are represented by a constant elasticity utility function. While this specification of preferences is convenient, it is also restrictive in that two key parameters, the elasticity of intertemporal substitution and the coefficient of risk aversion, become directly linked to one another and cannot vary independently. This is a significant limitation and one that can lead to seriously misleading impressions of the effects that each parameter plays in determining the precautionary savings. With the diversity of empirical evidence suggesting that this constraint, EIS*RA=1, may or may not be met, it is important that studies of these two parameters impinges on the equilibrium in very distinct and in some respects conflicting ways. Therefore, the general conclusion to be drawn is that errors committed by using the constant elasticity utility function, even for small violations of the compatibility condition within the empirically plausible range of the parameter values, can be quite substantial. While one certainly cannot rule out using the constant elasticity utility function, as a practical matter, their results suggest that it should be employed with caution, recognizing that if the condition for its valid use is not met, very different implications may be drawn.

Hall (1988) points out that intertemporal substitution by consumers is a central element of most modern macroeconomic models. Weil (1993) shows that when the coefficient of elasticity of intertemporal substitution increases savings increase. Atkeson and Ogaki (1996) develop and estimate a model of preferences which formalizes the intuition that poor consumers have a lower intertemporal elasticity of substitution than do rich consumers because expenditure inelastic goods (necessary goods) are less substitutable over time than are expenditure-elastic goods. Guvenen (2006) shows that aggregate saving is mostly determined by wealthy people who have high EIS and aggregate consumption is mostly determined by non-wealthy people who have low EIS. Weil (1993) and Van der Ploeg (1993) show that when the coefficient of risk aversion increases savings increase. The saving increases as EIS increases and as the coefficient of risk aversion increases is observed in this paper. More importantly, it is examined that EIS is a more important factor for precautionary savings than risk aversion because saving is more responsive to changes in EIS than changes in risk aversion. This finding sheds new light on precautionary savings. Knowing that EIS is more significant contributor to the precautionary savings is important since a significant fraction of the capital accumulation that occurs in the United States is due to precautionary savings according to Zeldes (1989a).

The main limitation of the model of precautionary savings I have introduced in this paper is in future income process. The Markov process is used in the paper where the future income takes only two different values, high income and low income, for simplicity. Investigating other income processes would be a good improvement and future research for giving more representation of the precautionary savings motive. Yet, this model sheds new light on the determinant of precautionary savings in multi-period economics and determines the coefficient of elasticity of intertemporal substitution is a more important factor for precautionary savings than the coefficient of risk aversion because saving is more responsive to changes in the coefficient of elasticity of intertemporal substitution than changes in the coefficient of risk aversion.

1.5 Numerical Solution

This section describes the numerical solution of the model. The state values of the agent are today's income and bond holding. Then, agent chooses the today's consumption and tomorrow's bond holding, none of them can be negative. Tomorrow's income is determined as a law of motion.

Step1: Initialization

- The interest rate, discount factor, coefficient vectors of EIS and risk aversion are determined. There are two different income values, income low and income high, and different probabilities ranging from 0.5 to 0.8 for the Markov process of income so uncertainty in income in the model comes from this process. EIS changes from 0.04 to 0.99 and Risk aversion changes from 1.01 to 25.The interest rate can be two different values, either 1.03 or 1.04. Thus, calculations are performed for these each different values of income, EIS, risk aversion, interest rate and probabilities.
- There are 100 grid points for the initial bond holdings. I execute value function iteration and determine tomorrow's bond holding for each case by initially assuming b'=b. I am able to use the linear interpolation to evaluate tomorrow's bond holding and the value function for off the grid points since the value function is linear in individual wealth in Epstein-Zin preferences .

Step 2: Household Dynamic Decision Problem

- I start with a household who has an initial income and zero bond at first period and the household decides for current consumption and bond holding of second period. I iterate the process unless the bond holding process converges to a stochastic steady state. I observe 1000 iterations are adequate for the convergence.
- For the income process, I generate pseudo random process for each probabilities of the Markov Process by using “randsrc” function in MATLAB. I generate two different pseudo random processes for two different income values according to probabilities and then produce the real income process that the agent faces in the iteration from those random processes.

Chapter 2: The Effects of Stock Index Futures Trading on Turkish Istanbul Stock Exchange

2.1 Introduction

Stock index futures have been rendered as financial products of increased importance in recent years. Although trading stock index futures started in February 1982 in the US and soon followed by other developed countries, it is a relatively recent phenomenon in emerging markets. After the introduction of futures trading, there has been concern about the impact of futures on underlying spot market. Specifically, the economic literature intensified the debate on the negative or positive impact of futures trading on the stock market volatility. There are two different arguments. The first argument is that futures market increases stock market volatility since it attracts uninformed traders because of their degree of leverage and the lower level of information of futures traders with respect to cash market traders is likely to increase the stock volatility. Furthermore, futures market promotes speculation with the consequence of a boost in volatility. The opposite argument is that futures market reduces spot market volatility since futures market plays an important role of price discovery, increases market depth and enhances efficiency. Moreover, futures market provides the hedging opportunities to the market participants and so it reduces the risk and stabilizes the market.

Lee and Ohk (1992) argue that the effect of the futures in index on the volatility of the spot market differs from country to country, not only because of the different structure of these markets but mainly due to the different macroeconomic conditions prevailing in each country. Although there are empirical studies for different countries with mixed results, most of them focus on developed countries. There are a few empirical researches on emerging markets. This paper contributes in the literature by studying the ongoing debate about the impact of futures trading on the volatility of the underlying spot market from an emerging stock market, Turkish Istanbul Stock Exchange (ISE).

In this paper, I examine the effect of the introduction of futures trading into the ISE 30 and the ISE 100 Return Indices separately. To analyze the relationship between the futures trading and the volatility, the Generalized Autoregressive Conditional Heteroskedastic (GARCH) family of statistical techniques is utilized. GARCH models are used since they capture one of the well-known empirical regularities of asset returns, the volatility clustering and because of this they are the econometric techniques employed in most of previous studies. This paper tries to determine whether the introduction of futures market affect the volatility of underlying spot market positively or negatively. Moreover, the study tries to find out how futures market influences underlying spot market in terms of transmission of information into stock prices. Furthermore, the change in asymmetric responses to information is investigated using the model proposed in Glosten, Jagannathan and Runkle (1989) (GJR) that captures the asymmetric response of conditional volatility to information.

The remainder of the paper is organized as follows. The next section presents a brief review of the theoretical literature and of the main results of previous empirical studies. Section 2.3 gives details about the Turkish Derivatives Exchange, the data set and the methodology used. Section 2.4 shows the empirical results of this study. Section 2.5 concludes the paper. Section 2.6 shows the figures and tables.

2.2 Literature Review

On the theoretical front, two opposing arguments exist in the literature about the impact of the introduction of futures trading into the underlying spot markets. The first group of researchers supports the argument that futures trading increase the volatility of the stock market and so destabilize the stock market. According to Cox (1976), the main cause of destabilization of the underlying spot market is the presence of uninformed traders in the derivatives market. Finglewski (1981) supports the same argument by stating that a lower level of information of futures participants compared to that of cash market traders results in increased spot market volatility. By explaining that futures markets attract uninformed traders as a consequence of their high degree of leverage, Stein (1987) points out the same argument that the activity of those traders reduces the information content of prices and increases cash market volatility. In this view, increase in the volatility of spot markets is a result of high degree of leverage and the presence of speculative uninformed traders in the futures markets.

The second group of researchers presents arguments in favor of the idea that futures trading have a beneficial effect on the underlying spot market by decreasing its volatility. Power (1970) claims that futures trading improves the market depth and informativeness. Danthine (1978) shows in his model that futures trading increases market depth and decreases spot market volatility. Bray (1981) and Kyle (1985) came up with alternative models asserting that futures trading lowers the volatility of the underlying cash market. Stroll and Whaley (1988) claims that futures trading enhances market efficiency. Furthermore, future markets are an important means of price discovery in spot markets as stated by Schwarz and Laatsch (1991). The theoretical debate about how futures trading affect underlying cash markets remains rather inconclusive since the proposed logical arguments both support and reject the proposition of futures markets having a destabilizing effect on spot markets. Therefore, the issue of whether and how futures markets affect underlying spot markets stays an empirical issue. Nevertheless, empirical literature presents also mixed results.

Although many empirical studies have examined to figure out whether futures markets stabilize or not spot markets, the results are still different from each other. Some researches alleged that the introduction of futures trading increases the volatility of the spot market. Finglewski (1981) investigated the impact of Government National Mortgage Association (GNMA) futures on the price volatility of the GNMA spot market and concludes that the future market has led to increased volatility of the underlying market. Harris (1989) observed an increase of volatility of the S&P 500 index after the introduction of derivatives in 1983 by conducting a cross sectional analysis of covariance for the period 1975-1987. Lee and Ohk (1992) examined the effect of introducing index futures trading on stock market volatility in Australia, Hong Kong, Japan, the UK and the US using daily index data for periods of approximately 4 years spanning the introduction of index futures trading. They observed that the stock market volatility increased significantly after the listing of stock index futures in Japan, the UK and the US. Yet, the stock market volatility decreased in Hong Kong and the futures trading did not influence the stock market in Australia. Antoniou and Holmes (1995) suggested an increased volatility following the introduction of the FTSE100 index futures contract for the London Stock Exchange. Pok and Poshakwale (2004) studied the impact of the introduction of futures trading on stock index into the Malaysian KLSE index and found that the futures increased the volatility of underlying spot market. Finally, Ryoo and Smith (2004) found that while futures increased the volatility of the underlying market, they simultaneously improved its effectiveness as well by increasing the speed at which information was impounded into the spot market prices in their studies on the Korean market.

On the contrary, some empirical studies provide evidence that the introduction of futures trading on stock index decreased the volatility of the underlying market. Edwards (1988a,b) found a decreased stock market volatility for the S&P500 after the introduction of the stock index futures contract. Bessembbinder and Seguin (1992) and Brown-Hruska and Kuserk (1995) studied the relationship between relative trading volumes in the stock market and the stock index future market one side and cash price volatility of the S&P500 index on the other side. The authors provided evidence suggesting that active futures markets are associated with decreased stock market volatility. Antoniou *et al.* (1998) studied the impact of the introduction of futures trading in the volatility of six stock markets worldwide. (Germany, Japan, Spain, Switzerland, the U.K and the U.S) They observed that the introduction of futures trading had a statistically significant negative effect on the volatility of the spot market in Germany and Switzerland. In the remaining countries the futures trading did not influence the volatility of the stock market significantly. Moreover, the authors showed that the asymmetric responses decreased for Germany, Japan, Switzerland, the U.K and the U.S and it is only increased for Spain. They explained this result by the absence of well-established financial markets in Spain. Bologna and Cavallo (2002) researched on the MIB30 index in the Italian stock market and found that the introduction of stock index futures had led to diminished stock market volatility. Pilar and Rafael (2002), in their analysis of Spanish market, concluded that the introduction of futures trading on stock index had beneficial results as it had diminished the volatility of the underlying market and it increased its liquidity. Finally, Drimbetas *et al.* (2007) investigated the impact of the introduction of futures trading on stock index into the Greek stock market and showed that the introduction of derivatives had induced a reduction of the conditional volatility of the underlying market.

In contrast to the abovementioned studies, some researchers alleged that the market of derivatives does not influence the underlying spot market. By using regression analysis to examine the variability of GNMA, Froewiss (1978) showed that weekly spot price volatility had not been altered by the introduction of futures. Simpson and Ireland (1982) suggested that futures did not affect spot price volatility either on a daily or a weekly basis. Corgel and Gay (1984) proposed results in line with Froewiss (1978) and Simpson and Ireland (1982). Santoni (1987) found that the daily and weekly volatilities of S&P500 are not different after the introduction of futures. Smith (1989) reported that the S&P500 futures volume had no effect on the volatility of the index returns. Becketti and Roberts (1990) found little or no relationship between the stock market volatility and the introduction of stock index futures market. Freris (1990) examined the effect of Hang Seng Index Futures on the behavior of the Hang Seng Index using data for the period from 1984 to 1987 and found that the introduction of stock index futures trading had no measurable effect on the volatility of the stock price index. Antoniou and Foster (1992) investigated the impact of introduction of futures contract on Brent Crude Oil on its spot market and showed that there is no substantial change in volatility from the pre-futures period to post-futures period. Moreover, Darrat and Rahman (1995), in their paper on the S&P500 over the period 1982-1991, found that S&P500 futures volume did not affect spot market volatility. Board *et al.* (1997) found that contemporaneous futures market trading had no effect on spot market volatility but lagged futures volume has been found to have a small positive effect. Kan (1999) studied the Hong Kong market over the period 1982-1992 and found similar conclusions in his research on the stocks volatility of the HIS index. Lastly, Calado *et al.* (2005) analyzed the volatility effect of the initial listing of futures on the Portuguese capital market. The authors did not find significant differences in the volatility of the underlying stock market after the introduction of futures.

2.3 Data and Methodology

The ISE 30 and ISE 100 indices are the only index futures in the Turkish Derivatives Exchange (TURKDEX) and these indices are used to examine the effect of the futures trading on the volatility of the spot market. Although TURKDEX was founded in 2003, the formal trading in futures contracts began in February 2005. Analysis is undertaken with the use of data for the period 3 years prior to through 3 years after the introduction of futures trading. Thus, the data ranges from February 2002 through February 2008 in which there are 1505 total observations. The daily value of German Stock Index, DAX, is used to isolate the impact on the underlying index volatility arising from factors in the market other than the introduction of derivatives.

The ISE 30 index is a capitalization-weighted index that comprises the 30 most liquid and highly capitalized shares traded on the Turkish market. The shares in the index account for approximately 60 % of the market capitalization. Similarly, the ISE 100 index is a capitalization-weighted index that tracks the continuous price performance of 100 actively traded, large capitalization common stocks listed on the ISE. It accounts for over 80 % of the market capitalization. The results were obtained on the basis of R_t, which is the rate of return R in period t, computed in the logarithmic first difference, $R_t = \ln (p_t/p_{t-1}) * 100$ where p_t is the value of stock price index at the end of period t.

The GARCH framework is used in order to investigate the impact of futures trading on the volatility of the spot market for the Istanbul Stock Exchange. The GARCH model has been developed by Bollerslev (1986) from the Autoregressive Conditional

Heteroskedastic Models (ARCH) model previously introduced by Engle (1982). In ARCH, the changing variance is included into estimation in order to obtain more efficient results. It is assumed that the error term of the return equation has a normal distribution with zero mean and time varying conditional variance of h_t ($\varepsilon_t \sim N(0,h_t)$) and so the forecast variance of return equation varies systemically over time. In this model, the conditional variance, h_t, relies on the past squared residuals and is calculated as
$h_t = V_{cons} + \sum_{i=1}^{m} Va_i \ \varepsilon_{t-i}^2$. In GARCH, h_t depends on not only lagged values of ε_t^2 but also lagged values of h_t. ($h_t = V_{cons} + \sum_{i=1}^{m} Va_i \ \varepsilon_{t-i}^2 + \sum_{j=1}^{n} Vg_j \ h_{t-j}$) One of the most appealing features of the GARCH framework, which explains why this model is so widely used in financial literature, is that it captures one of the well-known empirical regularities of asset returns, the volatility clustering. Therefore, following Holmes (1996), a GARCH representation would seem to be an appropriate means by which to capture market-wide price volatility. The GARCH (m,n) model is represented as follows:

$$y_t = \beta X_t + \varepsilon_t \tag{2.1}$$

$$\varepsilon_t \sim N(0,h_t) \tag{2.2}$$

$$h_t = V_{cons} + \sum_{i=1}^{m} Va_i \ \varepsilon_{t-i}^2 + \sum_{j=1}^{n} Vg_j \ h_{t-j} \tag{2.3}$$

In order to identify the most appropriate mean equation, five different models are compared with one through five autoregressive terms respectively.

$$R_t = cons + \sum_{i=1}^{k} \beta_i \ R_{t-i} \tag{2.4}$$

Table 1.1: Mean equation with different number of lags

Number of Lags	Akaike	Schwartz	F-test
1	-7195.01	-7184.38	0.65
2	-7190.95	-7175.00	0.44

3	-7186.47	-7165.21	0.28
4	-7185.09	-7158.52	0.25
5	-7178.67	-7146.79	0.23

Table 2.1 shows the values of the Akaike Information Criterion, the Schwartz Bayesian Criterion and the F-test for the three alternative specifications of the mean equation. From the equation with one lag to the one with five lags the increase of the Akaike Information Criterion and the Schwartz Bayesian Criterion is marginal (0.23% and 0.52% respectively) whereas the decrease of the F statistic is much larger (64.61%). Thus, extra lagged variables do not improve the model and so the equation with one lagged term has been chosen for the mean equation.

GARCH (1,1) model has been extensively used in the literature since it is the most convenient way to represent conditional variance for financial time series. Using likelihood ratio (LR) tests, the consistency of this finding for the Istanbul Stock Exchange is tested. Particularly, the restricted GARCH (1,1) is tested against a series of alternative unrestricted models; in all cases the null hypothesis that the return-generating process follows a GARCH (1,1) process relative to the alternative hypothesis is not rejected. To estimate the various GARCH models of Table 2.2 maximum likelihood estimations are employed as employed in Bologna and Cavallo (2002). LR test results are showed in Table 2.2.

Table 2.2: Variable exclusion tests for the GARCH model

	Likelihood ratio test	**Critical values at 5% level**
GARCH (1,2) vs. GARCH(1,1)	0.24	3.84

GARCH (1,3) vs. GARCH(1,1)	1.38	5.99
GARCH (2,1) vs. GARCH(1,1)	0.28	3.84
GARCH (2,2) vs. GARCH(1,1)	1.75	5.99
GARCH (2,3) vs. GARCH(1,1)	2.73	7.81
GARCH (3,1) vs. GARCH(1,1)	1.31	5.99
GARCH (3,2) vs. GARCH(1,1)	2.75	7.81
GARCH (3,3) vs. GARCH(1,1)	5.23	9.49

Following the results, GARCH (1,1) is employed for testing the impact of futures trading on the volatility of the spot market for the Istanbul Stock Exchange. Thus, the following model is exercised:

$$R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 DAX_t + \varepsilon_t \qquad (2.5)$$

$$\varepsilon_t \sim N(0, h_t) \qquad (2.6)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \gamma D_F \qquad (2.7)$$

where R_t is the daily return on the ISE index, R_{t-1} is a proxy for the mean of R_t conditional on past information and DAX_t is the variable reflecting the German market returns and indirectly the international systematic factors. As regards the conditional variance Equation 2.7, it has been augmented with the dummy variable D_F which takes value 0 for the pre-futures period and 1 for the post-futures period. This dummy allows us to determine the negative or positive impact of the introduction of futures trading.

Moreover, it is known that if a stock has high volatility, then risk averse investors will require higher expected return to hold that stock and so the omission of h_t from the conditional mean equation might potentially cause bias. In order to avoid this, GARCH in mean, GARCH-M, model is proposed. GARCH-M (1,1) is employed for checking the results of GARCH (1,1). In GARCH-M (1,1), the equation 2.5 becomes:

$$R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 DAX_t + \theta h_t + \varepsilon_t \qquad (2.8)$$

Integrated GARCH, IGARCH, model is employed since it is more appropriate model when volatility is persistent. In IGARCH, $\alpha_1 + \alpha_2 = 1$ in which case the past shocks do not dissipate but persist for very long periods of time.

Furthermore, in the GARCH model, news is assumed to have an equal effect irrespective of sign. If news has an asymmetric effect on volatility, then the GARCH model will be misspecified and subsequent inferences based on this model may be misleading. Thus, it is extended to allow for asymmetric effects. The GJR model is proposed in Glosten, Jagannathan and Runkle (1989) and it is an asymmetric model. The GJR model is less sensitive to outliers and higher likelihood than EGARCH model according to Engle and Ng (1993) and so it is chosen for the analyses in order to obtain asymmetric responses of volatility to news. In the GJR model the asymmetric response of conditional volatility to information is captured by including, along with the standard GARCH variables, squared values of ε_{t-1} when the sign on ε_{t-1} is negative. Thus the equation 2.7 becomes:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \tau D_{t-1} \varepsilon_{t-1}^2 + \gamma D_F \qquad (2.9)$$

where $D_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, $D_{t-1} = 0$ otherwise.

2.4 Empirical Results

The ISE 30 and ISE 100 indices are used to examine the effect of the futures in index on the volatility of the spot market.

Figure 2.1 : The time series graph of R_t for the ISE 30 Return Index

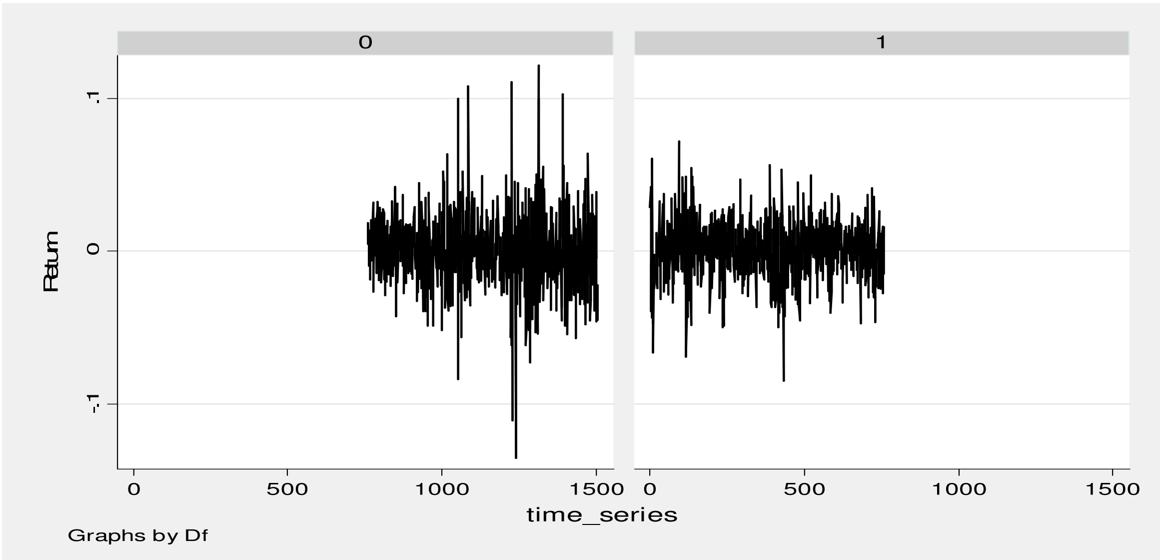
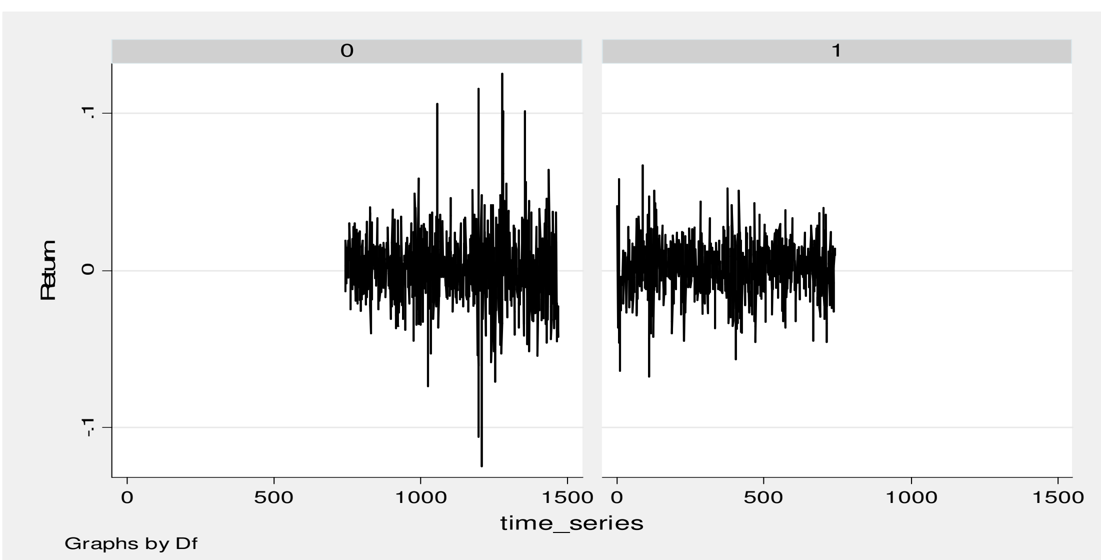


Figure 2.1 shows the time series graph of R_t for the ISE 30 Return Index. It is segmented by the dummy variable D_F which takes value 0 for the pre-futures period and 1 for the post-futures period. The variance of R_t is larger in the pre-futures period than the post-futures period as seen in Figure 2.1.

Figure 2.2: The time series graph of R_t for the ISE 100 Return Index



The time series graph of R_t for the ISE 100 Return Index is depicted in Figure 2.2. Similar to ISE 30, the variance of R_t has diminished after the introduction of futures trading as shown in Figure 2.2.

Table 2.3: ISE 30 Return Index

	Full Period	**Before Futures**	**After Futures**
Observation	1505	746	749
Mean	0.081	0.099	0.063
Std. Dev.	2.208	2.498	1.882

As shown in Table 2.3 above, ISE 30 Return Index has a 0.081 return average in full period, 0.099 return average before futures introduction and 0.063 after futures introduction. More importantly, the standard deviation of return is 2.498 in the pre-futures period and it is 1.882 in the post-future period. Hence, while volatility in the market without futures is higher, the volatility of the spot market has decreased about 24.5 % in the post-futures in period. The standard deviation of return is 2.208 in the full period.

Table 2.4: ISE 100 Return Index

	Full Period	**Before Futures**	**After Futures**
Observation	1505	746	749
Mean	0.096	0.123	0.070
Std. Dev.	2.067	2.355	1.740

Table 2.4 presents the general statistics of the return of ISE 100 Index. The average return in the full period is 0.096; it is 0.123 in the pre-futures period and 0.070 in the post-futures period. The standard deviation is 2.355 in the pre-futures period and it is lower than standard deviation of daily return in ISE 30 Index in the same period. The standard deviation has decreased about 26.1% and become 1.740 in the post-futures period. Again, the volatility of spot market has decreased after the introduction of futures. Similar to pre-futures-periods, the standard deviation of daily return in post-futures period of ISE 100 Index is lower than that of ISE 30 Index. In the full period, the standard deviation is 2.067 and it is lower than that of the full period of ISE 30 Index.

Table 2.5: ISE 30 Return Index GARCH

β_0	β_1	β_2	α_0	α_1	α_2	γ
Whole Period						
0.141** (0.048)	0.003 (0.027)	0.485** (0.020)	-1.285** (0.270)	0.099** (0.015)	0.857** (0.022)	-0.502** (0.143)
Pre-Futures						
0.145 (0.078)	-0.014 (0.040)	0.427** (0.022)	0.231** (0.087)	0.111** (0.023)	0.857** (0.028)	
Post-Futures						
0.141* (0.063)	0.024 (0.039)	0.513** (0.026)	0.309* (0.126)	0.137** (0.027)	0.804** (0.054)	

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively.

In order to assess whether there has been an increase in volatility after the inception of futures trading the methodology outlined in the data and methodology section is followed by estimating GARCH (1,1) models of conditional volatility. In the whole period estimation, a dummy variable takes on the value of 0 pre-futures and 1 post-futures is included. Table 2.5 shows the GARCH(1,1) results of the ISE 30 Return Index for the whole period, the pre-futures period and the post-futures period. The measure of the effect due to introduction of stock index futures is shown by the γ coefficient in the whole period. This coefficient is negative and statistically significant and so it can be said that the introduction of futures trading has a negative impact on the level of price volatility of the underlying stock market. This result suggests that futures trading has led to decreased volatility. The unconditional variance, given by α_0 / (1- α_1- α_2), is 7.219 in the pre-futures period and 5.237 in the post-futures period. The unconditional variance in the post-futures period is lower than that of the pre-futures period. This again indicates lower market volatility after stock index futures introduction for the ISE 30 Index.

Antoniou and Holmes (1995) observed that α_1 could be interpreted as a 'news' and α_2 could be defined as 'old news'. More specifically, α_1 relates to the impact of yesterday's market-specific price changes on price changes today and the higher value of α_1 implies that recent news has a greater impact on price changes. The value of α_1 has increased from 0.111 to 0.137 from the pre-futures to the post-futures period. This increase suggests that the information is being impounded in prices more quickly due to introduction of futures trading. On the other side, α_2 is the coefficient on the lagged variance term and as such is picking up the impact of price changes relating to days prior to the previous day and thus to news which arrived before yesterday. The value of α_2 has decreased from 0.857 to 0.804 from the pre-futures to the post-futures period. This can be explained by observing that the increased rate of information flow reduces the uncertainty about previous news. In other words, in the presence of stock index futures trading 'old news' play a smaller role in determining the volatility of the stock market. This argument seems to confirm the expectation of increased market efficiency as a consequence of the activity in stock index futures. In addition, the reduction in persistence of shocks, measured by $\alpha_1 + \alpha_2$, from the pre-futures to the post-futures period indicates increased market efficiency in the post-futures period. Furthermore, DAX has significant positive coefficient and it indicates that the German market exerts influence on the Turkish market.

Table 2.6: ISE 30 Return Index GARCH-M

β_0	β_1	β_2	α_0	α_1	α_2	θ	γ
Whole Period							
0.322**	0.001	0.462**	-1.216**	0.104**	0.849**	-0.048*	-0.488**
(0.102)	(0.028)	(0.021)	(0.266)	(0.016)	(0.023)	(0.023)	(0.140)
Pre-Futures							
0.175	-0.014	0.425**	0.230**	0.111**	0.857**	-0.006	
(0.176)	(0.040)	(0.024)	(0.087)	(0.023)	(0.028)	(0.031)	
Post-Futures							
0.958**	0.013	0.507**	0.497**	0.126**	0.727**	-0.268*	
(0.254)	(0.039)	(0.027)	(0.162)	(0.032)	(0.067)	(0.083)	

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively.

Table 2.6 shows the GARCH-in-mean, GARCH-M, results of the ISE 30 Return Index. Similar to GARCH results, the γ coefficient is negative and statistically significant at 1% level. It indicates that the introduction of stock futures has a negative impact on the volatility and so the volatility has lowered. The unconditional variance, given by $\alpha_0 / (1- \alpha_1- \alpha_2)$, is 7.187 in the pre-futures period and 3.381 in the post-futures period. The unconditional variance in the post-futures period is lower than that of the pre-futures period and it point outs lower market volatility in the post-futures period. The value of α_1 coefficient has increased from 0.111 to 0.126 from the pre-futures period to the post-futures period. Thus, it can be said that there is an increase of the speed at which information is incorporated in stock prices due to stock index futures trading. Again, α_1 could be interpreted as a "news" coefficient and the higher value of it implies that recent news has a greater impact on price changes. In contrast, the value of α_2 coefficient, reflecting the impact of "old news", has fallen in the post-futures period. Therefore, "old news" has less impact on the volatility of the stock market in the presence of stock index futures trading. Furthermore, the persistence of shocks, measured by α_1+ α_2, has decreased since the onset of derivative trading. Finally, it can be said that GARCH and GARCH-M have similar results for the ISE 30 Return Index.

Table 2.7: ISE 30 Return Index IGARCH

β_0	β_1	β_2	α_0	α_1	α_2	γ
Whole Period						
0.126*	0.014	0.514**	-1.251**	0.094**	0.906**	-0.492**
(0.052)	(0.029)	(0.025)	(0.269)	(0.009)	(0.009)	(0.141)
Pre-Futures						
0.119	-0.004	0.452**	0.224**	0.095**	0.905**	
(0.078)	(0.041)	(0.029)	(0.089)	(0.013)	(0.013)	
Post-Futures						
0.134	0.030	0.543**	0.364**	0.118**	0.882**	
(0.072)	(0.041)	(0.033)	(0.147)	(0.017)	(0.017)	

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively.

Integrated GARCH, IGARCH, results of the ISE 30 Return Index are shown in Table 2.7. The γ coefficient is -0.492 and it is statistically significant at 1% level as similar to results of GARCH and GARCH-M. Thus, it can be said that the introduction of stock futures has a negative impact on the volatility and so the volatility has lowered. As explained before, α_1 could be interpreted as a "news" coefficient and the higher value of it implies that recent news has a greater impact on price changes. The value of α_1 coefficient has increased in the post-futures period. This can be interpreted as there is an increase of the speed at which information is incorporated in stock prices due to stock index futures trading. On the contrary, the value of α_2 coefficient, reflecting the impact of "old news", has fallen from 0.905 to 0.882 from the pre-futures period to the post-futures period. Consequently, "old news" has less impact on the volatility of the stock market in the presence of stock index futures trading. As can be seen from the results, the results of IGARCH are similar to the results of GARCH and GARCH-M for the ISE 30 Return Index.

Table 2.8: ISE 30 Return Index GJR

β_0	β_1	β_2	α_0	α_1	α_2	τ	γ
Whole Period							
0.149** (0.050)	0.005 (0.027)	0.503** (0.024)	-1.303** (0.277)	0.088** (0.016)	0.857** (0.022)	0.045 (0.026)	-0.519** (0.148)
Pre-Futures							
0.129 (0.083)	-0.016 (0.040)	0.479** (0.027)	0.217** (0.083)	0.126** (0.026)	0.864** (0.026)	0.039 (0.031)	
Post-Futures							

0.156* (0.064)	0.028 (0.039)	0.548** (0.031)	0.300** (0.084)	0.058** (0.022)	0.847** (0.038)	0.082* (0.044)

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively.

In Table 2.8, the results of the GJR model of ISE 30 Return Index. In the GARCH model, news is assumed to have an equal effect irrespective of sign. If news has an asymmetric effect on volatility, then the GARCH model will be misspecified and subsequent inferences based on this model may be misleading. Thus, it is extended to allow for asymmetric effects. The GJR model is proposed in Glosten, Jagannathan and Runkle (1989) and it is an asymmetric model. The GJR model is less sensitive to outliers and higher likelihood than EGARCH model according to Engle and Ng (1993) and so it is chosen for the analyses. Similar to the GARCH and GARCH-M results, the γ coefficient is negative and statistically significant at 1% level. The value of γ coefficient is higher than the value of it in both the GARCH and GARCH-M results. The τ coefficient shows the asymmetric response of volatility to news. This asymmetric response has increased from the pre-futures period to the post-futures period. In this case, Turkey is similar to Spain since asymmetric response has increased after the introduction of futures stock trading in Spain according to the Antoniou *et al*. (1998). The authors show that the asymmetric response decreased for Germany, Japan, Switzerland, the U.K and the U.S and it is only increased for Spain. They explain this result by the absence of well-established financial markets in Spain. This explanation might be true for also Turkey since Istanbul Stock Exchange was founded in 1985 and so has been in operation only for 24 years.

Table 2.9: ISE 100 Return Index GARCH

β_0	β_1	β_2	α_0	α_1	α_2	γ

Whole Period						
0.152**	0.002	0.423**	-1.287**	0.114**	0.835**	-0.483**
(0.043)	(0.027)	(0.018)	(0.263)	(0.017)	(0.025)	(0.146)
Pre-Futures						
0.155*	-0.012	0.367**	0.218**	0.111**	0.837**	
(0.070)	(0.041)	(0.022)	(0.083)	(0.028)	(0.034)	
Post-Futures						
0.148*	0.018	0.448**	0.370**	0.125**	0.750**	
(0.059)	(0.038)	(0.027)	(0.143)	(0.032)	(0.068)	

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively.

The GARCH results for the ISE 100 Return Index for the whole period, the pre-futures period and the post-futures period are shown in Table 2.9. The measure of the effect due to introduction of stock index futures is -0.483. Similar to ISE 30 Return Index, this coefficient is negative and statistically significant. Therefore, the introduction of futures trading has a negative impact on the level of price volatility in ISE 100 Return Index. The unconditional variance is 4.19 in the pre-futures period and 2.96 in the post-futures period. Again, the price volatility is decreased after the introduction of futures for the ISE 100 Return Index since the unconditional variance in the post-futures period is lower than that of the pre-futures period.

As mentioned earlier, α_1 could be interpreted as a 'news' and α_2 could be defined as 'old news'. The value of α_1 has increased from 0.111 to 0.125 from the pre-futures to the post-futures period. Similar to ISE 30 Return Index, it can be said that the information is being impounded in prices more rapidly as the result of introduction of futures trading. The increase in the value of α_1 is 13% and it is 23% in ISE 30. The coefficient of 'old news' has decreased from 0.837 to 0.750 from the pre-futures to the post-futures period. Like ISE 30 case, the increased rate of information flow reduces the uncertainty about previous news and ‘old news’ plays a smaller role in determining the volatility of the stock market in the presence of future trading. The decrease in the value of α_2 is 10% and it is 6% in ISE 30. Market efficiency has increased in the post-futures period since the persistence of shocks, measured by $\alpha_1 + \alpha_2$, from the pre-futures to the post-futures period has decreased as alike in ISE 30 Return Index.

Table 2.10: ISE 100 Return Index GARCH-M

β_0	β_1	β_2	α_0	α_1	α_2	θ	γ
Whole Period							
0.303** (0.090)	0.000 (0.028)	0.407** (0.016)	-1.228** (0.259)	0.119** (0.018)	0.827** (0.026)	-0.047* (0.023)	-0.478** (0.142)
Pre-Futures							
0.136 (0.148)	-0.012 (0.041)	0.363** (0.021)	0.219** (0.084)	0.121** (0.029)	0.837** (0.035)	0.004 (0.031)	
Post-Futures							
0.993** (0.234)	-0.002 (0.038)	0.425** (0.025)	0.458** (0.131)	0.133** (0.033)	0.706** (0.062)	-0.329* (0.091)	

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively.

Table 2.10 shows the GARCH-M results of the ISE 100 Return Index for the whole period, the pre-futures period and the post-futures period. Like GARCH-M results of the ISE 30 Return Index, the γ coefficient is negative and statistically significant at 1% level. It again indicates that the volatility has lowered after the introduction of futures trading. The coefficient is -0.478 in ISE 100 and it is -0.488 in ISE 30 as shown in Table 2.6. The unconditional variance is 5.214 in the pre-futures period and 2.844 in the post-futures period. It once more presents lower market volatility in the post-futures period because the unconditional variance in the post-futures period is lower than that of the pre-futures period.

The value of α_1 coefficient has risen from 0.121 to 0.133 from the pre-futures period to the post-futures period that is similar to ISE 30 Return Index. Again, α_1 could be interpreted as a "news" coefficient and the higher value of it implies that recent news has a greater impact on price changes. Therefore, it can be said that there is an increase of the speed at which information is incorporated in stock prices due to stock index futures trading. The increase in the value of α_1 is 10 % and it is 14% in ISE 30. Quite the opposite, the value of α_2 coefficient, reflecting the impact of "old news", has fallen in the post-futures period. Therefore, "old news" has less impact on the volatility of the stock market in the presence of stock index futures trading. The decline in the value of α_2 is 15% and it is 16% in ISE 30. Moreover, reduce in the persistence of shocks reveals an increase in the market efficiency as a result of introduction of futures trading. In conclusion, it is observed that GARCH and GARCH-M have similar results not only for the ISE 30 Return Index but also for the ISE 100 Return Index.

Table 2.11: ISE 100 Return Index IGARCH

β_0	β_1	β_2	α_0	α_1	α_2	γ
Whole Period						
0.156** (0.042)	0.005 (0.028)	0.446** (0.020)	-1.245** (0.261)	0.132** (0.017)	0.868** (0.017)	-0.480** (0.144)
Pre-Futures						
0.157* (0.067)	-0.00785 (0.04197)	0.402** (0.023)	0.223** (0.086)	0.134** (0.026)	0.866** (0.026)	
Post-Futures						

0.154** (0.057)	0.015 (0.041)	0.478** (0.029)	0.415** (0.135)	0.148** (0.029)	0.852** (0.029)		

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively.

IGARCH results of the ISE 100 Return Index are shown in Table 2.11. The γ coefficient is negative and it is statistically significant at 1% level as similar to results of GARCH and GARCH-M. The coefficient is -0.480 in ISE 100 and it is -0.492 in ISE 30 as shown in Table 2.7. As explained before, α_1 could be interpreted as a "news" coefficient and the higher value of it implies that recent news has a greater impact on price changes. The value of α_1 coefficient has increased in the post-futures period. This can be interpreted as there is an increase of the speed at which information is incorporated in stock prices due to stock index futures trading. The increase in the value of α_1 is 10 % and it is 23% in ISE 30. On the contrary, the value of α_2 coefficient, reflecting the impact of "old news", has fallen from 0.866 to 0.852 from the pre-futures period to the post-futures period. Consequently, "old news" has less impact on the volatility of the stock market in the presence of stock index futures trading. The decline in the value of α_2 is 1.6% and it is 2.5% in ISE 30. As can be seen from the results, the results of IGARCH are similar to the results of GARCH and GARCH-M not only for the ISE 30 Return Index but also for the ISE 100 Return Index.

Table 2.12: ISE 100 Return Index GJR

β_0	β_1	β_2	α_0	α_1	α_2	τ	γ
Whole Period							
0.162** (0.046)	0.004 (0.027)	0.453** (0.021)	-1.310** (0.274)	0.099** (0.019)	0.836** (0.026)	0.032 (0.030)	-0.499** (0.152)
Pre-Futures							

0.138 (0.078)	-0.012 (0.041)	0.411** (0.023)	0.203** (0.077)	0.146** (0.032)	0.848** (0.032)	0.048 (0.039)
Post-Futures						
0.165** (0.060)	0.026 (0.038)	0.485** (0.031)	0.262 (0.112)	0.075** (0.029)	0.798** (0.054)	0.088 (0.052)

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively.

The results of the GJR model of ISE 100 Return Index for the whole period, the pre-futures period and the post-futures period are presented in Table 2.12. As explained before, GJR model is used to allow asymmetric effects and it is less sensitive to outliers and higher likelihood than EGARCH model. The γ coefficient is negative and statistically significant at 1% level in the whole period as similarly observed in GARCH, GARCH-M and IGARCH models. Likewise in the ISE 30 Return Index, the value of γ coefficient is higher than the value of it in the GARCH, GARCH-M and IGARCH results. Moreover, this coefficient is smaller than that of ISE 30 Return Index.

As explained earlier, the τ coefficient shows the asymmetric response of volatility to news. This coefficient has risen from 0.048 to 0.088 from the pre-futures period to the post-futures period. It is also witnessed for ISE 100 Return Index that the asymmetric response has increased after the introduction of futures stock trading and this can be explained by the absence of well-established financial markets in Turkey. The raise in the value of τ is 85 % in ISE 100 and it is 110% in ISE 30.

2.5 Conclusion

The impact of futures trading on the volatility of the underlying spot market is investigated by many authors for different countries in the literature. There are studies claiming futures market increases stock market volatility as a result of destabilizing effects of future trading associated with speculation. In contrary, some authors argue that futures market reduces spot market volatility since futures market plays an important role of price discovery, increases market depth and enhances efficiency. I examine the impact of futures trading on the volatility of the Turkish Istanbul Stock Exchange (ISE), an emerging stock market.

This paper analyzes whether futures trading has increased or decreased stock market volatility by considering the issue of volatility, information speed and asymmetries. First, the results suggest that the introduction of futures trading has decreased the volatility of Istanbul Stock Exchange. The present results conform to those of Antoniou *et al.* (1998), Bologna and Cavallo (2002), Pilar and Rafael (2002) and Drimbetas *et al*. (2007), that the introduction of derivatives decreases the level of volatility of the underlying market and therefore it has a stabilizing effect. Second, the results show that futures trading increases the speed at which information is impounded into spot market prices. Moreover, the reduction in persistence of shock from the pre-futures to the post-futures period indicates increased market efficiency in the post-futures period. This is similar to what Antoniou and Holmes (1995), Bologna and Cavallo (2002) and Ryoo and Smith (2004) found. Third, the asymmetric responses of volatility to the arrival of news for ISE have increased after the introduction of futures trading. Antoniou *et al.* (1998) observes that there has been a reduction in the asymmetric response of volatility to news in the German, Japanese, U.K and U.S markets but an increase in the Spanish market. This can be explained by the absence of well-established financial markets in both Spain and Turkey.

2.6 Figures and Tables

Figure 2.3: Autocorrelation Function of ISE 30 Return Index

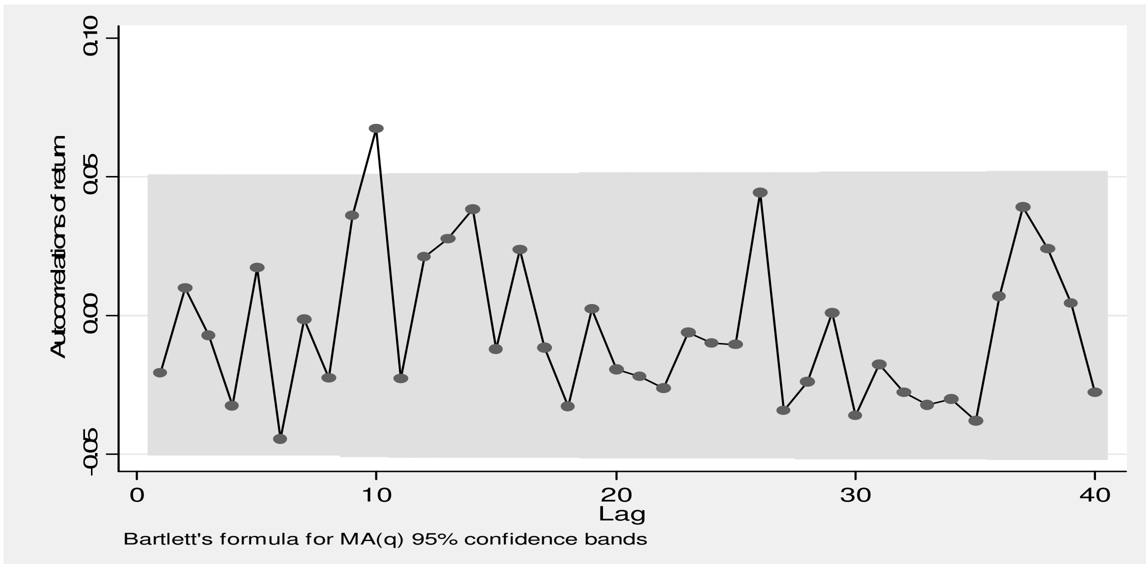


Figure 2.4 : Autocorrelation Function of ISE 100 Return Index

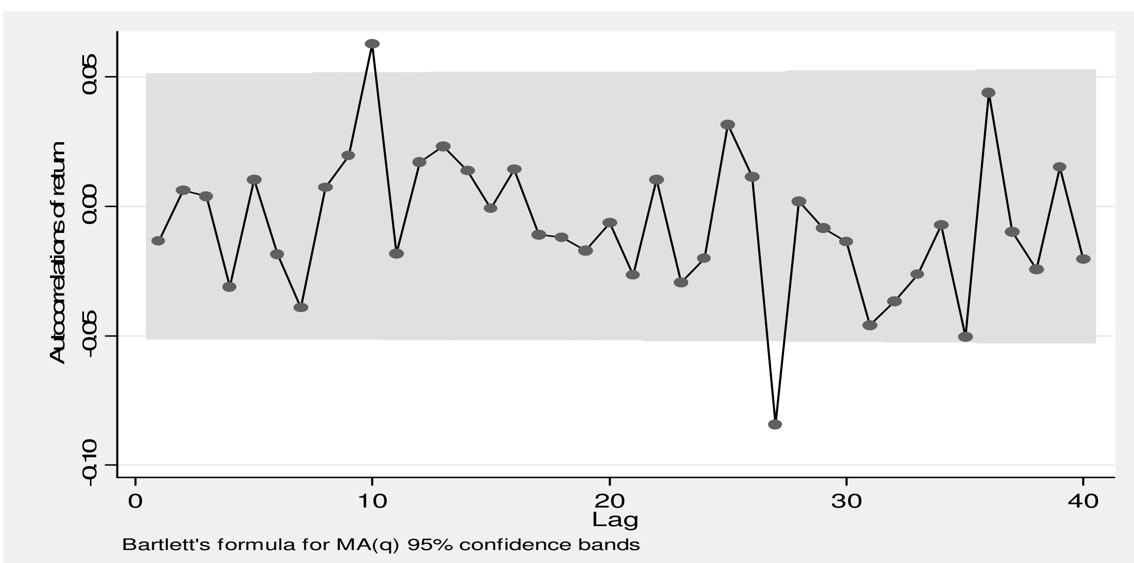


Table 2.13: Ljung-Box test for the normalized residuals for ISE 30 GARCH

Lags	Autocorrelation	Partial correlation	LB
1	0.018	0.018	0.467
3	-0.002	-0.002	0.631
5	0.014	0.014	1.185
8	-0.032	-0.032	3.745
10	0.005	0.004	4.514
13	0.032	0.032	6.921
16	-0.007	-0.008	8.574
20	0.018	0.021	11.375

Table 2.14: ARCH-LM test results for ISE 30 GARCH

Constant	Squared residuals	LM-statistics	F-statistics
0. 984 (0.000)	0.017 (0.495)	0.086 (0.770)	0.470 (0.495)

Note: The numbers in the parentheses are p-values

Table 2.15: Ljung-Box test for the normalized residuals for ISE 30 GARCH-M

Lags	Autocorrelation	Partial correlation	LB
1	0.012	0.012	0.228
3	-0.001	-0.001	0.384
5	0.009	0.009	0.909
8	-0.032	-0.032	3.419
10	0.004	0.002	4.014
13	0.034	0.034	6.889
16	-0.003	-0.004	8.527
20	0.014	0.017	11.181

Table 2.16: ARCH-LM test results for ISE 30 GARCH-M

Constant	Squared residuals	LM-statistics	F-statistics
0. 989 (0.000)	0.012 (0.633)	0.008 (0.929)	0.230 (0.633)

Note: The numbers in the parentheses are p-values

Table 2.17: Ljung-Box test for the normalized residuals for ISE 30 IGARCH

Lags	Autocorrelation	Partial correlation	LB
1	0.023	0.023	0.414
3	-0.016	-0.016	0.672
5	0.020	0.021	1.509
8	-0.027	-0.029	3.488
10	0.010	0.009	4.334
13	0.020	0.022	6.679
16	-0.009	-0.010	8.414
20	0.023	0.027	11.240

Table 2.18: ARCH-LM test results for ISE 30 IGARCH

Constant	Squared residuals	LM-statistics	F-statistics
0. 987 (0.000)	0.015 (0.542)	0.060 (0.808)	0.310 (0.581)

Note: The numbers in the parentheses are p-values

Table 2.19: Ljung-Box test for the normalized residuals for ISE 30 GJR

Lags	Autocorrelation	Partial correlation	LB
1	0.014	0.014	0.281
3	-0.003	-0.002	0.448
5	0.014	0.014	0.980
8	-0.031	-0.032	3.454
10	0.001	-0.001	4.221
13	0.032	0.033	6.781
16	-0.008	-0.009	8.430
20	0.019	0.022	11.290

Table 2.20: ARCH-LM test results for ISE 30 GJR

Constant	Squared residuals	LM-statistics	F-statistics
0.987 (0.000)	0.013 (0.596)	0.035 (0.852)	0.280 (0.596)

Note: The numbers in the parentheses are p-values

Table 2.21: Ljung-Box test for the normalized residuals for ISE 100 GARCH

Lags	Autocorrelation	Partial correlation	LB
1	-0.002	-0.002	0.007
3	0.016	-0.016	0.924
5	0.033	0.033	2.960
8	-0.027	-0.030	5.562
10	0.003	0.000	7.365
13	0.025	0.026	8.752
16	-0.017	-0.019	9.426
20	-0.024	-0.019	17.214

Table 2.22: ARCH-LM test results for ISE 100 GARCH

Constant	Squared residuals	LM-statistics	F-statistics
1. 003 (0.000)	-0.002 (0.933)	0.023 (0.879)	0.010 (0.933)

Note: The numbers in the parentheses are p-values

Table 2.23: Ljung-Box test for the normalized residuals for ISE 100 GARCH-M

Lags	Autocorrelation	Partial correlation	LB
1	-0.005	-0.005	0.032
3	0.015	0.015	0.840
5	0.027	0.028	2.523
8	-0.024	-0.027	4.929
10	0.005	0.002	6.724
13	0.026	0.027	8.419
16	-0.016	-0.018	9.044
20	-0.026	-0.020	17.041

Table 2.24: ARCH-LM test results for ISE 100 GARCH-M

Constant	Squared residuals	LM-statistics	F-statistics
1. 006 (0.000)	-0.005 (0.859)	0.042 (0.838)	0.030 (0.859)

Note: The numbers in the parentheses are p-values

Table 2.25: Ljung-Box test for the normalized residuals for ISE 100 IGARCH

Lags	Autocorrelation	Partial correlation	LB
1	-0.021	-0.021	0.308
3	0.004	0.004	0.473
5	0.034	0.034	1.793
8	-0.030	-0.032	3.966
10	0.022	0.016	5.283
13	0.058	0.061	8.639
16	-0.006	-0.007	8.8244
20	-0.022	-0.023	11.592

Table 2.26: ARCH-LM test results for ISE 100 IGARCH

Constant	Squared residuals	LM-statistics	F-statistics
1. 004 (0.000)	-0.003 (0.912)	0.035 (0.858)	0.022 (0.902)

Note: The numbers in the parentheses are p-values

Table 2.27: Ljung-Box test for the normalized residuals for ISE 100 GJR

Lags	Autocorrelation	Partial correlation	LB
1	-0.004	-0.004	0.021
3	0.015	0.015	0.937
5	0.030	0.031	2.781
8	-0.027	-0.029	5.301
10	0.002	0.001	7.163
13	0.025	0.026	8.577
16	-0.018	-0.020	9.2656
20	-0.024	-0.019	16.757

Table 2.28: ARCH-LM test results for ISE 100 GJR

Constant	Squared residuals	LM-statistics	F-statistics
1.005 (0.000)	-0.004 (0.885)	0.026 (0.872)	0.020 (0.885)

Note: The numbers in the parentheses are p-values

Chapter 3: Calendar Anomalies in Turkish Istanbul Stock Exchange

3.1 Introduction

The presence of calendar anomalies or seasonality in stock market returns is one of the most extensively studied subjects in the literature. A list of studies concerning calendar effects are: Cross (1973), Rozeff and Kinney (1976), French (1980), Gultekin and Gultekin (1983), Keim and Stambaugh (1984), Ariel (1987), Lakonishok and Smidt (1988), Cadsby and Ratner (1992), Kim and Park (1994), Balaban (1995), Jaffe and Westerfield (1995), Brockman and Michayluk (1998), Berument, Inamlik and Kiymaz (2004), Zhang and Li (2006), Lean *et al*. (2007) and Marrett and Worthington (2008). The usual asset-pricing models cannot explain these calendar anomalies and so these anomalies challenges the efficient market hypothesis in which investors should not be able to earn above-average returns. Moreover, their persistence presence since their first discovery still remains a puzzle to be solved.

On the other hand, there are some studies that argue these calendar anomalies tend to disappear. For instance, Chang *et al*. (1993), Steeley (2001), Coutts and Sheikh (2002), Hudson *et al.* (2002), Fountas and Segredakis (2002), Mehdian and Perry (2002), Yanxiang Gu (2003), Tonchev and Kim (2004) and Marquering, Nisser and Valla (2006). They claim that in general anomalies are much less pronounced after they became known to the public. Therefore, the findings of calendar effects caused the stock markets to become more efficient.

In this paper, I investigate the calendar anomalies for an emerging market, Turkish Istanbul Stock Exchange (ISE). Most of the studies above have examined the developed financial markets. It is important to test the calendar effects in data sets that are different from those in which they are originally discovered. As a result of empirical analysis, it is found that calendar anomalies are present at the marketwide and industry levels in ISE. First of all, Friday has the highest average stock return in ISE 100, ISE Service and ISE Industry indices and Thursday has the highest return in ISE Finance index. Monday has the lowest mean return in all indices. Second, the stock returns, on average, are abnormally high on 31st and 2nd days of the month and abnormally low on 7th and 11th days of the month. Third, the January's stock returns are the highest in all indices on average. The lowest average return belongs to June in all indices except the ISE Service Index in which September has the lowest mean return.

Turkey has an analogous pattern with the US and Canada among developed countries and Singapore among developing countries with both the highest mean return in Friday and lowest mean return in Monday and the highest mean return in January.

The remainder of the paper is organized as follows. The next section gives details about the data and methodology. Section 3.3 shows the empirical results of ISE indices. Section 3.4 reports international evidence Section 3.5 concludes the paper.

3.2 Data and Methodology

The calendar effects are examined using daily return values from Istanbul Stock Exchange (ISE). The ISE 100, ISE Service, ISE Financial and ISE Industry indices are studied. The data ranges from January 1997 to January 2009 in which there are 2916 total observations.

The presence of calendar anomalies is tested by running the following OLS regression model.

$$\mathrm{R_t} = \mathrm{cons} + \sum_{\mathrm{i}=1}^{\mathrm{k}} \beta_{\mathrm{i}}\, R_{t-i} + C_{Tue}\, D_{Tt} + C_{Wed}\, D_{Wt} + C_{Thu}\, D_{Ht} + C_{Fri}\, D_{Ft} + \varepsilon_t \quad (3.1)$$

where D_{Tt} is the dummy variable for Tuesday and it is 1 if day t is Tuesday and zero otherwise; D_{Wt} = 1 if day t is Wednesday and zero otherwise, and so on. The dummy variable for Monday is omitted since it has the lowest mean average in summary statistics. Therefore, the coefficients of weekdays should be interpreted by comparing the one of Monday. The lagged values of the return are included in order to remove the possibility of having auto correlated errors. In order to identify the most appropriate mean equation, five different models are compared with one to five autoregressive terms respectively.

Table 3.1: Mean equation with different number of lags

Number of Lags	Akaike	Schwartz	F-test
1	-12488.16	-12452.29	4.51
2	-12486.61	-12444.77	4.35
3	-12482.34	-12434.53	4.13
4	-12480.02	-12426.23	4.09
5	-12477.10	-12417.34	4.07

Table 3.1 shows the values of the Akaike Information Criterion, the Schwartz Bayesian Criterion and the F-test for the three alternative specifications of the mean equation. From the equation with one lag to the one with five lags the increase of the Akaike Information Criterion and the Schwartz Bayesian Criterion is marginal (0.09% and 0.28% respectively) whereas the decrease of the F statistic is much larger (9.76%). Thus, extra lagged variables do not improve the model and so the equation with one lagged term has been chosen for the mean equation.

The model in Equation 3.1 assumes the existence of a constant variance but the variance of the error terms may not be constant over time. Thus, the changing variance should be included into estimation in order to obtain more efficient results. It is assumed that the error term of the return equation has a normal distribution with zero mean and time varying conditional variance of h_t ($\varepsilon_t \sim N(0,h_t)$). Engle's (1982) conditional variance model is known as Autoregressive Conditional Heteroskedastic Models (ARCH) in which the forecast variance of return equation varies systemically over time. In this model, the conditional variance, h_t, relies on the past squared residuals shown in Equation 3.2.

$$h_t = V_{cons} + \sum_{i=1}^{m} Va_i \ \varepsilon_{t-i}^2 \qquad (3.2)$$

Bollerslev (1986) suggests the Generalized Autoregressive Conditional Heteroskedastic Models (GARCH) in which h_t depends on not only lagged values of ε_t^2 but also lagged values of h_t as shown in Equation 3.3.

$$h_t = V_{cons} + \sum_{i=1}^{m} Va_i \ \varepsilon_{t-i}^2 + \sum_{j=1}^{n} Vg_j \ h_{t-j} \qquad (3.3)$$

GARCH models are widely used in the calendar effect literature such as Nelson (1991), Camphell and Hentschel (1992), Berument and Kiymaz (2001) and Rosenberg (2004). The GARCH (1,1) has been found to be, at least within the GARCH class of models, the most convenient way to represent conditional variance for financial time series. Using likelihood ratio (LR) tests, the consistency of this finding for the Istanbul Stock Exchange is tested. Particularly, the restricted GARCH (1,1) is tested against a series of alternative unrestricted models; in all cases the null hypothesis that the return-generating process follows a GARCH (1,1) process relative to the alternative hypothesis is not rejected. To estimate the various GARCH models of Table 3.2 maximum likelihood estimations are employed as employed in Bologna and Cavallo (2002). LR test results are showed in Table 3.2.

Table 3.2: Variable exclusion tests for the GARCH model

	Likelihood ratio test	Critical values at 5% level
GARCH (1,2) vs. GARCH(1,1)	1.16	3.84
GARCH (1,3) vs. GARCH(1,1)	3.08	5.99
GARCH (2,1) vs. GARCH(1,1)	1.81	3.84
GARCH (2,2) vs. GARCH(1,1)	2.34	5.99
GARCH (2,3) vs. GARCH(1,1)	3.92	7.81
GARCH (3,1) vs. GARCH(1,1)	3.30	5.99
GARCH (3,2) vs. GARCH(1,1)	5.42	7.81
GARCH (3,3) vs. GARCH(1,1)	6.89	9.49

The GARCH-in-mean, GARCH-M (1,1), the exponential GARCH, EGARCH (1,1), and the integrated GARCH, IGARCH(1,1) are employed for testing calendar effects. The results are shown in Section 3.6 and they are similar to the results of GARCH (1,1). Following the results, GARCH (1,1) model is chosen to employ for testing calendar effects in the conditional variance of ISE Index returns using Equation 3.4.

$$\mathrm{h_t} = \mathrm{V_{cons}} + \mathrm{Va}\ \varepsilon_{t-1}^2 + Vg\ h_{t-1} \tag{3.4}$$

3.3 Empirical Results

Four different indices, ISE 100 index, service index, finance index and industry index are used to calculate the day and month effects on stock market returns. In all indices Monday has the lowest return and Friday has the highest return except finance index where Thursday has the highest return.

Table 3.3: ISE 100 Return Index for day of the week

	All	Mon	Tue	Wed	Thu	Fri
Observation	2916	569	589	589	583	586
Mean	0.152	-0.194	0.004	0.073	0.407	0.465
Std. Dev.	2.846	3.167	2.727	2.791	2.858	2.622
Skewness	0.196	0.071	0.719	-0.510	0.135	0.907
Kurtosis	7.357	6.561	8.803	7.936	5.009	9.094

As shown in Table 3.3 above, ISE 100 Index has a 0.152 return average for all days and this is the second highest average return among four indices. Only Monday has the negative average return and other days have positive average returns. Average return increases step-by-step from Monday through Friday and Friday has the highest average return. The increase in average return between Monday and Friday is 141.8 % and between Thursday and Friday is 12.3%.

Table 3.4 shows the returns of ISE Service Index. The average return for all days is 0.144 and it is the lowest average return among four indices. Monday and Tuesday has negative average returns and remaining days have positive average returns. Similar to Table 3.1, average return increases as going from Monday to Friday. Friday's average return is 134.9% more than Monday's return. Also, Friday's average return is 28.8% more than Thursday's return.

As seen in the Table 3.5, the average return is 0.170 for all days in the ISE Finance Index and it is the highest average return among four indices. Only Monday has a negative return average. In contrast to other indices where Friday has the highest average return, Thursday's average return is the highest in the ISE Finance Index. However, Friday has the second highest average return. Thursday's return is 137.4% more than Monday's return and only 4.0% more than Friday's return.

Table 3.6 presents the general statistics of the return of ISE industry index. The average return is 0.144 for all days and it is in the second lowest among for indices. Similar to Table 3.4, only Monday and Tuesday have negative returns and average returns increases as going from Monday to Friday. The increase in average return between Monday and Friday is 149.7 % and between Thursday and Friday is 18.8 %.

Table 3.7: ISE 100 Return Statistics with OLS and GARCH for day of the week

	OLS	**GARCH (1,1)**
R_{t-1}	6.4571 (18.535)	23.233 (19.184)
C_{tue}	1.980 (1.668)	0.213 (1.229)
C_{wed}	2.653 (1.670)	1.359 (1.183)
C_{thu}	5.998** (1.675)	3.162** (1.146)
C_{fri}	6.603** (1.671)	3.237** (1.235)
Constant	-1.943 (1.190)	0.052 (0.794)
V_a		125.393** (9.842)

V_g	867.617** (9.595)
V_{cons}	0.012** (0.002)

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^3.

In these estimations, a dummy variable for Monday, that has the lowest mean return, is excluded in order to avoid the dummy variable trap. Thus, the coefficients are interpreted by comparing the one of Monday. Table 3.7 shows the OLS and GARCH(1,1) results of the ISE 100 Return. In the OLS, all of the coefficients are positive and so these days have higher returns compared to Monday. Only Friday's and Thursday's coefficients are statistically significantly different than Monday's coefficient at 1 % level. Finally, it is seen that coefficients are increasing from Tuesday to Friday. In GARCH, similar to OLS, coefficients of weekdays are positive and so weekdays have higher returns than Monday have. The coefficients of Friday and Thursday are statistically significantly different than the coefficient of Monday at 1% level and the coefficient of Friday is the highest. Unlike OLS, Tuesday's coefficient is higher than Wednesday's coefficient.

In Table 3.8, the regression results of OLS and GARCH of ISE Service Returns are presented. In OLS, the weekdays have higher returns than Monday have since the coefficients are positive. Friday has the highest return and the estimated coefficients of Friday and Thursday are statistically significant at 1% level. In GARCH, only the coefficient of Tuesday is negative. The estimated coefficient of Thursday is statistically significant at 5% level and Friday is statistically significant at 1% level with Friday has the highest coefficient.

The OLS and GARCH results for the ISE Financial Return Index are showed in Table 3.9. Thursday has the highest coefficients in both OLS and GARCH. The estimated coefficients of Thursday and Friday are statistically significant at 1 % level in OLS and 5 % level in GARCH. The coefficients of the weekdays are positive in both OLS and GARCH and so Monday has the lowest return.

Table 3.10 shows the OLS and GARCH(1,1) results of the ISE Industry Return Index. In both OLS and GARCH, all of the coefficients are positive and so these days have higher returns compared to Monday. The estimated coefficient of Friday and Thursday are statistically significant at 1% level and of Wednesday is statistically significant at 5% level that is the only significant Wednesday coefficient among four indices.

Table 3.11: ISE 100 and Service Return Index for day of the month

		ISE 100		Service	
	Observation	**Mean**	**Std. errs.**	**Mean**	**Std. errs.**
All	2916	0.153	2.846	0.144	2.698
1	88	0.377	2.660	0.529	2.414
2	88	0.674	2.065	0.678	2.102
3	98	0.078	2.495	-0.097	2.427
4	97	0.671	3.319	0.429	3.103
5	99	0.173	3.360	0.322	3.062
6	100	0.293	3.163	0.329	2.914
7	101	-0.400	2.542	-0.246	2.097
8	100	-0.129	2.351	0.073	2.422
9	98	0.157	2.455	-0.168	2.260
10	98	0.022	2.574	-0.175	2.264
11	98	-0.460	2.933	-0.285	2.854
12	97	-0.007	3.012	-0.084	2.859
13	98	-0.205	2.988	-0.206	2.821
14	103	0.265	2.808	0.322	2.647
15	100	0.110	2.453	-0.047	2.438
16	99	0.483	2.955	0.160	2.530
17	99	-0.369	3.449	-0.114	3.111
18	99	0.604	3.010	0.461	2.780
19	91	0.328	3.460	0.221	3.297
20	89	0.270	2.673	0.291	2.853

21	98	-0.222	2.889	-0.154	2.930
22	97	0.142	2.448	0.024	2.673
23	90	0.484	2.994	0.651	2.983
24	92	0.202	3.203	0.088	2.778
25	97	0.320	2.619	0.361	2.624
26	95	0.287	2.570	0.545	2.455
27	100	0.196	3.490	-0.050	3.245
28	101	-0.369	2.512	-0.345	2.455
29	82	0.250	2.193	0.273	2.014
30	74	0.221	3.053	0.464	3.028
31	50	0.809	2.336	0.821	2.172

The first column of the Table 3.11 shows the summary statistics of ISE 100 Return Index for day of the month. The 31st day has the highest mean return with the value of 0.809. The second highest mean return of the day of the month is 2nd day with the value of 0.674. The third, fourth and fifth highest return means are 4th, 18th and 23rd days of the month. In contrast, with the value of -0.460 the 11th day has the lowest return mean. Then 7th, 28th, 17th and 21st days of the month come as the lowest return means respectively.

Table 3.12 reports the results of OLS and GARCH(1,1) for the ISE 100 Return Index. The day of the month that has the lowest mean return is excluded in the equations in order to avoid dummy trap. Thus, the estimates are interpreted by comparing the one of the day that has the lowest mean return. For the ISE 100 Return index, the 11th day has the lowest return mean and so it is excluded in the estimations for both OLS and GARCH. In OLS, the 31st day of the month has the highest estimated coefficient and it is statistically significant at 1% level. Then the 2nd, 4th and 18th days come with statistically significant returns at 1% level. Moreover, the return results on 23rd, 16th and 1st days are statistically significant different than the return of 11th day at 5% level. Similar to OLS, in GARCH, the 31st day has the highest estimated coefficient and it is statistically significant at 1% level. The 23rd and the 2nd days come after with the estimated coefficient of 23rd day is statistically significant at 5% level but coefficient of 2nd day is insignificant.

Table 3.12: ISE 100 Return Statistics with OLS and GARCH for day of the month

	OLS	**Std. errs.**	**GARCH(1,1)**	**Std. errs.**
R_{t-1}	6.500	18.625	19.004	19.666
C_1	8.326*	4.178	5.509	3.053
C_2	11.336**	4.177	6.109	3.454
C_3	5.331	4.066	2.083	3.568
C_4	11.286**	4.074	5.649	3.169
C_5	6.311	4.053	3.115	3.306
C_6	7.557	4.043	2.618	3.061
C_7	0.608	4.033	-0.355	3.162
C_8	3.306	4.043	-0.587	3.025
C_9	6.170	4.063	1.715	3.198
C_{10}	4.825	4.063	0.601	3.498
C_{12}	4.557	4.074	0.990	3.288
C_{13}	2.508	4.064	0.550	3.288
C_{14}	7.267	4.014	1.816	3.081
C_{15}	5.695	4.053	4.274	3.331
C_{16}	9.422*	4.053	4.733	3.199
C_{17}	0.865	4.055	0.392	2.965
C_{18}	10.641**	4.053	3.855	3.212
C_{19}	7.854	4.141	5.163	3.039
C_{20}	7.279	4.165	2.508	3.216
C_{21}	2.371	4.063	2.393	3.395
C_{22}	6.009	4.074	0.932	3.224
C_{23}	9.425*	4.153	6.017*	3.151
C_{24}	6.589	4.130	3.388	3.271
C_{25}	7.789	4.074	3.312	3.303
C_{26}	7.465	4.095	0.892	3.400
C_{27}	6.565	4.043	1.753	3.112
C_{28}	0.900	4.033	1.262	3.404
C_{29}	7.075	4.257	3.775	4.024
C_{30}	6.779	4.381	2.690	3.148
C_{31}	12.630**	4.946	10.999**	4.175
Constant	-4.598	2.873	19.004	19.666

V_a	122.185**	10.115
V_g	871.765**	9.820
V_{cons}	0.011**	0.002

Note: Standard errors are reported right to the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^3.

The summary statistics of ISE Service Return Index for the day of the month is presented in the second column of Table 3.11. The top five highest mean returns are 31st, 2nd, 23rd, 26th and 1st day of the month correspondingly where the values are 0.82, 0.68, 0.65, 0.54 and 0.52. In contrast, the 28th, 11th, 7th, 13th and 10th days of the months have the lowest average returns in that order.

Since the 28th day of the month has the lowest mean return, it is the omitted dummy variable for the calculations of OLS and GARCH (1,1) for the ISE Service Return Index. The results are presented in Table 3.13. In OLS, the 31st day has the highest estimated coefficient. Then the 2nd and 23rd days come. These three days have the statistically significant coefficients at 1% level. The following days have the statistically coefficients at 5 % level: 1st, 4th, 18th, 26th and 30th. In GARCH, similar to OLS, the highest estimated coefficient belongs to the 31st day and it is statistically significantly different at 1% level. The 2nd day has the second highest coefficient and it is statistically significant at 5% level. Moreover, the estimated coefficients of the 4th day and 19th day are statistically significantly different than the one of 28th day, omitted dummy variable.

The first column of the Table 3.14 shows the descriptive statistics of the ISE Financial Return Index. The 2nd day of the month has the highest mean return. The 4th, 31st, 18th and 16th days come as the following highest average return in the order given. The five lowest mean returns belong to 11th, 17th, 21st, 7th and 28th day of the month respectively where the values are -0.52, -0.48, -0.46, -0.33 and -0.32.

Table 3.15 presents the coefficients and standard errors of OLS and GARCH for the ISE Financial Return Index. In the descriptive statistics, the 11^{th} day of the month has the lowest average return and so it is excluded in the estimations for both OLS and GARCH in order to avoid dummy trap. In OLS, as expected the 2^{nd} day of the month has the highest estimated coefficient. The coefficients of 2^{nd}, 4^{th} and 18^{th} days are statistically significant at 1% level and the coefficients of 1^{st}, 16^{th}, 19^{th}, 23^{rd}, 27^{th} and 31^{st} days are statistically at 5% level. In GARCH, the highest estimated coefficient belongs to the 31^{st} day of the month and it statistically significant at 5% level. The 2^{nd} day has the second highest coefficient and the 1^{st} day has the third highest coefficient. The returns of both of these days are statistically significantly different than the return of 11^{th} day at 5% level.

In the second column of the Table 3.14, ISE Industry Return Index statistics is shown. The highest mean return is 0.80 and it belongs to 31^{st} day of the month. Following highest mean returns are 0.54, 0.50, 0.46 and 0.45 that belong to respectively 2^{nd}, 4^{th}, 6^{th} and 18^{th} day of the month. On the other hand, the lowest mean return belongs to 7^{th} day of the month with the value of -0.43. The 28^{th}, 11^{th}, 17^{th} and 13^{th} days come as the following lowest average return in the order given.

The results of OLS and GARCH(1,1) for the ISE Industry Return Index are presented in the Table 3.16. Since the 7^{th} day of the month has the lowest average return, it is the skipped dummy variable in both OLS and GARCH. As anticipated, the highest estimated coefficient belongs to the 31^{st} day of the month. Then the 2^{nd} day and 4^{th} day comes. These three coefficients are statistically significant at 1% level. The returns of these days are statistically significantly different than the return of 7^{th} day at 5% level: 1^{st}, 5^{th}, 6^{th}, 14^{th}, 16^{th}, 18^{th}, 20^{th}, 23^{rd} and 25^{th} days of the month. Similar to OLS, in GARCH, the 31^{st} day of the month has the highest coefficient and it is the only coefficient that is statistically significant at 1% level. The estimated coefficients of 1st, 2nd, 19th and 23rd days are statistically significant different at 5% level.

Table 3.17: ISE 100 and Service Return Index for month of the year

		ISE 100		Service	
	Observation	**Mean**	**Std. errs.**	**Mean**	**Std. errs.**
All	144	2.968	12.257	2.782	11.701
Jan	12	8.247	14.705	10.049	18.299
Feb	12	1.132	13.113	-1.893	11.782
Mar	12	0.812	10.748	1.399	7.872
Apr	12	5.566	7.581	3.332	6.335
May	12	2.079	10.661	1.426	7.519
Jun	12	-2.540	8.420	-0.876	9.152
Jul	12	2.162	8.992	1.481	8.837
Aug	12	1.165	7.165	-0.431	7.871
Sep	12	-0.738	13.734	-0.831	13.253
Oct	12	3.781	14.165	6.265	12.327
Nov	12	8.214	14.724	8.005	11.676
Dec	12	5.736	18.175	5.461	16.761

The first column of the Table 3.17 shows the descriptive statistics of the ISE 100 Return Index for month of the year. There are total 144 observations and 12 observations for each month presenting the 12 years data. The average return is 2.968. January has the highest mean return with the value of 8.247 and November has the second highest mean return. The lowest average return belongs to June and the second lowest belongs to September with the values of -2.540 and -0.738 respectively. These are the only two months that have negative average return. The second column presents the ISE Service Return Index. Similar to ISE 100, January and November comes as the top two in highest average return with the values of 10.049 and 8.005 in the order. February's mean return is -1.893 and it is the lowest among twelve months' returns. Then July, September and August comes in lowest returns. These are the only four months that have negative mean return. The average return for all 144 observations is 2.782 for the ISE Service Return Index and it is the lowest among four indices.

The descriptive statistics for the ISE Financial Return Index for month of the year is presented in the first column of the Table 3.18. The average return for all observation is 3.369 and it is the highest among four indices. June has the lowest mean return with the value of -3.461. September has the second lowest mean return. Only June and September has negative mean return among twelve months. The two highest average returns belong to November and January with the values of 10.756 and 8.861 respectively. The ISE Industry's summary statistics is showed in the second column of the Table 3.18. January has the highest mean return with the value of 7.482. April comes second and November comes third in having the highest mean return. Similar to the ISE Financial Return Index, June and September has the two lowest mean returns with the values of -1.468 and -0.401. Again, these are the only two months that have negative mean return. The average return for all 144 observations is 2.793 for the ISE Industry Return Index.

Table 3.19: ISE 100 Return with OLS and GARCH for month of the year

	OLS		GARCH(1,1)	
	Coef.	**Std. errs.**	**Coef.**	**Std. errs.**
R_{t-1}	31.345**	8.450	24.456*	12.035
C_{jan}	12.402*	4.918	11.293**	3.849
C_{feb}	4.095	4.805	9.388*	3.999
C_{mar}	2.285	4.812	4.827	3.956
C_{apr}	8.131	4.803	10.444*	4.304
C_{may}	6.093	4.820	8.208*	3.742
C_{jul}	5.014	4.804	8.260*	3.587
C_{aug}	4.613	4.809	8.335	5.808
C_{sep}	1.294	4.805	7.406	4.110
C_{oct}	4.424	4.830	10.258*	4.374
C_{nov}	9.633*	4.813	11.008**	3.587
C_{dec}	6.368	4.831	10.759*	4.812
Constant	-3.217	3.401	-6.071*	2.846

V_a	60.470**	18.204
V_g	22.680	19.012
V_{cons}	0.393*	0.198

Note: Standard errors are reported right to the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^2.

The first column of the Table 3.19 shows the OLS results for the ISE 100 Return for month of the year. June has the lowest mean return and it is excluded in the estimations for both OLS and GARCH in order to avoid dummy trap. Thus, estimates coefficients are interpreted by comparing the one of June. As expected, January has the highest estimated coefficient and November has the second highest estimated coefficient. Both of these coefficients are statistically significant at 5% level and only these two months have significant coefficients. Also, September has the lowest estimated coefficient. The second column shows the GARCH results. January has the highest estimated coefficient and it statistically significant at 1% level. Then November comes and it is also significant at 1% level. March and September has the two lowest estimated coefficients and they are both insignificant.

The OLS results of the ISE Service Return Index are shown in the first column of the Table 3.20. As anticipated, January has the highest estimated coefficient and it is statistically significant at 1% level. The second highest estimated coefficient belongs to November and this coefficient statistically significant at 5 % level. None of the coefficients of other months are statistically significantly different than the one of February that is excluded dummy variable. Lastly, September has the lowest estimated coefficient. The second column presents the GARCH results. However, they are all insignificant.

The first column of the Table 3.21 presents the OLS results for the ISE Financial Return Index for month of the year. January and November has the two highest estimated coefficients respectively. The coefficient of January is statistically significant at 1% level and of November is at 5% level. The coefficients of all other months are insignificant and so they are not statistically different than the one of June skipped dummy variable in the estimations. As expected, the lowest estimated coefficient belongs to September. The GARCH results are showed in the second column. January has the highest estimated coefficient and it is statistically significant at 1% level. Then, November and July comes in the order and they are also both statistically significant at 1% level. The other statistically different coefficients belong to February and October and they are significant at 5% level.

The OLS results for the ISE Industry Return Index for month of the year are presented in the first column of the Table 3.22. January has the highest estimated coefficient and it is statistically significantly different at 5% level than the one of June that is the omitted dummy variable. The coefficients of all other months are statistically insignificant. Lastly, September has the lowest coefficient as expected. The second column shows the GARCH results. However, the estimated coefficients of months are insignificant.

3.4 International Evidence

Including Cross (1973), French (1980), and Keim and Stambaugh (1984), numerous studies documented that the average return in the US is significantly negative on Mondays and abnormally large on Fridays. Jaffe and Westerfield (1985) find the similar result for Canada and the UK. In contrast, it is found in the same study that Tuesday returns are more negative than Monday returns for Australia and Japan. There are mixed results for European countries. Tuesday has the lowest and Wednesday has the highest mean return for France and Monday has the lowest and Wednesday has the highest mean return for Denmark according to Agrawal and Tandon (1994). It is reported in the same study that highest average return belongs to Friday and lowest average return belongs to Tuesday for stock markets of Belgium and the Netherlands. Similar to US, German and Italian stock markets have highest mean return on Friday and lowest mean return on Monday.

On the other hand in the developing countries, Monday has the lowest and Wednesday has the highest mean return for Brazil and Monday has the lowest and Friday has the highest mean return for Mexico and Singapore according to Agrawal and Tandon (1994). Tonchev and Kim (2004) found that return on Wednesday is significantly lower than on Monday in Slovenia and there is no day of the week effect in the Czech Republic and Slovakia. Friday has the highest mean return in stock markets of China according to Gao and Kling (2005). Lean *et al.* (2007) presents that day of the week effect exists in stock markets of Malaysia, Hong Kong and Taiwan.

With the highest mean return in Friday and lowest mean return in Monday, Turkey's stock market shows similar pattern with the US, Canada, the UK, Germany and Italy among developed countries and Mexico and Singapore among developing countries.

For the month of the year effect, Rozeff and Kinney (1976) found that January returns are significantly higher than the returns during the rest of the year using New York Stock Exchange (NYSE) prices for the period 1904-1974. Gultekin and Gultekin (1983) found that January seasonality in Toronto Stock Exchange, July seasonality in Australia and April seasonality in the U.K. Corhay *et al.* (1987) found that monthly return seasonality is not statistically significant in French and Belgian stock markets.

In the developing countries, Nassir and Mohammed (1987) detected that the January returns were higher than the returns in the other months for the period 1970-1986 for Malaysia. In the Hong Kong stock market, there is return seasonality in the months of

January, April and December according to Pang (1988). Ho (1990) found that January seasonality in Korea, Philippines, Singapore and Taiwan. Fountas and Segredakis (2002) found that January seasonality in Chile, December seasonality in Colombia, May seasonality in Mexico, August seasonality in India and no seasonality in Venezuela in which monthly returns do not differ significantly over the year. For China, Gao and Kling (2005) found that April returns were higher than the returns of the rest of the year.

Turkey has an analogous pattern with the US and Canada among developed countries and Malaysia, Korea, the Philippines, Singapore, Chile and Taiwan among developing countries with the January seasonality effect.

3.5 Conclusion

The presence of calendar effects in stock market returns is widely investigated by many authors in the literature. There are papers that claim there are seasonalities such as January effect or the-day-of-the-week effect in stock market returns. In contrast, some papers argue that these effects tend to disappear after they became known to the public. I investigate the presence of calendar anomalies in the Turkish Istanbul Stock Exchange (ISE), an emerging stock market, in this paper.

Not only the ISE 100 Return Index but also the ISE Service, ISE Finance and ISE Industry Return Indices are examined in order to gain knowledge about similarities and differences in different indices. OLS and Generalized Autoregressive Conditional Heteroskedastic Models (GARCH) estimations are employed in this paper. Similar results are obtained for these four indices with a few exceptions. First, Monday has the lowest mean return in all indices and Friday has the highest mean return in all indices except the Finance Index where Thursday has the highest return. Second, the stock returns, on average, are abnormally low on 7^{th} and 11^{th} days of the month and abnormally high on 31^{st} and 2^{nd} days of the month. Third, the lowest average return belongs to June in all indices except the ISE Service Index in which September has the lowest mean return. The January's stock returns are the highest in all indices.

As a result of estimations, it can be said that the calendar anomalies are still present at the Istanbul Stock Exchange. Thus, it may be profitable for investors to adjust their portfolios by these calendar anomalies. Further research can be constructed to test profitable of this trading strategy. Moreover, finding the possible reasons for these calendar effects is an important topic for further research.

3.6 Figures and Tables

Table 3.4: ISE Service Return Index for day of the week

	All	Mon	Tue	Wed	Thu	Fri
Observation	2916	569	589	589	583	586
Mean	0.143	-0.173	-0.054	0.087	0.354	0.497
Std. Dev.	2.698	3.011	2.649	2.632	2.673	2.454
Skewness	0.001	0.0001	0.001	0.001	0.001	0.001
Kurtosis	0.236	0.122	0.954	-0.495	0.030	0.908

Table 3.5: ISE Finance Return Index for day of the week

	All	Mon	Tue	Wed	Thu	Fri
Observation	2916	569	589	589	583	586
Mean	0.169	-0.173	0.025	0.078	0.464	0.445
Std. Dev.	3.164	3.485	3.031	3.149	3.17	2.928
Skewness	0.264	0.249	0.526	-0.314	0.272	0.832
Kurtosis	6.895	6.206	7.087	7.868	5.161	8.525

Table 3.6: ISE Industry Return Index for day of the week

	All	Mon	Tue	Wed	Thu	Fri
Observation	2916	569	589	589	583	586
Mean	0.144	-0.246	-0.002	0.063	0.401	0.495
Std. Dev.	2.539	2.783	2.398	2.52	2.599	2.312
Skewness	0.066	-0.589	0.808	-0.152	-0.016	0.913
Kurtosis	9.377	7.291	12.897	11.518	6.935	9.268

Table 3.8: ISE Service Return Statistics with OLS and GARCH for day of the week

	OLS	GARCH (1,1)
R_{t-1}	9.874 (18.535)	8.354 (18.771)
C_{tue}	1.176 (1.581)	-0.114 (1.116)
C_{wed}	2.576 (1.582)	1.454 (1.102)
C_{thu}	5.229** (1.588)	2.540* (1.073)
C_{fri}	6.7261** (1.582)	4.438** (1.117)
Constant	-1.733 (1.127)	-0.139 (0.7405)
V_a		100.691** (7.803)
V_g		895.914** (7.327)
V_{cons}		0.006** (0.001)

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^3.

Table 3.9: ISE Finance Return Statistics with OLS and GARCH for day of the week

	OLS	**GARCH (1,1)**
R_{t-1}	15.250 (18.535)	35.650 (20.008)
C_{tue}	1.984 (1.856)	0.387 (1.440)
C_{wed}	2.454 (1.858)	1.251 (1.336)
C_{thu}	6.325** (1.863)	3.320* (1.327)
C_{fri}	6.211** (1.863)	3.288* (1.454)
Constant	-1.737 (1.324)	0.161 (0.935)
V_a		146.602** (11.382)
V_g		837.057** (11.262)
V_{cons}		0.027** (0.004)

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^3.

Table 3.10: ISE Industry Return Statistics with OLS and GARCH for day of the week

	OLS	GARCH (1,1)
R_{t-1}	-6.045 (18.526)	30.914 (19.506)
C_{tue}	2.446 (1.486)	0.181 (1.075)
C_{wed}	3.119* (1.487)	2.259* (0.991)
C_{thu}	6.519** (1.493)	3.319** (0.987)
C_{fri}	7.405** (1.488)	3.934** (1.012)
Constant	-2.463* (1.059)	-0.513 (0.668)
V_a		208.781** (14.882)
V_g		770.099** (14.268)
V_{cons}		0.023** (0.003)

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^3.

Table 3.13: ISE Service Return Statistics with OLS and GARCH for day of the month

	OLS	**Std. errs.**	**GARCH(1,1)**	**Std. errs.**
R_{t-1}	9.262	18.643	3.449	19.283
C_1	8.718*	3.931	5.608	2.993
C_2	10.267**	3.932	6.765*	3.125
C_3	2.460	3.823	2.149	3.209
C_4	7.744*	3.832	5.371*	2.748
C_5	6.672	3.813	3.250	2.872
C_6	6.799	3.804	1.820	2.621
C_7	1.007	3.794	1.272	2.910
C_8	4.210	3.803	2.015	2.632
C_9	1.834	3.824	0.315	2.991
C_{10}	1.752	3.823	0.006	3.030
C_{11}	0.641	3.823	1.377	2.962
C_{12}	2.671	3.834	1.406	2.923
C_{13}	1.362	3.823	-0.169	2.996
C_{14}	6.737	3.777	3.033	2.673
C_{15}	2.970	3.814	3.610	2.836
C_{16}	5.053	3.813	2.554	2.785
C_{17}	2.275	3.813	2.411	2.676
C_{18}	8.096*	3.813	3.546	2.929
C_{19}	5.658	3.896	3.144	2.673
C_{20}	6.364	3.919	2.901	2.811
C_{21}	1.935	3.823	2.475	2.888
C_{22}	3.692	3.832	0.151	2.783
C_{23}	9.965**	3.908	3.975	2.889
C_{24}	4.312	3.885	3.035	2.935
C_{25}	7.081	3.832	3.063	2.947
C_{26}	8.937*	3.854	4.058	3.001
C_{27}	2.979	3.803	0.707	2.792
C_{29}	6.170	4.007	5.046	3.241
C_{30}	8.073*	4.125	5.038	2.855
C_{31}	11.640**	4.662	11.902**	3.621
Constant	-3.480	2.683	-1.338	-1.338
V_a			99.897**	8.179
V_g			897.233**	7.604
V_{cons}			0.006**	0.001

Note: Standard errors are reported right to the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^3.

Table 3.14: ISE Financial and Industry Return Index for day of the month

		Financial		Industry	
	Observation	Mean	Std. errs.	Mean	Std. errs.
All	2916	0.170	3.164	0.144	2.539
1	88	0.464	2.892	0.331	2.367
2	88	0.846	2.348	0.539	1.881
3	98	0.151	2.807	-0.002	2.176
4	97	0.797	3.586	0.498	2.959
5	99	0.107	3.624	0.297	3.064
6	100	0.202	3.574	0.463	2.658
7	101	-0.331	2.957	-0.427	2.266
8	100	-0.202	2.656	-0.030	2.016
9	98	0.298	2.805	0.171	2.266
10	98	0.013	2.895	0.039	2.200
11	98	-0.523	3.212	-0.368	2.550
12	97	0.019	3.244	0.038	3.378
13	98	-0.217	3.289	-0.287	2.964
14	103	0.286	3.063	0.377	2.555
15	100	0.234	2.708	-0.002	2.313
16	99	0.502	3.253	0.381	2.523
17	99	-0.483	3.910	-0.336	2.910
18	99	0.726	3.220	0.456	2.774
19	91	0.397	3.769	0.179	2.972
20	89	0.321	2.897	0.304	2.162
21	98	-0.458	3.200	-0.068	2.572
22	97	0.303	3.029	0.202	2.425
23	90	0.474	3.251	0.448	2.575
24	92	0.223	3.565	0.156	2.838
25	97	0.255	2.899	0.393	2.210
26	95	0.155	3.178	0.276	2.105
27	100	0.359	4.017	0.143	3.002
28	101	-0.324	2.786	-0.397	2.397
29	82	0.105	2.177	0.091	1.597
30	74	0.304	3.212	0.283	2.606
31	50	0.753	2.655	0.797	1.908

Table 3.15: ISE Financial Return with OLS and GARCH for day of the month

	OLS	**Std. errs.**	**GARCH(1,1)**	**Std. errs.**
R_{t-1}	15.751	18.616	31.534	20.824
C_1	9.744*	4.644	7.132*	3.541
C_2	13.679**	4.641	8.222*	3.976
C_3	6.597	4.518	2.789	3.965
C_4	13.141**	4.527	5.996	3.603
C_5	6.283	4.503	3.165	3.724
C_6	7.304	4.493	2.033	3.462
C_7	1.957	4.481	0.050	3.659
C_8	3.194	4.492	-1.987	3.433
C_9	8.207	4.515	3.719	3.666
C_{10}	5.393	4.515	0.439	4.024
C_{12}	5.476	4.527	1.446	3.757
C_{13}	2.970	4.516	-0.798	3.686
C_{14}	8.129	4.460	1.891	3.540
C_{15}	7.594	4.503	5.792	3.763
C_{16}	10.236*	4.503	5.457	3.588
C_{17}	0.269	4.506	-0.172	3.447
C_{18}	12.493**	4.503	4.576	3.741
C_{19}	9.135*	4.601	6.220	3.520
C_{20}	8.418	4.628	2.874	3.706
C_{21}	0.596	4.515	0.494	3.852
C_{22}	8.243	4.527	3.391	3.606
C_{23}	9.945*	4.614	4.919	3.276
C_{24}	7.383	4.589	3.535	3.621
C_{25}	7.792	4.527	2.833	3.882
C_{26}	6.737	4.551	0.034	3.799
C_{27}	8.847*	4.492	3.237	3.562
C_{28}	2.007	4.481	0.585	3.858
C_{29}	6.225	4.730	3.586	4.675
C_{30}	8.202	4.868	4.133	3.444
C_{31}	12.598*	5.496	10.378*	4.720
Constant	-5.231	3.192	-1.162	2.744
V_a			145.428**	12.035
V_g			839.595**	12.142
V_{cons}			0.025**	0.004

Note: Standard errors are reported right to the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^3.

Table 3.16: ISE Industry Return with OLS and GARCH for day of the month

	OLS	**Std. errs.**	**GARCH(1,1)**	**Std. errs.**
R_{t-1}	-3.893	18.627	29.798	19.950
C_1	7.594*	3.700	6.023*	2.486
C_2	9.664**	3.699	5.724*	2.536
C_3	4.272	3.598	2.701	2.652
C_4	9.264**	3.607	4.514	2.519
C_5	7.255*	3.588	4.198	2.769
C_6	8.878*	3.579	4.311	2.565
C_8	3.976	3.578	2.044	2.580
C_9	5.979	3.597	2.087	2.621
C_{10}	4.653	3.597	2.746	2.680
C_{11}	0.600	3.597	1.753	2.690
C_{12}	4.631	3.607	3.794	2.661
C_{13}	1.426	3.598	-0.162	2.508
C_{14}	8.026*	3.552	2.708	2.356
C_{15}	4.265	3.587	3.665	2.542
C_{16}	8.088*	3.587	4.441	2.430
C_{17}	0.934	3.589	-1.668	2.163
C_{18}	8.825*	3.587	4.490	2.473
C_{19}	6.078	3.667	7.075*	2.322
C_{20}	7.327*	3.688	3.539	2.531
C_{21}	3.594	3.597	4.308	2.567
C_{22}	6.296	3.606	1.477	2.389
C_{23}	8.762*	3.677	5.840*	2.456
C_{24}	5.851	3.657	3.084	2.627
C_{25}	8.206*	3.606	1.795	2.315
C_{26}	7.038	3.625	3.039	2.732
C_{27}	5.690	3.578	2.319	2.461
C_{28}	0.304	3.569	1.963	2.570
C_{29}	5.189	3.771	3.237	3.420
C_{30}	7.118	3.882	3.637	2.642
C_{31}	12.258**	4.387	11.192**	3.561
Constant	-4.270	2.524	-1.858	1.728
V_a			211.611**	15.674
V_g			770.698**	14.861
V_{cons}			0.022**	0.003

Note: Standard errors are reported right to the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^3.

Table 3.18: ISE Financial and Industry Return Index for month of the year

		Financial		Industry	
	Observation	**Mean**	**Std. errs.**	**Mean**	**Std. errs.**
All	144	3.369	13.658	2.793	11.786
Jan	12	8.861	15.041	7.482	15.726
Feb	12	2.428	14.764	0.611	11.673
Mar	12	0.053	11.928	2.534	10.190
Apr	12	5.769	8.092	6.137	8.321
May	12	2.029	11.834	3.193	10.024
Jun	12	-3.461	9.203	-1.468	6.819
Jul	12	2.836	10.711	3.058	8.188
Aug	12	0.768	9.697	1.574	7.695
Sep	12	-0.699	14.081	-0.401	14.518
Oct	12	4.408	17.055	2.019	12.359
Nov	12	10.756	17.705	4.894	12.880
Dec	12	6.685	18.261	3.885	19.119

Table 3.20: ISE Service Return with OLS and GARCH for month of the year

	OLS		GARCH(1,1)	
	Coef.	**Std. errs.**	**Coef.**	**Std. errs.**
R_{t-1}	28.090**	8.476	12.577	11.521
C_{jan}	13.780**	4.677	1.664	2.428
C_{mar}	2.750	4.561	-3.533	2.719
C_{apr}	5.218	4.558	-1.371	2.556
C_{may}	3.959	4.562	-4.468	2.636
C_{jun}	0.994	4.558	-3.341	2.745
C_{jul}	3.890	4.561	-0.377	3.373
C_{aug}	2.088	4.562	-2.052	2.887
C_{sep}	-0.304	4.577	0.725	2.902
C_{oct}	6.304	4.592	1.397	2.548
C_{nov}	8.978*	4.571	2.142	2.950
C_{dec}	4.926	4.616	0.216	3.353
Constant	-2.287	3.225	3.093	1.506
V_a			18.262*	7.525
V_g			84.865*	5.524
V_{cons}			0.001	0.013

Note: Standard errors are reported right to the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^2.

Table 3.21: ISE Financial Return with OLS and GARCH for month of the year

	OLS		GARCH(1,1)	
	Coef.	**Std. errs.**	**Coef.**	**Std. errs.**
R_{t-1}	31.582**	8.462	28.701**	10.875
C_{jan}	14.110**	5.433	13.350**	3.567
C_{feb}	6.769	5.314	9.540*	3.887
C_{mar}	2.589	5.314	2.187	3.744
C_{apr}	9.486	5.309	7.063	5.147
C_{may}	7.480	5.335	3.064	3.892
C_{jul}	6.951	5.311	10.265**	3.960
C_{aug}	5.346	5.317	6.104	7.024
C_{sep}	2.265	5.310	5.162	4.343
C_{oct}	5.368	5.351	9.040*	3.633
C_{nov}	13.002*	5.318	10.711**	4.023
C_{dec}	8.244	5.333	8.369	4.853
Constant	-4.357	3.761	-4.725	2.737
V_a	0.000	0.000	14.108*	6.635
V_g			84.338**	5.569
V_{cons}			0.021	0.026

Note: Standard errors are reported right to the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^2.

Table 3.22: ISE Industry Return with OLS and GARCH for month of the year

	OLS		GARCH(1,1)	
	Coef.	**Std. errs.**	**Coef.**	**Std. errs.**
R_{t-1}	31.197**	8.462	9.872	11.512
C_{jan}	10.783*	4.810	1.809	4.409
C_{feb}	2.243	4.690	3.456	4.040
C_{mar}	3.041	4.697	1.865	4.259
C_{apr}	7.563	4.689	4.366	4.304
C_{may}	6.073	4.705	3.538	5.245
C_{jul}	4.989	4.691	2.691	4.139
C_{aug}	4.121	4.699	3.484	7.753
C_{sep}	1.391	4.690	0.961	4.136
C_{oct}	2.914	4.692	2.947	4.217
C_{nov}	6.104	4.690	5.566	4.030
C_{dec}	3.973	4.704	4.092	4.317
Constant	-2.422	3.326	-0.279	3.427

V_a	65.716**	19.149
V_g	-7.001	18.271
V_{cons}	0.715**	0.231

Note: Standard errors are reported right to the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^2.

Figure 3.1: The Time Series Graph for R_t of ISE 100 by Day

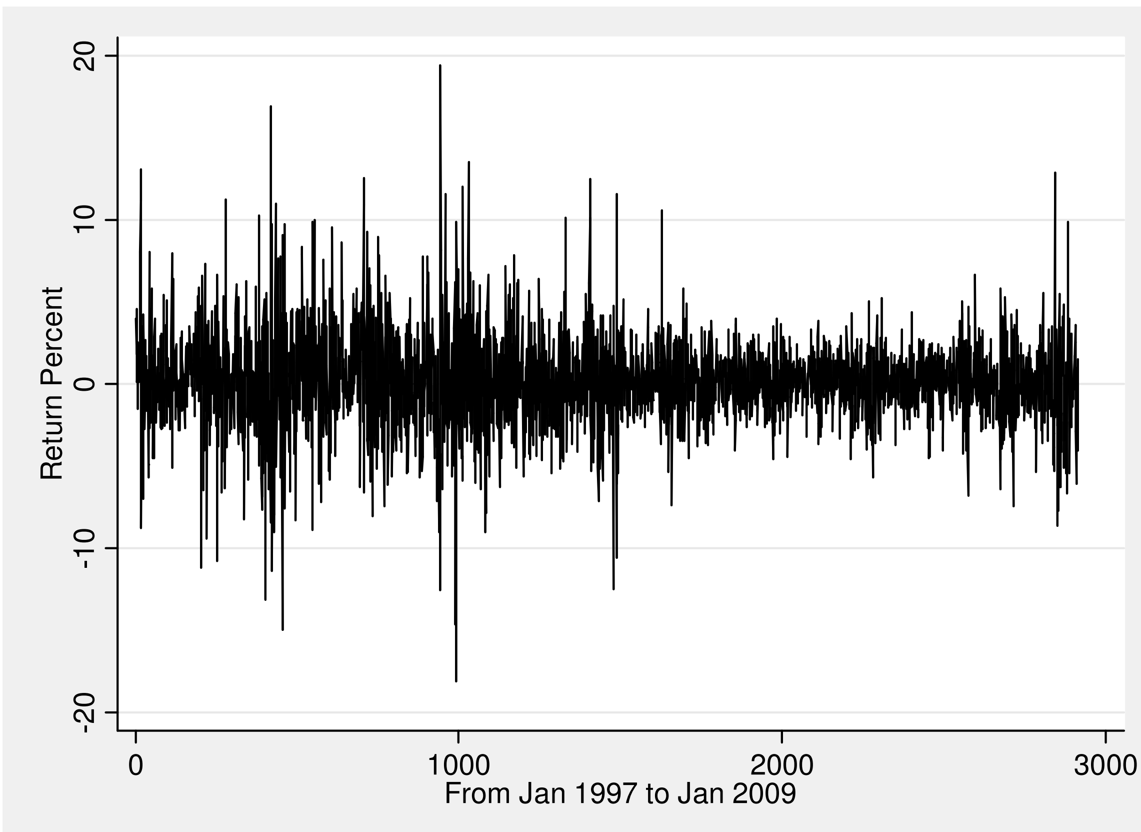


Figure 3.2: Autocorrelation Function of ISE 100 Return Index by day

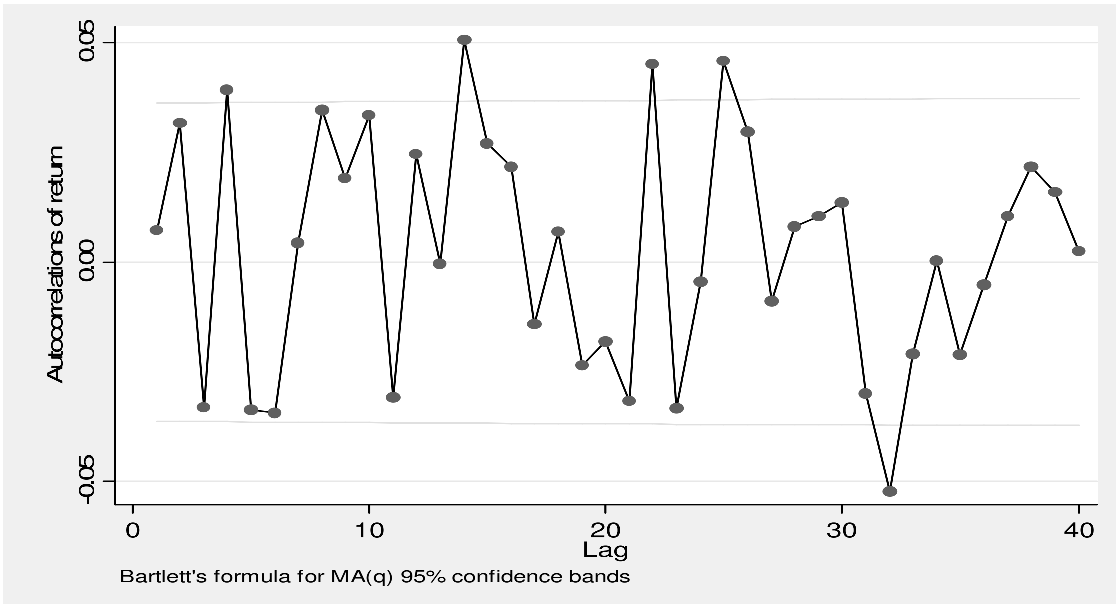


Figure 3.3: Autocorrelation Function of ISE 100 Return Index by month

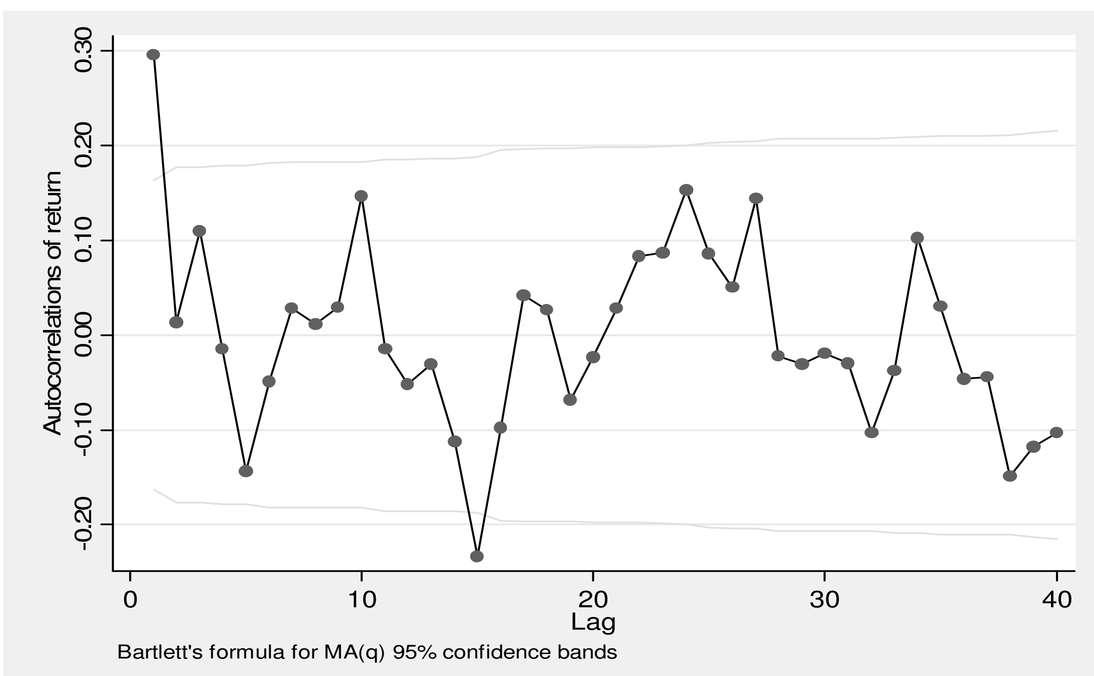


Table 3.23: Ljung-Box test for the normalized residuals for ISE 100 GARCH by day

Lags	Autocorrelation	Partial correlation	LB
1	0.012	0.012	0.424
3	-0.018	-0.018	1.413
5	0.022	0.021	3.187
8	-0.029	-0.028	7.225
10	-0.019	-0.019	11.421
13	0.006	0.007	17.312
16	-0.015	-0.016	19.040
20	-0.022	-0.026	26.646

Table 3.24: ARCH-LM test results for ISE 100 GARCH by day

Constant	Squared residuals	LM-statistics	F-statistics
0. 988 (0.000)	0.012 (0.515)	0.013 (0.910)	0.420 (0.515)

Note: The numbers in the parentheses are p-values

Table 3.25: Ljung-Box test for the normalized residuals for ISE 100 GARCH by day of the month

Lags	Autocorrelation	Partial correlation	LB
1	0.010	0.010	0.274
3	-0.017	-0.017	1.127
5	0.025	0.025	3.646
8	-0.029	-0.028	7.842
10	-0.018	-0.018	11.556
13	0.004	0.005	17.806
16	-0.012	-0.012	19.229
20	-0.024	-0.028	26.745

Table 3.26: ARCH-LM test results for ISE 100 GARCH by day of the month

Constant	Squared residuals	LM-statistics	F-statistics
0. 990 (0.000)	0.010 (0.601)	0.022 (0.882)	0.270 (0.601)

Note: The numbers in the parentheses are p-values

Table 3.27: Ljung-Box test for the normalized residuals for ISE 100 GARCH by day of the month

Lags	Autocorrelation	Partial correlation	LB
1	-0.052	-0.059	0.389
3	-0.081	-0.081	1.666
5	0.093	0.120	3.016
8	0.099	0.149	5.252
10	-0.033	-0.056	8.508
13	-0.063	-0.146	12.661
16	0.235	0.245	22.727
20	0.114	0.058	28.199

Table 3.28: ARCH-LM test results for ISE 100 GARCH by day of the month

Constant	Squared residuals	LM-statistics	F-statistics
1.062 (0.000)	-0.059 (0.514)	0.035 (0.774)	0.430 (0.514)

Note: The numbers in the parentheses are p-values

Table 3.29: ISE 100 Return with GARCH-M, EGARCH and IGARCH for day of the week

	GARCH-M	EGARCH	IGARCH
R_{t-1}	22.891 (19.275)	31.025 (18.616)	23.625 (19.543)
C_{tue}	0.145 (1.227)	0.585 (1.185)	0.217 (1.204)
C_{wed}	1.352 (1.183)	1.125 (1.153)	14.132 (1.174)
C_{thu}	3.138** (1.146)	3.100** (1.131)	3.214** (1.138)
C_{fri}	3.213** (1.235)	3.718** (1.230)	3.294** (1.218)
Constant	0.792 (0.929)	1.118 (0.801)	0.079 (0.788)
V_a	127.886** (10.090)	61.256** (10.887)	130.500** (9.351)

V_g	865.071** (9.794)	978.937** (4.050)	869.500* (9.352)
V_{cons}	0.012** (0.002)	-146.066** (29.594)	0.010** (0.002)
Theta	-1488.296 (943.434)		
Tau		245.665** (17.519)	

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^3.
Equation for GARCH-M (1,1) $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 DAX_t + \theta h_t + \varepsilon_t$
Equation for EGARCH (1,1) $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \tau D_{t-1} \varepsilon_{t-1}^2 + \gamma D_F$, where $D_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, $D_{t-1} = 0$ otherwise.

Table 3.30: ISE 100 Return with GARCH-M, EGARCH and IGARCH for day of the month

	GARCH-M	EGARCH	IGARCH
R_{t-1}	18.642 (19.756)	19.721 (19.178)	18.926 (20.137)
C_1	5.512 (3.057)	5.051 (3.004)	5.597 (3.025)
C_2	5.975 (3.461)	5.950 (3.272)	6.086 (3.427)
C_3	2.1060 (3.574)	1.628 (3.313)	2.280 (3.537)
C_4	5.632 (3.161)	5.722 (3.075)	5.772 (3.157)
C_5	3.072 (3.303)	2.705 (3.175)	3.211 (3.293)
C_6	2.617 (3.056)	2.181 (2.975)	2.590 (3.053)
C_7	-0.350 (3.171)	-0.520 (3.034)	-0.367 (3.134)
C_8	-0.602 (3.035)	-0.454 (2.918)	-0.5672 (2.999)
C_9	1.716 (3.209)	1.271 (2.921)	1.723 (3.173)
C_{10}	0.720 (3.501)	0.103 (3.305)	0.584 (3.173)
C_{12}	0.996 (3.286)	1.414 (3.076)	1.0123 (3.247)

C_{13}	0.566 (3.288)	0.806 (3.203)	0.664 (3.277)
C_{14}	1.843 (3.082)	1.548 (2.968)	1.902 (3.057)
C_{15}	4.289 (3.332)	3.541 (3.245)	4.355 (3.323)
C_{16}	4.785 (3.193)	3.808 (3.0495)	4.801 (3.193)
C_{17}	0.507 (2.969)	0.123 (2.837)	0.508 (2.960)
C_{18}	3.762 (3.210)	3.848 (2.976)	3.911 (0.0031956)
C_{19}	5.111 (3.034)	4.380 (2.911)	5.206 (3.025)
C_{20}	2.472 (3.214)	1.523 (3.148)	2.573 (3.212)
C_{21}	2.408 (3.394)	1.552 (3.202)	2.428 (3.387)
C_{22}	0.890 (3.2267)	1.559 (3.216)	1.024 (3.210)
C_{23}	6.044 (3.1477)	6.226* (3.081)	6.052 (3.139)
C_{24}	3.405 (3.271)	2.563 (3.261)	3.349 (3.264)
C_{25}	3.275 (3.300)	2.127 (3.151)	3.347 (3.286)
C_{26}	0.915 (3.397)	0.855 (3.289)	0.887 (3.393)
C_{27}	1.720 (3.109)	1.558 (3.002)	1.781 (3.102)
C_{28}	1.225 (3.407)	1.649 (3.307)	1.378 (3.393)
C_{29}	3.780 (4.020)	3.499 (3.761)	3.095 (4.011)
C_{30}	2.642 (3.151)	2.106 (2.998)	2.771 (3.133)
C_{31}	10.987** (4.172)	10.110** (3.986)	11.241** (4.177)
Constant	-0.403 (2.506)	-0.119 (2.321)	-1.088 (2.432)
V_a	124.522** (10.331)	63.353** (11.062)	126.900** (9.585)

V_g	869.414** (9.993)	979.819** (4.259)	873.100** (9.595)
V_{cons}	0.011** (0.002)	-140.066** (30.956)	0.009** (0.002)
Theta	-1386.229 (959.001)		
Tau		241.067** (18.074)	

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^3.
Equation for GARCH-M (1,1) $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 DAX_t + \theta h_t + \varepsilon_t$
Equation for EGARCH (1,1) $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \tau D_{t-1} \varepsilon_{t-1}^2 + \gamma D_F$, where $D_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, $D_{t-1} = 0$ otherwise.

Table 3.31: ISE 100 Return with GARCH-M, EGARCH and IGARCH for month of the year

	GARCH-M	EGARCH	IGARCH
R_{t-1}	24.067* (12.162)	32.250** (5.904)	25.321* (10.722)
C_{jan}	11.031** (4.031)	10.386** (3.899)	10.433** (3.204)
C_{feb}	9.271** (3.486)	8.087* (3.469)	8.525* (3.486)
C_{mar}	4.645 (4.058)	3.901 (4.419)	2.881 (3.367)
C_{apr}	10.369* (4.381)	9.628* (4.252)	8.942 (4.210)
C_{may}	8.113* (3.858)	6.399 (4.263)	6.881 (3.321)
C_{jul}	8.071* (3.724)	6.674 (4.081)	7.353* (3.112)
C_{aug}	8.290 (5.961)	6.037 (4.149)	5.042 (5.723)
C_{sep}	7.095 (4.190)	5.476 (3.959)	7.543 (4.175)
C_{oct}	9.962* (3.965)	9.290* (3.366)	9.072* (3.176)
C_{nov}	11.553** (3.673)	10.865** (3.840)	10.731** (3.491)
C_{dec}	10.498* (5.154)	9.825* (3.979)	9.729* (3.991)

Constant	-6.223* (3.159)	-3.271 (2.675)	-2.224 (2.132)
V_a	58.509** (18.320)	48.535** (4.955)	15.000* (6.071)
V_g	22.724 (19.495)	26.149** (3.366)	85.000** (6.273)
V_{cons}	0.403 (0.206)	0.215 (0.202)	0.166 (0.132)
Theta	30.405 (133.912)		
Tau		28.120* (12.629)	

Note: Standard errors are reported under the coefficients, ** and * indicate the level of significance at the 1% and 5% level, respectively. Coefficients are multiplied by 10^2.

Equation for GARCH-M (1,1) $R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 DAX_t + \theta h_t + \varepsilon_t$

Equation for EGARCH (1,1) $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \tau D_{t-1} \varepsilon_{t-1}^2 + \gamma D_F$, where $D_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, $D_{t-1} = 0$ otherwise.

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