THREE ESSAYS ON THE BEHAVIOR OF EQUITY MARKET RETURNS

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To my family for their constant and unconditional support

ABSTRACT

The first chapter of this thesis analyzes return comovements phenomena known as correlation asymmetry. The phenomena has its two manifests: asymmetric correlations, referring to stock return correlations being higher during downside movements than during upside movements, and counter-cyclical correlations, referring to correlations being higher during recessions than during boom periods. We show that, unlike the asymmetric correlations, the counter-cyclical correlations are driven by the counter-cyclical market volatility. This finding has important implications for understanding the correlation risk as well as modeling correlation asymmetry.

The next two chapters investigate the turn-of-the-month (ToM) effect, a pattern of high returns around month-ends: the second chapter examines the presence of the effect in the G7 equity markets, while the last chapter focuses on the ToM effect in the Turkish market. We show that the ToM effect is statistically and economically significant in all G7 equity markets over 1998–2015, and in the Turkish equity market over 1988–2015. The effect is stronger following months with (a) significant information inflow and (b) above average market return. We find that the effect strengthens in the U.S. and Canada and weakens in the U.K, Germany, France, Italy, and Japan in the latter half of the sample. The effect also gains importance in the Turkish equity market over the later subsamples. Estimating an e-GARCH model with daily index returns, we link the ToM effect to a decline in expected volatility in the days leading up to month-turns. These findings provide support for the information-risk hypothesis wherein the resolution of uncertainty towards reporting deadlines leads to a reduction in expected risk premiums, sending equity valuations up.

ÖZET

Bu tezin ilk bölümünde finansal getirilerin eş hareketliliklerinde (comovement) gözlemlenen ve korelasyon asimetrisi olarak bilinen olgu incelenmektedir. Bu olgu iki şekilde karşımıza çıkmaktadır: İlki, finansal piyasaların aşağı yönlü hareketlerinde (ayı piyasaları) gözlemlenen korelasyonun yukarı yönlü hareketler boyunca olana göre daha yüksek olması iken ikincisi ise ekonomik durgunluk dönemlerindeki korelasyonların ekonominin büyüdüğü dönemlere göre daha yüksek olmasıdır. Bu çalışmada, benzer olarak düşünülebilecek bu iki olgunun sebeplerinin ve sonuçlarının önemli derecede farklı oldukları gösterilmektedir. İş çevrimleri üzerinden incelenen ve ekonomik durgunluk dönemlerinde gözlemlenen yüksek korelasyon tamamen yüksek oynaklığın bir sonucudur. Ayı piyasalarında gözlemlenen korelasyonun boğa piyasalarındakinden yüksek olması ise oynaklık ile açıklanamamaktadır. Bu iki olgunun refah etkileri karşılaştırıldığında ise boğa ve ayı piyasalarında gözlemlenen korelasyonlar farklılıklarının olumsuz etkilerinin daha kuvvetli olduğu gösterilmektedir.

Tezin son iki bölümü ay sonlarında gözlemlenen yüksek getiriler olarak tanımlanan ay dönümü etkisini konu alır: ikinci bölüm G7 ülke piyasalarında ay dönümü etkisini incelerken, son bölüm Türkiye hisse senedi piyasasına odaklanır. Bu bölümlerdeki analizler, ay dönümü etkisinin 1998–2015 yılları arasında G7 hisse senedi piyasalarında ve 1988–2015 yılları arasında Türkiye hisse senedi piyasasında istatistiksel ve ekonomik açıdan önemli olduğunu göstermektedir. Bu etki (a) önemli miktarda bilgi girişi ve (b) ortalamanın üzerinde piyasa getirisi olan aylarda daha güçlüdür. Etkinin, örneklemin ikinci yarısında ABD ve Kanada'da güçlendiği, İngiltere, Almanya, Fransa, İtalya ve Japonya'da zayıfladığı, Türkiye'de ise alt-örneklem güncelleştikçe önem kazandığı tespit edilmiştir. Son olarak, günlük endeks getirileri ile bir e-GARCH modeli tahmin edilerek, ay dönümü etkisi bu periyodun etrafındaki günlerde getiri oynaklık beklentilerinin gerilemesi ile ilişkilendirildi. Bu bulgular, piyasadaki belirsizliğin mali raporlama tarihleri etrafında çözümlenerek daha düşük risk primleri ve yüksek hisse senedi değerlemelerine yol açtığı bilgi riski hipotezini desteklemektedir.

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Table of Contents

List of Tables

List of Figures

Chapter I

CORRELATION ASYMMETRY: THE ROLE OF VOLATILITY†

1.1 Introduction

Time variation of correlations in financial markets has drawn considerable attention in the literature. One common pattern found is the heightened correlations during "bad" times, namely the *correlation asymmetry*. However, two different phenomena are associated with the same pattern. Regarding the first empirical regularity, "bad" times are defined with respect to realized returns: when realized returns are relatively low, correlations are relatively high. The second type, however, pertains to the correlations over the business cycles: correlations during recessions are higher relative to correlations during booms. Because both periods of low realized returns and recessions can be considered as "bad" times, one might think that these two empirical regularities are different manifestations of a common phenomenon. Erb, Harvey, and Viskanta (1994), for example, make separate references to the two types of time-variation in correlations when studying the pairwise correlations of international equity returns. They show that the international equity correlations are higher during joint downside movements of realized returns (bear market) compared to joint upside movements (bull market). They also study the correlations of international equity returns over the business cycles and show that correlations are counter-cyclical, meaning that the latter

†This chapter is a result of my work with my thesis advisor S. Mehmet Özsoy.

are higher during recessions than during booms. To distinguish the two types of correlation asymmetry, we label the first one as "asymmetric correlations" and the second one as "counter-cyclical" correlations. This chapter shows that both the causes and consequences of these two types of correlation asymmetry differ significantly. While higher correlations during recessions are driven by heightened market volatility, that is not the case for higher correlations during bear markets. When the welfare implications of the two type of correlation asymmetry is compared we find the impact of asymmetric correlations on welfare to be stronger than that of counter-cyclical correlations.

As it is known in the literature, high correlations can be a byproduct of high volatility.[2] Even if the unconditional correlations are constant, conditioning on high volatility time periods can create spuriously high correlations. For instance, a simple model of asset returns, such as the bivariate normal distribution with a constant correlation, would generate relatively high correlations for periods of high volatility. Boyer, Gibson, and Loretan (1999), among others, derive this result in a closed form for the case of the bivariate normal distribution. Therefore, one needs to be careful while comparing the correlations estimates from different subsamples of data. This implies that we observe higher correlations during periods of high volatility than periods of low volatility by construction. In other words, splitting the sample into subsamples induces a conditioning bias in the correlation estimates.

In this study we claim that asymmetric and counter-cyclical correlations are different in nature. We show that, unlike the asymmetric correlations, the

[2] For a detailed discussion, please see Boyer, Gibson, and Loretan (1999), Stambaugh (1995), Corsetti, Pericoli, and Sbracia (2005), Ronn, Sayrak, and Tompaidis (2009), and Forbes and Rigobon (2002).

counter-cyclical correlations are driven by the counter-cyclical market volatility. Specifically, we show that correlations between portfolios, formed on different asset characteristics, and the aggregate U.S. market are higher during bear markets (recessions) than those during bull markets (booms). While the increase in correlations from booms to recessions can be explained by heightened volatility in those periods, this is not the case with the increase from up to down market periods. Although the marginal impact of volatility on correlations is stable across different periods, the role of volatility in explaining asymmetric correlations is limited since the increase in volatility from bull to bear markets is much less compared to the increase from booms to recessions.

Because the causes of asymmetric and counter-cyclical correlations are different, their implications for portfolio allocation and risk diversification might differ as well. We first show that this is indeed the case. We then study and compare the economic significance of asymmetric and counter-cyclical correlations. Similar to Ang and Chen (2002), we consider the portfolio choice problem of an investor in an environment with asymmetric correlations and we ask what utility loss she would incur if she does not incorporate the asymmetric correlations into her portfolio choice decision. We repeat the same exercise for counter-cyclical correlations and compare the cost associated with ignoring two types of correlation asymmetry. When two costs are compared, we find that ignoring asymmetric correlations, i.e. higher correlations in bear markets than bull markets, is significantly more costly than ignoring counter-cyclical correlations.

Our empirical results are robust in several dimensions. First, our results are not specific to correlations of asset portfolios with the aggregate market.

Specifically, when we study interportfolio correlations we again find evidence of asymmetric and counter-cyclical correlations. More importantly, we show that while the latter can be explained by heightened volatility, we cannot make the same claim for the former. Second, we show that the way we define recessions does not alter our findings. In particular, besides using the NBER defined business-cycle variable, we use the growth rate of industrial production as our business cycle indicator and our results remain unchanged. Third, following Reinhart and Rogoff (2009), we categorize crises into currency, stock market, and banking crises, and study each of them separately. We find that heightened volatility causes correlations to increase during currency and stock market crises, while we find no significant increase in correlations during banking crises.

The chapter proceeds as follows. Section 1.2 summarizes the relevant literature. In section 1.3 we describe the data and methodologies we use in this study. The results are presented in Section 1.4. Section 1.5 explores the economic significance of our results. Section 1.6 concludes.

1.2 Literature Review

Measuring correlations of international equity markets is an issue widely debated in the literature. While the earlier studies had shown low and invariant correlations[3], advocating the benefits of international portfolio diversification, a more recent strand of the literature has documented that correlations of international equity markets vary strongly over time.[4]

One manifest of time-varying correlations, known as correlation asymmetry, refers to higher correlation levels during certain time periods. Correlation asymmetry can be further categorized into two types. The first type stems from relating correlations to the realized returns: comparing correlations in periods when realized returns are high and when realized returns are low. The second, however, relates to the correlations over the business cycles: comparing correlations during recessions and during booms. Erb, Harvey, and Viskanta (1994), for example, refer to both types of time-variation in correlations when they study the pairwise correlations of international equity returns. They divide the data according to ex-post returns with respect to joint downside movements – when both returns are below their average levels (capturing bear markets) and joint upside movements – when both returns are above their average levels (capturing bull markets). With this in mind, they show that the international equity market correlations are higher during joint downside movements compared to joint upside movements. They also study the correlations of international equity returns

[3]See Levy and Sarnat (1970), Grubel and Fadner (1971), and Lessard (1973).

[4]See Corsetti, Pericoli and Sbracia (2005), Forbes and Rigobon (2002), Karolyi and Stultz (1996), Lee and Kim (1993), Lin et al. (1994), and Longin and Solnik (1995, 2001).

over the business cycles and show that correlations are counter-cyclical, meaning that they are higher during recessions than during booms.

The literature on time-varying correlations has shown that high correlations can also be a byproduct of high volatility.[5] Namely, a volatility shock in one country can lead to higher correlations between the two equity markets although the link between the two countries has remained the same. For instance, Forbes and Rigobon (2002) study the 1997 Asian crises, 1994 Mexican devaluation, and 1987 U.S. market crash and show that unadjusted correlation coefficients between different country pairs suggest evidence of contagion.[6] Once the correlation coefficients are adjusted for the effect of volatility, virtually no evidence of contagion is found. Following Forbes and Rigobon (2002), Corsetti et al. (2005) generalize their model of cross-country links by allowing them to be affected by the shock in the crises-originating-country as well as by the shock specific to the crises originating country. They focus on the 1997 Asian crises and find that strong evidence of contagion exists in at least five out of 17 countries studied.

Our paper investigates the two manifests of correlation asymmetry, namely asymmetric and counter-cyclical correlations, and their susceptibility to the critique that correlations might be a byproduct of heightened volatility.

[5]For instance, see Boyer, Gibson, and Loretan (1999), and Forbes and Rigobon (2002).

[6]Forbers and Rigobon (2002) define contagion as a significant increase in cross-market linkages after a shock in one country, while interdependence refers to any continued high level of market correlation that exists in all states of the world.

1.3 Data and Methodology

We use daily and monthly data for the publicly traded US stocks. We obtain data on stock returns, stock prices, shares outstanding, and exchange listings for the universe of stocks available from the Center for Research on Security Prices (CRSP). We also obtain daily and monthly risk-free rates from the data library of Kenneth French.[7] The data spans the period between January 1963 and December 2015.

In order to study the effect of aggregate uncertainty on correlation asymmetry, we employ three different methods. The first one is a regression based method of Andersen et al. (2001) which we describe in detail below. The second one is due Forbes and Rigobon (2002) and it adjusts the correlation coefficient for the change in the aggregate market uncertainty. We also use the method of Corsetti et al. (2005) which generalizes the method of Forbes and Rigobon (2002).

To see the effect of aggregate market volatility on asymmetric correlations we run the following panel regression, in the spirit of Andersen et al. (2001):

$$corr_{i,t} = \delta_0 + \delta_1 \mathbb{I}(R_{i,t} * R_{m,t} > 0) + \delta_2 \mathbb{I}(R_{i,t} < 0, R_{m,t} < 0) + \beta_0 \sigma_{m,t} + \beta_1 corr_{i,t-1} + \epsilon_{i,t} \quad (1)$$

where $corr_{i,t}$ is the realized correlation between the excess returns of portfolio i and of the aggregate market in month t. $R_{i,t}$ and $R_{m,t}$ are the monthly excess returns of portfolio i and of the aggregate market, respectively. As is common in the literature both excess returns are standardized.[8] $\mathbb{I}(\cdot)$ is the indicator function

[7] The data library is available at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

[8] See Ang and Chen (2002), Hong et. al. (2007).

which takes the value of one when the condition in parentheses is satisfied and zero otherwise. $\mathbb{I}(R_{i,t} * R_{m,t} > 0)$ captures the effect of joint upside and downside movements in returns while $\mathbb{I}(R_{i,t} < 0, R_{m,t} < 0)$ controls only for the joint downside movements. Therefore, the impact of upside movements on correlations is δ_1 and the impact of downside movements is $\delta_1 + \delta_2$. Thus, δ_2 captures the additional effect of the downside movements and a statistically significant positive δ_2 implies that correlations are asymmetric, being higher during joint downside movements.

The term $\beta_0 \sigma_{m,t}$ captures the effect of market volatility on correlations. We run the above regression with and without the volatility term to understand the extend of the impact of market volatility. In principle, the increase in volatility can account for the increase in during downside movements, which would cause an insignificant coefficient of δ_2.

For the counter-cyclical correlations over the business cycle we can run a very similar regression. The panel regression is specified as follows:

$$corr_{i,t} = \delta_0 + \gamma_1 Recession_t + \beta_0 \sigma_{m,t} + \beta_1 corr_{i,t-1} + \epsilon_{i,t} \tag{2}$$

where $Recession_t$ is a dummy variable that takes the value of one for the months during which the economy is in recession and zero otherwise. We utilize the NBER determined recession dates to define recessionary periods.[9] Testing the significance of γ_1 suffices for seeing whether the counter-cyclical correlations survive after controlling for the changes in aggregate market volatility.

The second and the third method of testing for the effect of volatility on

[9]As a robustness check, in Section 1.4.3 we use the monthly growth rate of industrial production as our business cycle indicator, and show that the results are not affected.

correlation asymmetry are due to Forbes and Rigobon (2002) and Corsetti et al. (2005). In order to understand this method let us suppose the following linear relation between the two asset returns:

$$r_i = \alpha_i + \beta_i f + \epsilon_i \tag{3}$$

$$r_j = \alpha_j + \beta_j f + \epsilon_j \tag{4}$$

where α_i and α_j are constants, β_i and β_j are factor loadings. The term f represents the common factor, and idiosyncratic risks are denoted by ϵ_i and ϵ_j. All the shocks are mutually independent random variables with finite variance.

Given the factor structure we derive the correlation coefficient between the two returns as follows:

$$corr(r_i, r_j) = \frac{\beta_i \beta_j var(f)}{\sqrt{\beta_i^2 var(f) + var(\epsilon^i)}\sqrt{\beta_j^2 var(f) + var(\epsilon^j)}} \tag{5}$$

$$= \frac{1}{\sqrt{1 + \frac{var(\epsilon^i)}{\beta_i^2 var(f)}}\sqrt{1 + \frac{var(\epsilon^j)}{\beta_j^2 var(f)}}} \tag{6}$$

Equation 6 suggests that the correlation between the returns is increasing in $var(f)$. Therefore a higher correlation is expected whenever the volatility of common factor increases. In other words, correlations in high-volatility subsamples are by construction larger than the ones in low-volatility subsamples. Studies comparing the correlations from different subsamples should take this into account.

Importantly, the same equation shows that the effect of $var(f)$ on correlation depends on idiosyncratic volatilities as well. Thus the extend of the impact of volatility on correlation is related to the ratio of idiosyncratic volatility to aggregate volatility. Therefore, given the increase in aggregate volatility, one can back out the required ratio of idiosyncratic volatility to aggregate volatility that explains the observed increase in correlations. Corsetti et al. (2005) follow such approach, and derive a test that compares the required volatility ratios to the empirical volatility ratios. However, whether we take the approach of comparing the volatility ratios or the approach of comparing the correlations is immaterial to our results.[10]

Applying the assumptions of Corsetti et al. (2005) to our case, we have:

$$Var(r_j|Down) = (1 + \delta)Var(r_j|Up) \tag{7}$$

$$Cov(\epsilon_i, \epsilon_j|Down) = Cov(\epsilon_i, \epsilon_j|Up) = 0. \tag{8}$$

Given the assumptions, the theoretical correlation coefficient for recessions can be written as follows:

$$\phi(\lambda_j, \delta, \rho) \equiv \rho \left[\frac{1 + \delta}{1 + \delta\rho^2(1 + \lambda_j)} \right]^{1/2} \tag{9}$$

where

$$\lambda_j = \frac{Var(\epsilon_j)}{\gamma_j^2 Var(f)} \tag{10}$$

and δ is the increase in the observed variance of returns. The parameter λ_j denotes the ratio between the variance of the idiosyncratic shock ϵ_j and the variance of the common factor f, scaled by the factor loading β_j.

[10] In an earlier draft of the present paper we carried out the results using the volatility ratios following Corsetti et al. (2005). Similar to Forbes and Rigobon (2002), we currently compare the volatility adjusted correlations with the observed correlations.

Next, the test of Corsetti et al. (2005) boils down to comparing the theoretical correlation coefficient (ϕ) to the realized one ($\hat{\rho}$). To perform the equality test we use the Fisher z-transformation of the two coefficients[11]:

$$\frac{z(\hat{\rho}) - z(\phi(\lambda_j, \delta, \rho))}{\sigma_z} = l \tag{11}$$

where l is a critical value for the test statistics given the significance level.

Formally, the test hypothesis are:

$$H_0 \ : \ \hat{\rho} \leq \phi$$

$$H_A \ : \ \hat{\rho} > \phi$$

This simple setup is general enough to describe both Forbes and Rigobon (2002) approach and Corsetti et al. (2005) approach. When we analyze the correlation of portfolio returns with the aggregate market return we treat r_j as the market return by setting ϵ_j equal to zero. In this case the test corresponds to Forbes and Rigobon (2002)'s approach, satisfies their assumptions in the sense that an increase in the volatility of r_j can only come from the volatility of the common factor, f. However, in a more general case where ϵ_j is non-zero random variable, i.e. idiosyncratic risk, the increase in the volatility of r_j can be coming from an increase in the idiosyncratic risk, which would cause correlation to decrease actually. If the increase in volatility comes from common factor correlation would go up while if it is because of an increase in idiosyncratic volatility the corre-

[11] The Fisher z-transformation is calculated as follows, and it is robust to non-normality.

$$z(\hat{\rho}) = \frac{1}{2} ln \frac{1+\hat{\rho}}{1-\hat{\rho}}$$

where $\hat{\rho}$ is the estimated correlation coefficient.

lation would decrease. Therefore the distinction is important and ignoring the idiosyncratic risk may bias the findings which is the main point of Corsetti et al. (2005).

Thus the critical question is whether the volatility of the common factor increases enough to justify the increase in the observed correlation. One could also derive the required amount of increase in the volatility of the common factor to justify the observed increase in correlations and check whether the observed increase in volatility is statistically different than the required amount.

This method is due to Forbes and Rigobon (2002) and Corsetti et al. (2005), where they study the contagion during the East Asian financial crisis. Interpreting the heightened correlations as "contagion", their main question is whether the increase in correlations can be explained by the increase in volatility. The crises originates in one country and then spreads out to other countries, leading to increase in correlations. Therefore, they compare the correlation levels during the financial crisis to those corresponding to non-crises times.

Suppose that country j is the origin of the financial crisis. According to the Forbes and Rigobon (2002) approach, the stock returns or country j (r_j) becomes more volatile and this is due to increase in the volatility of common component, f. They assume that the idiosyncratic shock is equal to zero ($\epsilon_j = 0$). This assumption can be justified if every shock to country j turns to a global shock immediately, or if it affects other countries directly as well. For instance, a shock to U.S. stock market can be considered as a common shock, and this approach is often used in the literature. Similarly, a shock to the Hong Kong stock market can be considered as a common shock in the East Asian region as well. Corsetti et al. (2005) generalizes Forbes and Rigobon (2002) by allowing the root of the crisis to be in ϵ_j, i.e. the idiosyncratic shock to the crisis country. Second, they also allow this idiosyncratic volatility to be time varying as well. To be specific, they allow the increase in the volatility of r_j to be due to the increase in the volatility of ϵ_j. This distinction can be important because as we will see shortly the effects of $var(f)$ and σ_j^2 on correlation are in opposite directions. Therefore whether the increase in $var(r_j)$ is due to an increase in $var(f)$ or σ_j^2 is important.

1.4 Results

This section presents the empirical findings when using the methodologies discussed in Section 1.3. We start with the panel and time-series regressions in the spirit of Andersen et al. (2001), as specified in equations 1 and 2.

Table 1 presents the panel regressions that study the effect of aggregate volatility on asymmetric correlations and counter-cyclical correlations, separately. The first column reports the panel regression estimates for asymmetric correlations, without controlling for the effect of volatility. The coefficient of dummy variable $\mathbb{I}(R_{i,t} < 0, R_{m,t} < 0)$ which captures the joint downside movements is positive and statistically significant. This confirms the finding in the literature: Correlations are higher during downside movements. The critique of Forbes and Rigobon (2002) suggests that higher correlations can be due to heightened volatility during downside movements. Thus we incorporate this possibility by explicitly controlling for the market volatility and report the results in the second column. The coefficient of the dummy variable capturing the joint downside movements is still positive and statistically significant. That is, correlations are higher conditional on joint downside movements even after controlling for the effect of aggregate market volatility. In other words, the higher correlations observed during downside movements are not byproducts of the heightened market volatility during those times. Below we show that the same statement does not hold for the counter-cyclical correlations.

Next, we estimate a similar regression for the counter-cyclical correlations over the business cycle. The results are shown in third and fourth column of

Table 1. The coefficient of the *Recession* dummy is positive and statistically significant, consistent with the empirical finding about correlations being higher during recession than during boom periods. However, once we control for the market volatility, the coefficient of the *Recession* dummy becomes negative and statistically insignificant. Thus we can claim that *counter-cyclical correlations* are driven by heightened volatility and that the critique of Forbes and Rigobon (2002) applies to this case. Our further analysis confirms this claim.

Next, in order to show that our findings are not specific to the panel regression setup, we run a separate time-series regression for each of the portfolios. Panel regression can be restrictive as it imposes the coefficients to be equal for different portfolios. It is also possible that panel regression results are driven by only certain portfolios. As a solution to these concerns, we run two time-series regressions (the ones given by equations 1 and 2) for each portfolio separately.

The results are reported in Tables 2 and 3. Table 2 reports the results for correlation asymmetry with respect to the joint upside and downside return movements. The left panel of Table 2, columns numbered I to V, reports the estimates of the regressions specified by equation 1 for five size-sorted portfolios, without controlling for volatility. The right panel, columns numbered I to V, presents the regressions estimates with controlling for volatility. The coefficient of the volatility term $Log(\sigma_{m,t})$ is positive and significant for each portfolio, consistent with the critique of Forbes and Rigobon (2002). Importantly, the sign and the statistical significance of the coefficient of dummy variable capturing the downside movements are not affected by controlling for the volatility. Four out of five portfolios show higher correlations during downside movements and this is not driven by higher volatility during downside movements. Heightened volatility during downside movements does lead to some increase in correlations as it is evident from the decrease in magnitude of the $\mathbb{I}(R_{i,t} < 0, R_{m,t} < 0)$ dummy variable coefficient once the volatility is introduced into the regression. For instance, in the case of smallest portfolio, the coefficient of the downside dummy variable decreases from 5 to 3 percentage points once we control for volatility. Similar patterns are observed for other portfolios as well. Thus, although the heightened volatility plays a role in higher correlations during downside movements, it cannot account for all of the increase, so the Forbes and Rigobon (2002) critique does not constitute a concern for the finding of heightened correlations during downside movements.

We repeat a similar analysis for *counter-cyclical correlations* and report the results in Table 3. As before, the left panel corresponds to five time-series regressions without controlling for volatility, while the right panel includes the volatility term as a regressor. The left panel shows that the *Recession* variable has a positive and statistically significant coefficient, suggesting a stronger comovement between size-sorted portfolios and the aggregate market during recessions. However, the right panel of the table shows that the coefficient of the *Recession* variable changes its sign and loses the statistical significance once the volatility term is added to the regression. Thus the time-series regressions deliver similar findings to the panel regressions we discussed above.

Results using the regression methodology point out the difference between asymmetric correlations and counter cyclical correlations: While counter-cyclical correlations can simply be explained by counter-cyclical aggregate market volatility, the correlation asymmetry with respect to joint upside and downside movements of returns is not only due to the heightened market volatility during those times. Next, we study the effect of volatility using the approach of Forbes and Rigobon (2002) and Corsetti et al. (2005). Unlike the regression framework, this method allows for nonlinear dependency between the aggregate market volatility and correlations. Moreover, this method allows us to find a volatility-adjusted correlation, i.e. to find what would the correlation be if the only change was an increase in return volatility.

Table 4 collects the results for asymmetric correlations. The second and third columns present the empirical correlation coefficients for upside and downside moves separately, where upside (downside) subsample is defined when the excess aggregate market return is above (below) its historical average. Correlations are asymmetric in the sense that they are higher during downside movements than during upside movements, i.e. (ρ^-) is larger than (ρ^+). The next two columns present the volatility-adjusted correlations for downside movements, following the approaches of Forbes and Rigobon (2002) and Corsetti et al. (2005), respectively. The two methodologies yield similar results. The two volatility adjusted correlation coefficients are not very different from the upside movement correlation coefficient, i.e. ϕ^{FR} and ϕ^{CPS} are not very different than ρ^+, suggesting that the effect of volatility is minimal. More importantly, the empirical downside correlations ρ^- are much larger than the volatility-adjusted correlations, ϕ^{FR} and ϕ^{CPS}. In other words, correlations during downside movements of the market increase more than what the increase in volatility can account for. The last two columns of Table 4 present the test statistics for the statistical difference between

ρ^- and the volatility-adjusted correlations, as described in Section 1.3. The test statistic larger than the critical value implies the rejection of the null hypothesis and suggests that $\rho^- > \phi^i$, where $i = \{FR, CPS\}$. The results show that the null hypothesis is rejected for all of the portfolios suggesting that asymmetric correlations persist after correcting for the volatility. In other words, the correlation between the five size-sorted portfolios and the aggregate market returns is higher during bear markets and this cannot be explained by higher volatility during those periods.

Table 5 collects the results for counter-cyclical correlations. The second and third columns present the empirical correlation coefficients during boom and recession subsamples, ρ^{Boom} and $\rho^{Recession}$, where boom and recession subsamples are defined according to NBER determined recession periods. The two columns confirm our earlier finding that correlations are higher during recessionary periods, namely *counter-cyclical correlations*. However, the difference between $\rho^{Recession}$ and ρ^{Boom} is not as large as in the case of *asymmetric correlations*. More importantly, the volatility-adjusted correlations, ϕ^{FR} and ϕ^{CPS}, are very close to, or even higher than, $\rho^{Recession}$. The test statistics, z^{FR} and z^{CPS}, suggest that the difference between the volatility-adjusted correlations and the empirical correlations during recessions, $\rho^{Recession}$, is almost always insignificant. This is in contrast to the results from the previous table. Therefore we conclude that, unlike asymmetric correlations, counter-cyclical correlations are driven by counter-cyclical volatility.

One might argue that the reason why the jump in correlations can be explained by increased volatility in the case of *counter-cyclical correlations* but not in the case of *asymmetric correlations* is that the increase in correlations is smaller in the first case. This would be a valid argument if the volatility adjustments were similar in magnitude in the two cases. However, the results from Tables 4 and 5 suggest that the adjustment is much smaller in the case of *asymmetric correlations*. In another words, the volatility adjustment is negligible in the case of *asymmetric correlations*. If the marginal impact of volatility is similar for asymmetric and counter-cyclical correlations, the question that poses is whether the amount of increase in volatility is different for the two cases. Section 1.4.1 tries to answer this question.

1.4.1 How Much Does the Market Volatility Increase During Recessions and Bear-Markets?

In this section we try to understand why the impact of volatility differs for the two types of correlation asymmetry studied in this paper.

Coefficients of the volatility term in time-series regressions estimated earlier (see Tables 2 and 3) are similar for asymmetric and counter-cyclical correlations. One percent increase in market volatility increases the correlations with the aggregate market up to 3 percentage points. This suggests that the two types of correlations increase by a similar amount for a given increase in volatility. Having this in mind, the fact that volatility accounts for a smaller increase in correlations in the case of asymmetric correlations must be due to a smaller increase in volatility during downside movements. To see if this is indeed the case we compare the increase in volatility from upside to downside movements to the one from expansion to recession periods.

Figure 1 plots the density distributions of market volatility for upside and downside periods. The figure shows that although the market volatility is usually higher during bear markets, the difference compared to the market volatility during bull markets is not that large. The figure also plots the density distribution of market volatility for boom and recession periods. In this case, the difference in volatility is much greater than that in the case of upside and downside periods. What these two figures indicate is that the aggregate market volatility increases during recessions and market downturns, although the increase is much greater in the former. Specifically, annualized average market volatility increases from 8.97% to 15.6% from bull to bear markets, while it increases from 9.50% to 28.43% from boom to recessions. In another words, the aggregate market volatility increases by 73% from bull to bear markets while it increases by almost 200% from booms to recessions.[12] Thus, we conclude that adjusting correlations for the effect of volatility is especially relevant for heightened correlations during recessions.

To sum up, as volatility does not increase as much from bull to bear markets, the volatility adjustment cannot account for the observed increase in correlation from bull to bear markets. However, the relatively larger surge in volatility during recessions is enough to explain the observed increase in correlations.

[12]Our measure of volatility is the realized variance over each calendar month. After annualizing the variances we take their average over different subsamples. Comparing the medians rather than means yield similar results: The increase in median volatility from bull to bear markets is just 42% while it is 178% from expansion to recession periods. As common in the literature returns are in excess of risk free rate and are standardized (please see Ang and Chen (2002), Hong et. al. (2007)). Using gross and unstandardized market return yields the same results in volatility comparison in different subsamples.

1.4.2 Interportfolio Correlations

In our previous tests, following the literature, we studied the correlation of portfolio returns with the aggregate market return which is defined as the value-weigthed average of all individial stock returns. However, this methodology creates heterogeneity across portfolios as some of them by construction constitute a larger fraction of the aggregate market. This is especially a concern for size-sorted portfolios because the weight of portfolios in the aggregate market monotonically increases as we move from smallest portfolio to biggest. Thus the returns of portfolios with larger stocks are closer to that of the aggregate market, partly because of this mechanical relationship.

To mitigate this problem, we calculate correlations *among* the portfolios and study how those are affected by heightened volatility. Table 6 presents the results when the regression method is used.[13] The first two columns pertain to the *asymmetric correlations.* Similar to our earlier results, the pairwise correlations are asymmetric: they are higher during bear markets. Market volatility does have an impact on the pairwise correlations, yet it is far from accounting for the increase in correlations. When market volatility is added to the regression, the coefficient of bear-market dummy decreases from 0.037 to 0.027, and remains statistically significant. Columns III and IV report the results for the *counter-cyclical correlations.* Column III shows that the NBER recession dummy variable has a positive and significant coefficient, implying that the pairwise correlations among five size-sorted portfolios are higher during recessions than during boom periods. The coefficient, however, becomes negative once we control for volatility

[13] To conserve space, we only report the results for the panel regressions. Time series regressions yield similar results and are available from authors upon request.

as it is the case in the previous sections for the correlations with the aggregate market. Thus we conclude that the neither the correlation asymmetry nor the role of volatility in generating correlation asymmetry is particular to the correlations with aggregate market.

1.4.3 How to Define Recessions? Recessions and Financial Crises.

While studying the *counter-cyclical correlations* we used a binary variable to depict the expansionary and recessionary periods, meaning that every expansion and recession are treated the same way. However, the business-cycle periods might be heterogeneous: the depth of recessions (and expansions) might differ as well as the causes of different recessions. In this section we first use a continuous variable to track the business cycles. We further try to understand if the impact of crises on correlations differs depending on the types of crises.

We use the growth rate of industrial production as our business cycle indicator variable. The advantage of using a continuous variable over a binary one is that if correlations are even higher in deeper recessions the continuous variable can identify that while the binary variable cannot. If it is the case that correlations are higher in deeper recessions, the volatility term might be capturing this effect. Therefore we replicate our previous results replacing the recession dummy variable with the industrial production growth rate.[14] We also note that the industrial production can be a noisy measure as it is quite volatile. Earlier findings in the literature as well as the ones in our paper suggest that correlations should be higher when the industrial production growth rate is lower. Results are collected

[14]The industrial production data is from the FRED database of the Federal Reserve Bank of St. Louis and available at `https://alfred.stlouisfed.org/series/downloaddata?seid=INDPRO`

in tables numbered 7 to 10. Our main findings regarding the role of volatility on correlations remains unchanged: once controlled for volatility the business cycle indicator is not statistically significant.[15]

Recessions may not be all alike, or there might be a financial crisis during expansionary periods. Following the categorization of Reinhart and Rogoff (2009) we study how correlations change during different type of crisis episodes. During our sample period three kinds of crisis are observed according to Reinhart and Rogoff (2009) classification: currency, stock market and banking crises.[16] We create separate dummy variables for each type of crises and run similar regressions to the ones in previous sections. Regression results displayed in columns numbered I and III of Table 11 indicate that the correlations are higher during currency and stock market crises. Once we control for the effect of volatility (columns II and IV), the crisis dummy variables become either insignificant or change their sign suggesting that high correlations in currency and stock market crises are volatility driven. The banking crisis dummy is insignificant as shown in column V. We should note that there are only two banking crisis episodes in post-1963 period. The first one, between 1984 and 1991, is not a systemic crisis and the second one is the banking crises of 2008 and 2009 during which correlations in fact increased. These results suggest that the type of crises has no particular importance for the impact of volatility on correlations studied in this paper and correlations do not increase in any crisis period beyond the effect of heightened volatility.

[15]As an alternative we use the Chicago Fed National Activity Index (CFNAI) to track business-cycle as well. The results are basically the same and available upon request from the authors.

[16]Please see Reinhart and Rogoff (2009) for the methodology of classification. The description provided in Table 11 also includes the time span of each crisis.

1.5 Economic Significance

In this section, we study the economic significance of correlation asymmetry and the cost associated with ignoring or not realizing such asymmetry. We have two main findings. Firstly, there is an economically significant cost of ignoring the asymmetry and whether it is the heightened volatility that causes the increase in correlations or not is important for this cost. Secondly, we show that the cost of asymmetric correlations is much higher over bear and bull markets than the cost of counter-cyclical correlations. As the heightened volatility plays a much greater role in generating high correlations during recessions than those during bear markets, this difference manifests itself in the cost of ignoring the two types of correlation asymmetry.

We start by examining the economic significance of asymmetric correlations and how it changes depending on the cause of increase in correlations. Specifically, we study the portfolio allocation problem of a representative investor and compare her welfare when the asymmetry in correlations is ignored and not.[17] The investor chooses to allocate her investment between two risky assets and a risk-free asset. She maximizes her expected end-of-period utility, given as follows:

$$\max_{\{\alpha_1,\alpha_2\}} \mathbb{E}\frac{W^{1-\gamma}}{1-\gamma} \tag{12}$$

where α_1 and α_2 represent the weights of the two risky assets in her portfolio while γ is the investor's coefficient of risk aversion. The end-of-period wealth is denoted with W, which can be represented as $W = (1-\alpha_1-\alpha_2)e^{r_f}+\alpha_1 e^{r_1}+\alpha_2 e^{r_2}$,

[17] The portfolio allocation problem is very similar to that of Ang and Chen (2002).

where r_1 and r_2 stand for the returns of the two risky assets. The returns are continuously compounded and their stochastic behavior is explained next.

The two risky assets are ex-ante identical with same mean and variance. To model the time-variation in correlations, we assume a regime-switching (RS) model for the actual distribution of returns, similar to Ang and Chen (2002). The two regimes correspond to "High" and "Low" correlation states, and correlation between returns of risky assets in those regimes are denoted as ρ_H and ρ_L, where $\rho_H > \rho_L$. In order to focus only on the dependency between risky assets we assume equal mean returns for the risky assets, i.e. $\mu_H = \mu_L$ where $\mu_{s_t} = (\mu_1, \mu_2)'$.

Conditional on the regime, asset returns are normally distributed with mean μ_{s_t} and covariance matrix Σ_{s_t}. Under the regime-switching model, returns can be represented as follows:

$$(r_1, r_2) \sim \mathcal{N}(\mu_{s_t}, \Sigma_{s_t}), \qquad s_t \in \{H, L\} \tag{13}$$

for high and low correlation regime. Transition between high and low correlation regimes follows a Markov chain process with the following transition probabilities:

$$\begin{pmatrix} P_L & 1 - P_L \\ 1 - P_H & P_H \end{pmatrix}$$

where $P_L = Pr(s_t = L | s_{t-1} = L)$ and $P_H = Pr(s_t = H | s_{t-1} = H)$.

The portfolio weights are dependent on the regime of the RS model, and we denote them as $\alpha_s^* = (\alpha_L^*, \alpha_H^*)$.

In order to understand the importance of asymmetric correlations for the investor we ask the following question: 'What is the cost of ignoring asymmetric correlations?'. When the true data-generating process of returns exhibits asymmetric correlations, neglecting this fact leads to non-optimal portfolio weights and thus lower utility. To measure this utility loss, we find how much the 'naive' investor, who ignores the asymmetric correlations, should be compensated such that he is better off as the 'informed' investor who is aware of the regime-switching structure.

The problem of the 'naive' investor is similar to that of the 'informed' one, except for the belief regarding the behavior of risky assets' returns. The bi-variate normal distribution has the same mean as in the RS model and the same covariance matrix as the unconditional covariance matrix of the RS model. The parameters of the RS model are calibrated to ensure that the unconditional correlations are the same, i.e. $\rho = \frac{1}{2}(\rho_L + \rho_H)$. The 'naive' investor thus solves the portfolio allocation problem under the following return distribution: $(r_1, r_2) \sim \mathcal{N}(\mu, \Sigma)$ where $\mu = \mu_{s_t}$ and Σ is the unconditional covariance matrix of the RS model. In other words, the two investors share the same beliefs about the unconditional correlation, while the 'naive' investor ignores the time variation in correlations. We denote the portfolio allocations of the naive investor with α^*.

The cost of ignoring correlation asymmetry is derived from the following equation:

$$\mathbb{E}\Big[(1+\bar{w})\frac{W_{\alpha^*}^{1-\gamma}}{1-\gamma}\Big] = \mathbb{E}\Big[\frac{W_{\alpha_s^*}^{1-\gamma}}{1-\gamma}\Big] \tag{14}$$

where $W_{\alpha_s^*}$ is the end-of-period wealth given the optimal portfolio weights under the RS regime, and W_{α^*} is the counterpart for the normally distributed returns case assumed by the naive investor. The equation includes the necessary monetary compensation, $\bar{w}$, that makes the 'naive' investor as better off as the fully informed investor. The larger the compensation, the greater is the cost of ignoring asymmetry in correlations.

To illustrate the calculation of the monetary compensation, $\bar{w}$, we set the parameters of our Exercise 1 as follows. The expected continuously compounded return on risky assets is set as $\mu = 0.07$, and the volatility of the continuously compounded returns as $\sigma = 0.15$. The unconditional correlation of asset returns is set as $\rho = 0.55$, while correlations conditional on the state of the RS model are set as $\rho_L = 0.50$ and $\rho_H = 0.60$. We set the constant risk-free rate as $r_f = 0.05$, and the constant relative risk aversion as $\gamma = 4$. Lastly, the transition probabilities are $P_L = P_H = 0.66$ which implies equal steady state probabilities, $Pr(s_t = L) = Pr(s_t = H) = 1/2$.[18] Given this setting, we calculate that the naive investor should receive 43 basis points per dollar of her wealth to be as better off as the informed investor.

Exercise 1 was designed such that increase in correlation is purely due to increase in volatility of the common factor, or aggregate market return in a CAPM structure. Market volatility increase from 15 percent to 18.3 percent causes correlation to increase from 50 percent to 60 percent. Next, in exercise 2, we show that once the cause of increase in correlations changes, the amount of required compensation changes as well. Specifically, we let the betas and idiosyncratic volatilities of risky assets to differ between High and Low correlation regimes as well. Table 12 collects the key parameters of the two exercises and the required compensation amounts. The levels of required compensation per dollar invested

[18] The detailed solution of the portfolio allocation problems and the calibration method used in this exercise are collected in Appendix 1.8. The Appendix also includes further examples. One of those examples studies the required compensation for a rare increase in correlation.

are comparable to those in Ang and Chen (2002). The results suggest that although the increase in correlation and market volatility is the same as in exercise 1, the required compensation is much higher. This exercise demonstrates that the reason behind the correlation increase matters significantly for its cost.

Once we showed that time-variation in correlation matters for the investor, we next examine whether monetary compensation differs in the case of countercyclical and asymmetric correlations. We start with the time variation over the business cycle and use the returns of size portfolios used in our earlier tests. Specifically, as two risky asset returns we use the third and forth quintile portfolios.[19] The regime-switching model for bull/bear markets can be denoted as follows:

$$(r_1, r_2) \sim \mathcal{N}(\bar{\mu}, \Sigma_{s_t}), \qquad s_t \in \{Boom, Recession\} \tag{15}$$

where the corresponding variance-covariance matrices are:

$$\Sigma_{boom} = \begin{pmatrix} 0.0024 & 0.0021 \\ 0.0021 & 0.0020 \end{pmatrix} \text{ and } \Sigma_{recession} = \begin{pmatrix} 0.0061 & 0.0058 \\ 0.0058 & 0.0057 \end{pmatrix}$$

and the transition matrix is $P_{bc} = \begin{pmatrix} 0.98 & 0.02 \\ 0.09 & 0.91 \end{pmatrix}$ and $\bar{\mu} = (0.0112,\ 0.0107)'$. The monthly risk-free rate is 0.4 percent as calculated from the data. The informed investor is aware of the time-variation in variance-covariance matrix over the business cycle and solves the portfolio allocation problem accordingly. The naive investor, on the other hand, ignores the time-variation and solves the prob-

[19] Although moments differ to some extent when we use other portfolios, neither the amount of required compensation nor the main result changes. Therefore, to conserve space, we only report the results for the third and forth quintile portfolios. Other results are available from the authors upon request.

lem under a belief of bivariate normal distribution, $(r_1, r_2) \sim \mathcal{N}(\bar{\mu}, \Sigma_{uncond})$ where $\bar{\mu}$ is the unconditional mean of returns while Σ_{uncond} is the unconditional variance-covariance matrix. Thus, the beliefs of informed and naive investors differ only with regards to variance-covariance properties of the returns while we assume the equality of unconditional means to focus on the effects of time variation in variance-covariance matrix over the business cycle.

$$\Sigma_{uncond} = \begin{pmatrix} 0.0029 & 0.0026 \\ 0.0026 & 0.0025 \end{pmatrix}$$

Next, we study the time-variation of variance-covariance matrix of returns from bull to bear markets. In this case, the informed investor is aware of the regime switching property of return dependencies, i.e. that correlations are higher during down markets. The regime-switching model for up/down markets can be denoted as follows:

$$(r_1, r_2) \sim \mathcal{N}(\bar{\mu}, \Sigma_{s_t}), \qquad s_t \in \{Up, Down\} \tag{16}$$

where the corresponding variance-covariance matrices are:

$$\Sigma_{up} = \begin{pmatrix} 0.0011 & 0.0009 \\ 0.0009 & 0.0009 \end{pmatrix} \text{ and } \Sigma_{down} = \begin{pmatrix} 0.0017 & 0.0015 \\ 0.0015 & 0.0014 \end{pmatrix}$$

while the transition matrix is $P_{up/down} = \begin{pmatrix} 0.56 & 0.44 \\ 0.53 & 0.47 \end{pmatrix}$.

Table 13 compares the required compensations to naive investor for neglecting counter-cyclical and asymmetric correlations. The compensations are reported for different coefficients of risk aversion. For instance, when $\gamma = 2$, naive investor should receive 6 basis points for each dollar of her wealth for neglecting countercyclical correlations and 35 basis points for neglecting asymmetric correlations. These results suggest that ignoring the time variation from bull to bear markets is much more costly than ignoring the time variation over the business cycle.

1.6 Conclusion

In this paper we study the correlation asymmetry phenomena observed in financial markets. Correlations of portfolio returns with the aggregate market are shown to be higher during recessions and during downside movements of the markets. We show that these two manifests of correlation asymmetry are different in their nature. While higher correlations during recessions can be explained by heightened market volatility during those periods, volatility is insufficient to explain the increase in correlations during market downside movements. We also show that the reason behind increased correlations is important for their cost. Lastly, we show that the cost of neglecting *asymmetric correlations* is significantly higher than the cost of neglecting *counter-cyclical* correlations.

1.7 Chapter I Figures and Tables

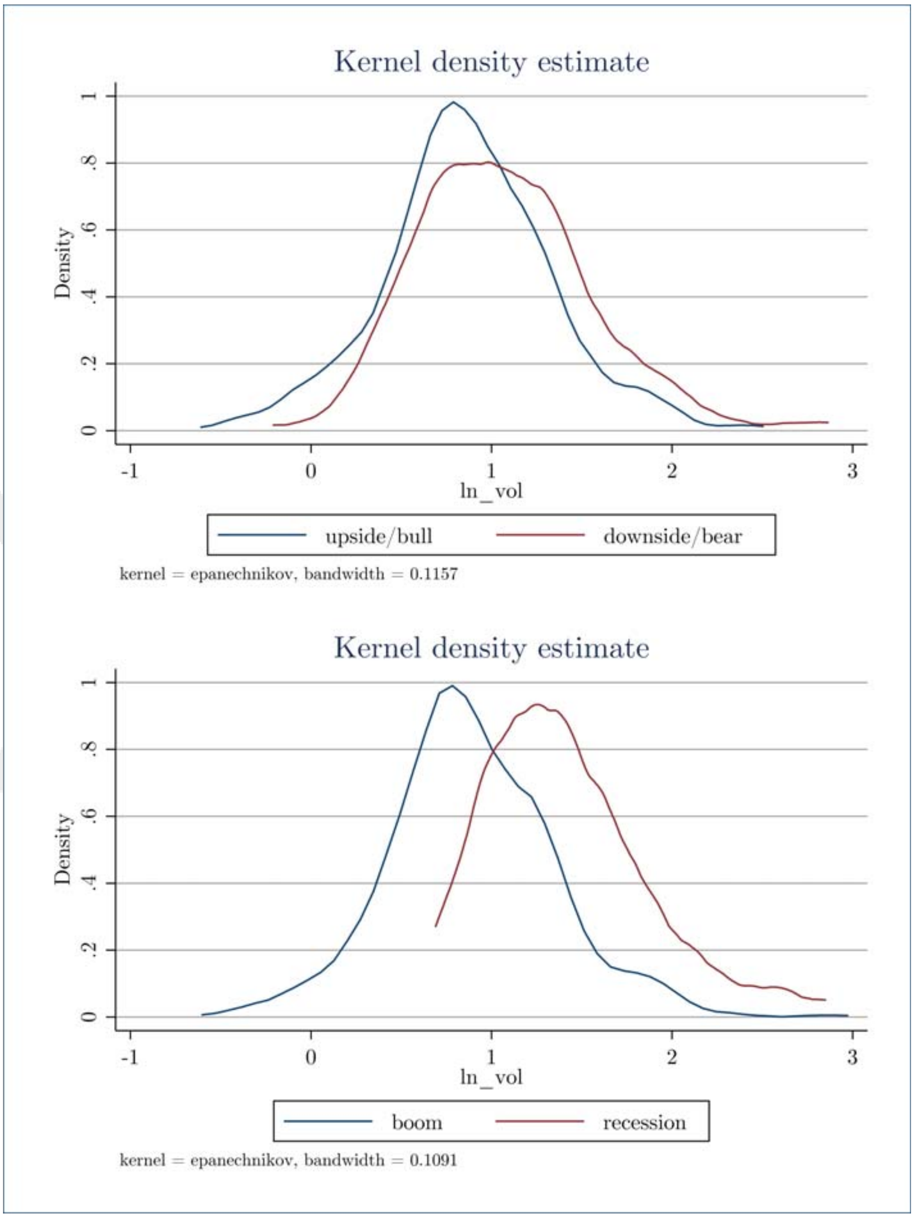

Figure 1: Volatility Distribution over Different Subperiods

Using daily data, volatility of the aggregate market return is calculated for each month. The distributions of market volatility are plotted separately for subsamples of recessions and booms, and upside and downside periods. Monthly data spans the period from January, 1963 to December, 2015 (636 observations).

Table 1: Asymmetric vs. Counter-Cyclical Correlations: Volatility Effect

	I	II	III	IV
I($r_{i,t} * r_{m,t} > 0$)	-0.003	-0.001		
	(0.52)	(0.11)		
I($r_{i,t} < 0 \& r_{m,t} < 0$)	0.028	0.021		
	(2.95)**	(2.90)**		
I($NBER_{recession}$)			0.009	-0.010
			(2.13)**	(2.49)**
Ln($\sigma_{m,t}$)		0.015		0.019
		(2.12)**		(2.56)**
$corr_{i,t-1}$	0.629	0.610	0.629	0.614
	(8.64)**	(7.52)**	(8.29)**	(7.40)**
Intercept	0.331	0.357	0.338	0.365
	(5.42)**	(5.00)**	(5.38)**	(5.02)**
R^2	0.42	0.45	0.40	0.44
N	3,180	3,180	3,180	3,180

* $p < 0.1$; ** $p < 0.05$

The table reports estimates from panel regressions, including coefficients estimates and t-statistics (in parentheses). The dependent variable is the monthly correlation with the aggregate market excess return, for five portfolios sorted according to the market capitalization. Monthly data spans the period from January, 1963 to December, 2015 (636 observations), for five portfolios in cross section. Data comes from the library of Kenneth French. The regressors are as follows: first and second independent variables are dummy variables, the second one identifying the market downturns. If the condition in the parentheses is satisfied the dummy variable takes the value of one and otherwise zero. Other regressors are natural logarithm of aggregate market volatility, a dummy variable that takes the value of one for the months within the NBER determined recession periods, and the lagged correlation (the first lag of the regressand). Estimates from four different specifications are reported where the standard errors are clustered for time and cross sectional dependence, with the method proposed by Petersen (2009). Return variables are in the excess of risk free rate which is approximated by the one-month Treasury bill rate. As is in the literature, the return variables have been standardized so that each variable has a mean zero and a standard deviation of one.

Table 2: Higher Correlations During Downside Movements: Volatility Effect

Dep var: $corr_{i,t}$	I	II	III	IV	V	I	II	III	IV	V
	Before controlling for volatility					After controlling for volatility				
$I(r_{i,t} * r_{m,t} > 0)$	-0.012	-0.015	-0.014	-0.014	0.002	-0.010	-0.011	-0.010	-0.010	0.002
	(1.09)	(1.78)*	(2.12)**	(1.68)*	(1.14)	(0.89)	(1.31)	(1.60)	(1.35)	(1.56)
$I(r_{i,t} < 0 \& r_{m,t} < 0)$	0.050	0.043	0.029	0.019	0.001	0.036	0.032	0.018	0.012	0.000
	(5.30)**	(6.01)**	(5.31)**	(4.81)**	(1.26)	(3.97)**	(5.09)**	(4.06)**	(3.29)**	(0.13)
$Log(\sigma_{m,t})$						0.027	0.024	0.022	0.016	0.002
						(4.86)**	(5.85)**	(5.69)**	(4.77)**	(3.99)**
$corr_{i,t-1}$	0.410	0.416	0.384	0.379	0.459	0.385	0.372	0.304	0.289	0.414
	(7.73)**	(7.85)**	(7.35)**	(6.18)**	(7.48)**	(7.12)**	(6.56)**	(4.62)**	(4.64)**	(7.14)**
Intercept	0.481	0.511	0.566	0.596	0.534	0.520	0.565	0.654	0.690	0.580
	(10.96)**	(11.07)**	(12.13)**	(10.33)**	(8.68)**	(10.85)**	(10.81)**	(10.70)**	(12.01)**	(10.01)**
R^2	0.21	0.23	0.20	0.19	0.22	0.26	0.31	0.32	0.30	0.28
N	636	636	636	636	636	636	636	636	636	636

* $p < 0.1$; ** $p < 0.05$

The table reports estimates from time-series regressions, including coefficient estimates and t-statistics (in paranthesss). The dependent variable is the monthly correlation with the aggregate market excess return, for five portfolios sorted according to the market capitalization. Column numbers from I to V indicates the corresponding size portfolio, I being the smallest and V being the largest. Monthly data spans the period from January, 1963 to December, 2015 (636 observations), for five portfolios in cross section. Data comes from the library of Kenneth French. The regressors are as follows: First and second independent variables are dummy variables, the second one identifying the market downturns. If the condition in the parenthesis is satisfied the dummy variable takes the value of one and otherwise zero. Other regressors are logarithm of aggregate market volatility and the lagged correlation (the first lag of the regressand). Standard errors are clustered by year. Return variables are in excess of risk free rate which is approximated by the one-month Treasury bill rate. As is in the literature, the return variables have been standardized so that each variable has a mean zero and a standard deviation of one.

Table 3: Higher Correlations over the Business Cycle: Volatility Effect

Dep var: $corr_{i,t}$	I	II	III	IV	V	I	II	III	IV	V
	Before controlling for volatility					After controlling for volatility				
Recession	0.025	0.022	0.018	0.012	0.002	-0.007	-0.006	-0.007	-0.005	-0.000
	(2.10)**	(2.75)**	(3.15)**	(3.57)**	(3.25)**	(0.52)	(0.66)	(1.03)	(0.95)	(0.52)
Log($\sigma_{m,t}$)						0.032	0.029	0.025	0.018	0.002
						(5.34)**	(6.10)**	(5.79)**	(4.86)**	(3.79)**
$corr_{i,t-1}$	0.405	0.401	0.367	0.355	0.449	0.386	0.368	0.298	0.277	0.417
	(7.46)**	(7.02)**	(6.40)**	(5.54)**	(7.19)**	(7.05)**	(6.25)**	(4.41)**	(4.73)**	(7.07)**
Intercept	0.490	0.525	0.578	0.612	0.545	0.528	0.575	0.659	0.698	0.579
	(11.28)**	(10.59)**	(11.14)**	(10.02)**	(8.79)**	(11.16)**	(10.64)**	(10.11)**	(12.03)**	(9.90)**
R^2	0.18	0.18	0.16	0.15	0.22	0.24	0.28	0.30	0.29	0.28
N	636	636	636	636	636	636	636	636	636	636

* $p < 0.1$; ** $p < 0.05$

The table reports estimates from time-series regressions, including coefficient estimates and t-statistics (in paranthesss). The dependent variable is the monthly correlation with the aggregate market excess return, for five portfolios sorted according to the market capitalization. Column numbers from I to V indicates the corresponding size portfolio, I being the smallest and V being the largest. Monthly data spans the period from January, 1963 to December, 2015 (636 observations), for five portfolios in cross section. Data comes from the library of Kenneth French. The regressors are as follows: the logarithm of aggregate market volatility, a dummy variable which takes the value of one for the months within the NBER determined recession periods, and the lagged correlation (the first lag of the regressand). Standard errors are clustered by year. Return variables are in excess of risk free rate which is approximated by the one-month Treasury bill rate. As is in the literature, the return variables have been standardized so that each variable has a mean zero and a standard deviation of one.

Table 4: Asymmetric Correlations Adjusted for Volatility

Portfolio	ρ^+	ρ^-	ϕ^{FR}	ϕ^{CPS}	z^{FR}	z^{CPS}
Smallest size	0.521	0.785	0.565	0.561	**5.23**	**5.30**
Size 2	0.686	0.843	0.729	0.723	**3.82**	**3.97**
Size 3	0.791	0.893	0.824	0.817	**3.34**	**3.60**
Size 4	0.881	0.942	0.902	0.894	**3.38**	**3.90**
Biggest size	0.961	0.977	0.969	0.960	**1.78**	**3.43**

* $p < 0.1$; ** $p < 0.05$

The table compares empirical correlation coefficients with theoretical correlation coefficients implied by the change in volatility. Correlation coefficients are estimated for each of five size sorted portfolio returns with the returns of the aggregate market. Return variables are in the excess of risk free rate which is approximated by the one-month Treasury bill rate. Monthly data spans the period from January, 1963 to December, 2015 (636 observations), for five portfolios in cross section. Data comes from the library of Kenneth French. Columns 2 and 3 present upside and downside correlation coefficients, ρ^+ and ρ^-, where subsamples for upside (downside) movements are defined when aggregate market excess return is above (below) its mean. In the fourth column the volatility adjusted downside correlations (ϕ^{FR}) are presented, following the methodology of Forbes and Rigobon (2002). The correlations in the fifth column (ϕ^{CPS}) are adjusted for volatility according to the methodology of Corsetti et al. (2005). For this method, λ_j is calculated as in equation 10 using Fama-French three factor model. The last two columns display the test statistics for comparing the empirical downside correlations with the volatility adjusted downside correlations, calculated according to the two methodologies. Under the null hypothesis, the increase in volatility is sufficient to explain the observed increase in empirical correlations. The test statistic follows a standard normal distribution. Thus, any test statistic greater than the critical value of 1.645, which corresponds to a 5% significance level, implies the rejection of the null hypothesis, suggesting that the increase in volatility is not sufficient to justify the observed downside correlations. The test statistics that are in excess of the critical value are displayed in **bold** format.

Table 5: Counter-Cyclical Correlations Adjusted for Volatility

Portfolio	ρ^{Boom}	$\rho^{Recession}$	ϕ^{FR}	ϕ^{CPS}	z^{FR}	z^{CPS}
Smallest size	0.793	0.882	0.906	0.894	-0.99	-0.49
Size 2	0.879	0.925	0.950	0.937	-1.75	-0.74
Size 3	0.924	0.953	0.970	0.956	-1.85	-0.23
Size 4	0.957	0.979	0.983	0.969	-0.90	**1.76**
Biggest size	0.984	0.993	0.994	0.979	-0.54	**4.72**

* $p < 0.1$; ** $p < 0.05$

The table compares empirical correlation coefficients with theoretical correlation coefficients implied by the change in volatility. Correlation coefficients are estimated for each of five size sorted portfolio returns with the returns of the aggregate market. Return variables are in the excess of risk free rate which is approximated by the one-month Treasury bill rate. Monthly data spans the period from January, 1963 to December, 2015 (636 observations), for five portfolios in cross section. Data comes from the library of Kenneth French. Columns 2 and 3 present boom and recession correlation coefficients, ρ^{Boom} and $\rho^{Recession}$, where boom and recession subsamples are defined according to NBER determined recession periods. In the fourth column the volatility adjusted recession correlations (ϕ^{FR}) are presented, following the methodology of Forbes and Rigobon (2002). The correlations in the fifth column (ϕ^{CPS}) are adjusted for volatility according to the methodology of Corsetti et al. (2005). For this method, λ_j is calculated as in equation 10 using Fama-French three factor model. The last two columns display the test statistics for comparing the empirical recession correlations with the volatility adjusted recession correlations, calculated according to the two methodologies. Under the null hypothesis, the increase in volatility is sufficient to explain the observed increase in empirical correlations. The test statistic follows a standard normal distribution. Thus, any test statistic greater than the critical value of 1.645, which corresponds to a 5% significance level, implies the rejection of the null hypothesis, suggesting that the increase in volatility is not sufficient to justify the observed recession correlations. The test statistics that are in excess of the critical value are displayed in **bold** format.

Table 6: Interquintile Asymmetric vs. Counter-Cyclical Correlations: Vol. Effect

	I	II	III	IV
$I(r_{i,t} * r_{m,t} > 0)$	-0.004	0.000		
	(0.51)	(0.06)		
$I(r_{i,t} < 0 \& r_{m,t} < 0)$	0.037	0.027		
	(5.96)**	(5.14)**		
$I(NBER_{recession})$			0.015	-0.011
			(3.28)**	(1.76)*
$Ln(\sigma_{m,t})$		0.022		0.027
		(5.80)**		(6.21)**
$corr_{i,t-1}$	0.579	0.548	0.579	0.551
	(11.37)**	(9.38)**	(10.80)**	(9.21)**
Intercept	0.363	0.404	0.374	0.417
	(7.36)**	(7.09)**	(7.57)**	(7.33)**
R^2	0.37	0.41	0.34	0.40
N	6,360	6,360	6,360	6,360

* $p < 0.1$; ** $p < 0.05$

The table reports estimates from panel regressions, including coefficients estimates and t-statistics (in parentheses). The dependent variable is the monthly pairwise correlations of the returns of five portfolios sorted according to the market capitalization. Ten pairwise correlations are calculated every month using the daily excess return data of five size-sorted portfolios. Monthly data spans the period from January, 1963 to December, 2015 (636 observations). Data comes from the library of Kenneth French. The regressors are as follows: first and second independent variables are dummy variables, the second one identifying the market downturns. If the condition in the parentheses is satisfied the dummy variable takes the value of one and otherwise zero. Other regressors are natural logarithm of aggregate market volatility, a dummy variable that takes the value of one for the months within the NBER determined recession periods, and the lagged correlation (the first lag of the regressand). Estimates from four different specifications are reported where the standard errors are clustered for time and cross sectional dependence, with the method proposed by Petersen (2009). Return variables are in the excess of risk free rate which is approximated by the one-month Treasury bill rate. As is in the literature, the return variables have been standardized so that each variable has a mean zero and a standard deviation of one.

Table 7: Asymmetric vs. Counter-Cyclical Correlations: Vol. Effect (Ind. Prod.)

	I	II	III	IV
	(0.52)	(0.11)		
I($r_{i,t} < 0 \& r_{m,t} < 0$)	0.028	0.021		
	(2.95)**	(2.90)**		
Ind. Prod.			-0.002	0.004
			(1.13)	(2.32)**
Ln($\sigma_{m,t}$)		0.015		0.018
		(3.18)**		(3.24)**
$corr_{i,t-1}$	0.629	0.610	0.632	0.613
	(8.64)**	(7.52)**	(8.45)**	(7.39)**
Intercept	0.331	0.357	0.337	0.363
	(5.42)**	(5.00)**	(5.40)**	(5.01)**
R^2	0.42	0.45	0.40	0.44
N	3,180	3,180	3,180	3,180

* $p < 0.1$; ** $p < 0.05$

The table reports estimates from panel regressions, including coefficients estimates and t-statistics (in parentheses). The dependent variable is the monthly correlation with the aggregate market excess return, for five portfolios sorted according to the market capitalization. Monthly data spans the period from January, 1963 to December, 2015 (636 observations), for five portfolios in cross section. Data comes from the library of Kenneth French. The regressors are as follows: first and second independent variables are dummy variables, the second one identifying the market downturns. If the condition in the parentheses is satisfied the dummy variable takes the value of one and otherwise zero. Other regressors are natural logarithm of aggregate market volatility, change in real industrial production, and the lagged correlation (the first lag of the regressand). Estimates from four different specifications are reported where the standard errors are clustered for time and cross sectional dependence, with the method proposed by Petersen (2009). Return variables are in the excess of risk free rate which is approximated by the one-month Treasury bill rate. As is in the literature, the return variables have been standardized so that each variable has a mean zero and a standard deviation of one.

Table 8: Higher Correlations over the Business Cycle: Volatility Effect (Ind. Prod.)

Dep var: $corr_{i,t}$	I	II	III	IV	V	I	II	III	IV	V
	Before controlling for volatility					After controlling for volatility				
Ind. Prod.	-0.006	-0.006	-0.005	-0.004	-0.001	0.004	0.003	0.002	0.002	-0.000
	(1.31)	(2.02)**	(1.98)*	(1.86)*	(2.30)**	(0.88)	(0.95)	(0.83)	(1.01)	(0.35)
$\text{Log}(\sigma_{m,t})$						0.032	0.028	0.025	0.017	0.002
						(5.64)**	(6.43)**	(6.07)**	(5.26)**	(3.94)**
$corr_{i,t-1}$	0.411	0.409	0.373	0.360	0.453	0.385	0.367	0.297	0.277	0.415
	(7.69)**	(7.34)**	(6.75)**	(5.66)**	(7.21)**	(7.06)**	(6.31)**	(4.44)**	(4.66)**	(7.06)**
Intercept	0.489	0.523	0.576	0.610	0.542	0.527	0.574	0.658	0.697	0.581
	(11.24)**	(10.76)**	(11.48)**	(10.02)**	(8.68)**	(11.21)**	(10.79)**	(10.29)**	(11.94)**	(9.94)**
R^2	0.17	0.18	0.15	0.14	0.22	0.24	0.28	0.30	0.29	0.28
N	636	636	636	636	636	636	636	636	636	636

* $p < 0.1$; ** $p < 0.05$

The table reports estimates from time-series regressions, including coefficient estimates and t-statistics (in parentheses). The dependent variable is the monthly correlation with the aggregate market excess return, for five portfolios sorted according to the market capitalization. Column numbers from I to V indicates the corresponding size portfolio, I being the smallest and V being the largest. Monthly data spans the period from January, 1963 to December, 2015 (636 observations), for five portfolios in cross section. Data comes from the library of Kenneth French. The regressors are as follows: the logarithm of aggregate market volatility, change in real industrial production, and the lagged correlation (the first lag of the regressand). Standard errors are clustered by year. Return variables are in excess of risk free rate which is approximated by the one-month Treasury bill rate. As is in the literature, the return variables have been standardized so that each variable has a mean zero and a standard deviation of one.

Table 9: Counter-Cyclical Correlations Adjusted for Volatility (Ind. Prod.)

Portfolio	ρ^{Boom}	$\rho^{Recession}$	ϕ^{FR}	ϕ^{CPS}	z^{FR}	z^{CPS}
Smallest size	0.816	0.822	0.856	0.852	-1.35	-1.16
Size 2	0.893	0.892	0.919	0.914	-1.77	-1.38
Size 3	0.931	0.934	0.948	0.943	-1.50	-0.86
Size 4	0.960	0.969	0.970	0.964	-0.23	0.90
Biggest size	0.984	0.990	0.988	0.982	1.26	**3.88**

* $p < 0.1$; ** $p < 0.05$

The table compares empirical correlation coefficients with thoeretical correlation coefficients implied by the change in volatility. Correlation coefficients are estimated for each of five size sorted portfolio returns with the returns of the aggregate market. Return variables are in the excess of risk free rate which is approximated by the one-month Treasury bill rate. Monthly data spans the period from January, 1963 to December, 2015 (636 observations), for five portfolios in cross section. Data comes from the library of Kenneth French. Columns 2 and 3 present boom and recession correlation coefficients, ρ^{Boom} and $\rho^{Recession}$, where boom subsample is defined as periods of positive growth in real industrial production and recession subsamples is defined as periods of negative growth in real industrial production. In the fourth column the volatility adjusted recession correlations (ϕ^{FR}) are presented, following the methodology of Forbes and Rigobon (2002). The correlations in the fifth column (ϕ^{CPS}) are adjusted for volatility according to the methodology of Corsetti et al. (2005). For this method, λ_j is calculated as in equation 10 using Fama-French three factor model. The last two columns display the test statistics for comparing the empirical recession correlations with the volatility adjusted recession correlations, calculated according to the two methodologies. Under the null hypothesis, the increase in volatility is sufficient to explain the observed increase in empirical correlations. The test statistic follows a standard normal distribution. Thus, any test statistic greater than the critical value of 1.645, which corresponds to a 5% significance level, implies the rejection of the null hypothesis, suggesting that the increase in volatility is not sufficient to justify the observed recession correlations. The test statistics that are in excess of the critical value are displayed in **bold** format.

Table 10: Interquintile Asymmetric vs. Counter-Cyclical Correlations: Volatility Effect (Ind. Prod.)

	I	II	III	IV
I($r_{i,t} * r_{m,t} > 0$)	-0.004	0.000		
	(0.51)	(0.06)		
I($r_{i,t} < 0 \& r_{m,t} < 0$)	0.037	0.027		
	(5.96)**	(5.14)**		
Ind. Prod.			-0.005	0.004
			(1.98)**	(1.54)
Ln($\sigma_{m,t}$)		0.022		0.026
		(5.80)**		(6.29)**
$corr_{i,t-1}$	0.579	0.548	0.582	0.550
	(11.37)**	(9.38)**	(11.06)**	(9.18)**
Intercept	0.363	0.404	0.374	0.415
	(7.36)**	(7.09)**	(7.64)**	(7.29)**
R^2	0.37	0.41	0.34	0.40
N	6,360	6,360	6,360	6,360

* $p < 0.1$; ** $p < 0.05$

The table reports estimates from panel regressions, including coefficients estimates and t-statistics (in parentheses). The dependent variable is the monthly pairwise correlations of the returns of five portfolios sorted according to the market capitalization. Ten pairwise correlations are calculated every month using the daily excess return data of five size-sorted portfolios. Monthly data spans the period from January, 1963 to December, 2015 (636 observations). Data comes from the library of Kenneth French. The regressors are as follows: first and second independent variables are dummy variables, the second one identifying the market downturns. If the condition in the parentheses is satisfied the dummy variable takes the value of one and otherwise zero. Other regressors are natural logarithm of aggregate market volatility, change in real industrial production, and the lagged correlation (the first lag of the regressand). Estimates from four different specifications are reported where the standard errors are clustered for time and cross sectional dependence, with the method proposed by Petersen (2009). Return variables are in the excess of risk free rate which is approximated by the one-month Treasury bill rate. As is in the literature, the return variables have been standardized so that each variable has a mean zero and a standard deviation of one.

Table 11: Counter-Cyclical Correlations over Different Types of Crises

	I	II	III	IV	V	VI
Currency Crisis	0.015	0.010				
	(2.06)**	(1.19)				
Stock Market Crisis			0.012	-0.015		
			(2.64)**	(-5.85)**		
Banking Crisis					0.001	-0.007
					(0.43)	(1.50)
Ln($\sigma_{m,t}$)		0.017		0.019		0.018
		(3.22)**		(3.28)**		(3.12)**
$corr_{i,t-1}$	0.628	0.608	0.630	0.613	0.633	0.611
	(8.19)**	(7.12)**	(8.38)**	(7.40)**	(8.58)**	(7.32)**
Intercept	0.339	0.367	0.337	0.365	0.335	0.367
	(5.35)**	(4.95)**	(5.41)**	(5.02)**	(5.48)**	(5.00)**
R^2	0.40	0.44	0.40	0.44	0.40	0.44
N	3,175	3,175	3,175	3,175	3,175	3,175

* $p < 0.1$; ** $p < 0.05$

Years of currency crisis are 1969, 1971, 1975, 2002 and 2003. Stock market crises are during years 1974, 2002 and 2008, while the banking crises are from 1984 to 1992, and from 2007 to 2010.

The table reports estimates from panel regressions, including coefficients estimates and t-statistics (in parentheses). The dependent variable is the monthly correlation with the aggregate market excess return, for five portfolios sorted according to the market capitalization. Monthly data spans the period from January, 1963 to December, 2015 (636 observations), for five portfolios in cross section. Data comes from the library of Kenneth French. The regressors are natural logarithm of aggregate market volatility, three dummy variables identifying the three types of crises, and the lagged correlation (the first lag of the regressand). Estimates from six different specifications are reported where the standard errors are clustered for time and cross sectional dependence, with the method proposed by Petersen (2009). Return variables are in the excess of risk free rate which is approximated by the one-month Treasury bill rate. As is in the literature, the return variables have been standardized so that each variable has a mean zero and a standard deviation of one.

Table 12: Cost of Correlation Asymmetry

	Exercise 1	Exercise 2
ρ_L	0.50	0.50
ρ_H	0.60	0.60
$\rho_H - \rho_L$	0.10	0.10
$\sigma_{m,L}$	0.15	0.15
$\sigma_{m,H}$	0.18	0.18
Required compensation $\bar{w}$ (in basis points)	43	161

* $p < 0.1$; ** $p < 0.05$

The table reports the monetary compensations to naive investor as explained in Exercise 1 and Exercise 2. Exercise 1 sets the expected continuously compounded return on risky assets as $\mu = 0.07$, and the volatility of the continuously compounded return increases from 15 percent in low volatility state to 18.3 percent in high volatility state. This increase in volatility causes the correlation of asset returns in low volatility state, $\rho_L = 0.50$, to increase to $\rho_H = 0.60$ in high volatility state. The constant risk-free rate is set as $r_f = 0.05$, and the constant relative risk aversion as $\gamma = 4$. Exercise 2 uses the same parameters, but lets the betas and idiosyncratic volatilities of risky assets to differ between High and Low correlation regimes.

Table 13: Cost of Asymmetric vs. Counter-Cyclical Correlations

		BC	up/down
γ =2	w_s	(0.02, 0.25)	(0.35, 0.34)
	$\bar{w}$	0.06	0.35
γ =4	w_s	(0.01, 0.13)	(0.18, 0.17)
	$\bar{w}$	0.03	0.17
γ =6	w_s	(0.01, 0.09)	(0.12, 0.11)
	$\bar{w}$	0.02	0.11
γ =8	w_s	(0.01, 0.06)	(0.09, 0.08)
	$\bar{w}$	0.01	0.09

* $p < 0.1$; ** $p < 0.05$

The table reports the weights of the risky assets across different states of the RS model as well as the monetary compensations to naive investor for counter-cyclical and asymmetric correlations separately. The results are reported for different coefficients of risk aversion.

1.8 Appendix to Chapter I: Portfolio Allocation Problem

$$\max_{\{\alpha_1,\alpha_2\}} \mathbb{E}\frac{W^{1-\gamma}}{1-\gamma}$$

where W is the end-of-period wealth, $W = (1-\alpha_1-\alpha_2)e^{r_f} + \alpha_1 e^{r_1} + \alpha_2 e^{r_2}$. Corresponding first order conditions;

$$\mathbb{E}[W^{-\gamma}\alpha_i(e^{r_i} - e^{r_f})] = 0 \qquad \text{for } i \in \{1,2\} \tag{17}$$

We solve this system of equations with two first order conditions and two unknowns, α_1 and α_2, numerically. Using the numerical quadrature technique described in Tauchen and Hussey (1991), we calculate the expectations in 17 as

$$\Sigma_{s=1}^{M}[W_s^{-\gamma}(\tilde{r_{s,i}} - r_f)q_s] = 0 \qquad \text{for } i \in \{1,2\} \tag{18}$$

where $\tilde{r_{s,i}}$ are the M different optimal quadrature points and q_s are the corresponding probabilities. W_s is the investor's end of period wealth, calculated M different quadrature points of $\tilde{r_{s,1}}$ and $\tilde{r_{s,2}}$. As shown by Tauchen and Hussey (1991), 18 calculated even at small number of points, i.e. M is small, provides an accurate value for 17 as long as the quadrature points are chosen optimally. We set M to be 5. Investor's optimal portfolio weights are the non-linear solutions to equation in 18. We find these solutions using non-linear root finder in MATLAB.

For the regime-switching (RS) model the same idea is applied in a slightly complicated way. Conditional on each regime, i.e. $s_t = H$, the bivariate normal distribution is approximated using 5×5 quadrature points and the correlation in bivariate normal distribution is achieved using a Cholesky decomposition transformation. Once the bivariate normal distributions are approximated conditional on the regime s_t, transitional probabilities are used to form the conditional expectation. For instance, conditional on regime $s_t = H$ we use probabilities P_H and $1-P_H$. Similarly, conditional on regime $s_t = L$, the probabilities are P_L and $1 - P_L$.

We match the conditional and unconditional moments as follows. We can derive the unconditional mean of RS model as $\pi_H\mu_H + \pi_L\mu_L$ where π_H and π_L are the steady state probabilities. We can derive the steady state probabilities from $(\pi_L\ ,\ \pi_H)\begin{pmatrix} P_L & 1-P_L \\ 1-P_H & P_H \end{pmatrix} = (\pi_L\ ,\ \pi_H)$. When conditional means are equal as we assume, the unconditional variance-covariance matrix can be derived from conditional ones simply as $\pi_H\Sigma_H + \pi_L\Sigma_L$.

Chapter II

TURN-OF-THE-MONTH-EFFECT: NEW EVIDENCE FROM THE G7 COUNTRIES[††]

2.1 Introduction

The turn-of-the-month (ToM) effect is one of the most commonly studied calendar anomalies in the finance literature. The pioneering study in this strand of literature is by Ariel (1987), who documents a pattern of high equity returns in the few days surrounding the turn of the month. Specifically, using the CRSP value- and equal-weighted index returns from 1963 to 1981, Ariel finds that the mean daily return in the 10-day period including the last trading day of the month and the first nine trading days of the next month is high and positive, while the mean return in the remaining days of the month is negative.

Defining the turn of the month as the 4-day period beginning with the last trading day of the month and ending with the third trading day of the next month, Lakonishok and Smidt (1988) show that the ToM period returns account for all positive return to the DJIA from 1897 to 1986. Ogden (1990) confirms the findings in Lakonishok and Smidt (1998) and argues that the effect is at least in part driven by concentration of cash flows around month end due to the standardized payment system in the U.S. Hensel and Ziemba (1996) devise a portfolio strategy that invests in the S&P500 in the ToM period and in T-bills outside this period and find that this strategy outperforms a buy-and-hold strategy on S&P500 by 0.6% per year in

[††]This chapter is a result of my work with my thesis advisor N. Volkan Kayaçetin.

the period from 1928 to 1993. More recently, McConnel and Xu (2008) update these results over a more recent sample and show that the ToM effect is alive and well over the 1987–2004 period. The authors also find that the returns accrued during the ToM period account for all positive return to the U.S. equity market over the period from 1897 to 2005.

This study investigates the ToM effect in G7 countries' equity markets over the period from January 1998 to December 2015. Defining the ToM as the last four days of each month and the first day of the subsequent month, we find a strong pattern of high returns over this 5-day period. Specifically, we demonstrate that the mean daily ToM and rest-of-the month (RoM) returns are 0.11% versus 0.01% in the United States, 0.11% versus –0.02% in Canada, 0.12% versus –0.04% in the United Kingdom, 0.16% versus –0.02% in Germany, 0.16% versus –0.04% in France, 0.12% versus –0.04% in Italy, and 0.09% versus –0.02% in Japan. The negative mean returns in the RoM suggest that all positive return to the British, German, French, Italian, and Japanese markets is generated over the five-day period surrounding the month-turn. In addition to these, we also provide evidence of strong ToM effects in broader equity market indices: MSCI developed markets index (MSW) yields a mean daily ToM return of 0.09% versus –0.01% during the rest of the month. Similarly, MSCI emerging markets index (MSE) yields mean ToM and RoM returns of 0.13% versus –0.02%.

Conditioning on the month of the year, we then observe that the mean excess ToM return, defined as the difference between the mean daily ToM and RoM returns, is strongest in month-turns that lead to January, May, June, July, and November over our sample period, and consistently significant across the seven countries included in our cross-section. In January, the mean excess ToM return is statistically significant and exceptionally high in all countries, measured at 0.71% in Germany, 0.68% in France, 0.55% in Italy, 0.51% in Canada, 0.49% in the U.K, 0.30% in Japan, and 0.23% in the U.S. The mean excess ToM return in July ranges between 0.40% in Italy and 0.26% in the U.S., and is significant in all markets except Canada and the U.K. In May, the mean excess ToM return is statistically significant in five out of the seven countries, and it ranges from 0.42% in Italy and 0.24% in the U.S. The mean excess ToM returns in June and November are economically notable, but statistically insignificant except for 0.28% in Canada in June, and 0.36% and 0.41% in the U.S. and U.K. in November.

In subsample analyses, we observe that the ToM effect strengthens in the U.S. and Canada and weakens in the U.K., Germany, France, Italy, and Japan in the latter half of the sample. As we go from the early half to the late half of our sample period, the mean excess ToM return increases from 0.08% to 0.17% in Canada and from 0.09% to 0.11% in the U.S., and declines from 0.19% to 0.12% in the U.K., from 0.21% to 0.15% in Germany, from 0.24% to 0.16% in France, from 0.17% to 0.16% in Italy, and from 0.12% to 0.10% in Japan. In particular, the mean excess ToM return for the emerging markets index MSE doubles, rising from 0.10% in the first half of the sample to 0.21% in the second half. We further study the ToM effect conditional on the market performance in the month leading to each of these periods and find that it only exists in up markets. Specifically, the mean excess ToM return ranges between 0.30% in France and 0.10% in the U.S. following months with above-average market returns, and it is statistically significant in all markets. By contrast, the ToM effect is statistically insignificant in all countries following months with below-average market performance.

In addition to these findings, we also estimate an international CAPM using ToM and RoM returns and show that the index betas are significantly lower during the ToM period than in the RoM period for four out of six countries in our sample. This evidence indicates an even starker difference in terms of risk-adjusted returns generated during the ToM period compared to the remaining days of the month. Last, we explore the conditional volatility of international indices through fitting an exponential GARCH model in the spirit of Nelson (1991) and show that month-turns with significant excess ToM returns are also associated with a significant decline rather than an increase in expected volatility.

What should one make of the evidence on the ToM effect in international stock market returns? The finding that ToM returns are strongest in month-turns that coincide with the ends of the second and last quarters of the year is consistent with (a) a window-dressing story wherein fund managers close out their embarrassing positions prior to reporting deadlines only to reopen these positions subsequently as in Haugen and Lakonishok (1987) and Ritter (1988) and (b) an information risk story, wherein the uncertainty regarding firm fundamentals is gradually resolved around the financial reporting deadlines, pushing expected risk premia down and equity prices up. The finding that the expected volatility of returns across different international equity indices consistently displays significant declines as the month-turn draws closer provides further evidence in support of the information risk explanation. To the best of our knowledge, this latter finding is novel to the literature.

Our study adds to the strand of research investigating the ToM effect in international markets. Among others, Cadsby and Ratner (1992) show that the ToM effect is significant in six out of the ten countries included in their sample over the period from January 1962 to December 1989. Similarly, Kunkel, Compton, and Beyer (2003) study daily index returns in nineteen countries over the sample period from January 1988 to December 2000 and find that the ToM effect exists in fifteen of these countries, accounting on average for 87% of their monthly stock returns. In country-specific research, Kayacetin and Lekpek (2016) examine daily Turkish equity market returns over January 1988 to December 2014 and show that the ToM effect is strongly significant over this period and that it explains a greater fraction of index returns in later years of the sample in comparison to its earlier years. Similarly, Depenchuk, Compton, and Kunkel (2010) show existence of ToM effect in Ukrainian market over the 2003–2007 period. Other notable studies of ToM anomaly in international stock markets include Jaffe and Westerfield (1989), and Nikkinen, Sahlstrom, and Aijo (2007). Our study updates this literature using a more recent sample period, conducts subperiod tests, provides a monthly decomposition of the ToM effect, examines conditional volatility dynamics around month-ends, and analyzes the comovement of international index returns around month-ends.

The rest of the chapter is organized as follows. The next section summarizes the extant research on the ToM effect and lays out several possible explanations for the existence and persistence of this pervasive seasonal pattern. Section 2.3 describes our data and methodology. Section 2.4 presents and discusses our empirical findings. Section 2.5 concludes.

2.2 Literature Review

Jacobs and Levy (1988) argue that calendar anomalies occur at turning points in time that may invoke special patterns of behavior despite having little economic significance. The turn-of-the-month effect, formally examined first by Ariel (1987), is among the most commonly studied calendar anomalies in the finance literature together with the day-of-the-week and turn-of-the-year effects. The existence of calendar patterns in stock market returns is difficult to explain with traditional asset pricing models and the existence of such patterns would pose a challenge to the efficient markets view that has dominated the finance literature.

Using the CRSP value- and equal-weighted stock index returns from 1963 to 1981, Ariel (1987) finds that the mean daily return in the 10-day period including the last trading day of the month and the first nine trading days of the next month is high and positive, while the mean return in the remaining days of the month is negative. Lakonishok and Smidt (1988) define the turn-of-the-month as a four-day period beginning with the last trading day of the month and ending with the third trading day of the next month and show that ToM period returns account for all positive return to the DJIA from 1897 to 1986. Ogden (1990) confirms the findings of Lakonishok and Smidt (1998), arguing that the effect is, at least in part, driven by concentration of cash flows around month end due to the standardized payment system in the U.S. Hensel and Ziemba (1996) devise a portfolio strategy that invests in the S&P500 in the ToM period and in T-bills outside this period and find that this strategy outperforms a buy-and-hold strategy on S&P500 by 0.6% per year in the period from 1928 to 1993. More recently, McConnel and Xu (2008) study a 108-year period from 1897 to 2005, and show that the ToM effect in U.S. equity returns accounts for all positive return over this period.

Another strand of literature investigates the ToM effect in international index returns. Cadsby and Ratner (1992) show that the ToM effect is significant in six out of the ten countries included in their sample over the period from 1962 to 1989. Similarly, Kunkel et al. (2003) examine daily index returns in nineteen countries over the period from 1988 to 2000 and find that ToM effect exists in fifteen out of those nineteen, accounting on average for 87% of monthly stock returns in these countries. In country-specific research, Kayacetin and Lekpek (2016) show that not only ToM effect exists in Turkish equity market, but it also got stronger over the last two decades. Similarly, Depenchuk, Compton, and Kunkel (2010) demonstrate the existence of a ToM effect in Ukrainian stock market over the 2003–2007 period. Other notable studies exploring the ToM anomaly in international stock markets include Jaffe and Westerfield (1989), and Nikkinen, Sahlstrom, and Aijo (2007).

In an excellent survey of the literature on the seasonal patterns in stock market returns, Thaler (1987) lays out three plausible stories for the existence of such calendar effects:

1. *Liquid funds hypothesis* relates to payment day customs that influence fund flows in and out of the equity market. Following this thread, Ogden (1990) argues that regularity in payment dates of wages and interest/dividend income would create a supply of 'liquid funds' at month-ends and the flow of these liquid funds into the market push equity prices up, resulting in a monthly seasonal characterized by higher mean returns at the turn of the month.

2. *Window dressing hypothesis* suggests that fund managers adjust their port-

folios to close out embarrassing positions in advance of reporting deadlines and the fund flows generated as these managers return to their prior portfolio compositions after the reporting dates may result in a seasonal pattern characterized by high returns around reporting dates (Haugen and Lakonishok, 1987; Ritter, 1988).

3. *News clustering hypothesis* relates to systematic patterns in the dissemination of good and bad news. McNichols (1988) shows that firms tend to disseminate good news voluntarily in early days of the month and suppress bad news until reporting deadlines. This induces a clustering of good news and positive return shocks in early days of the month, which may explain the high equity returns accrued at the turn of the month.

To these three hypotheses suggested by Thaler, we add a fourth story that is based on gradual resolution of uncertainty following periods of increased information flow:

4. *Information risk hypothesis* argues that investors face greater information risk around particular month-turns due to an increase in the arrival rates of key macroeconomic and firm-specific data during month-ends (Ross, 1989). This increase in information arrival rates drives information uncertainty and expected volatility up until the information is released and the uncertainty is resolved. The gradual resolution of uncertainty in days around month-turns thus leads to a reduction in expected short-run risk premiums, sending equity valuations up.

Our study thus provides an explorative investigation of the ToM effect in stock markets of the G7 countries. In addition to updating the evidence on this pervasive seasonal pattern, we offer new evidence by analyzing mean returns in the ToM period conditional on the month of the year and market states, and by investigating how expected volatility, extracted through fitting an exponential GARCH model in the spirit of Nelson (1991) to index returns, behaves around the ToM period. Though we do not aim for a direct test of the alternative hypotheses above, the results from these parts of our analysis are likely to provide suggestive evidence.

2.3 Data and Variables

2.3.1 Data Sources and the Choice of Indices

The stock return data used in the chapter comes from two different sources. We obtain the U.S. value-weighted equity market returns from the Center for Research in Security Prices (CRSP) database, while the international equity market index returns come from the Thomson Reuters Datastream database. We limit the scope of our analysis to the G7 countries, which consists of the United States and Canada in North America; Japan in Asia; and Germany, France, Italy, and the United Kingdom in Europe. To provide a broader perspective, we include the MSCI World Index (MSW), which captures large and mid-cap representation across 23 developed markets.[21] While our focus here is on developed markets, we also include the MSCI Emerging Markets Index[22] (MSE) to make the comparison with the emerging markets possible. The countries, indices and market capitalizations as of 2015 are reported in Table 14.

We obtain U.S. dollar denominated daily closing prices for all stock market indices for the period from January 1998 to December 2015, over which we have complete data on all of the indices included in our sample. These closing prices are used to calculate daily log returns, $r_t = ln(P_t/P_{t-1})$, where P_t and P_{t-1} are the closing prices of the index at the end of trading days t and t-1, and r_t is the log index return from day t-1 to day t.

[21]With 1,643 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in each country. For more information, see https://www.msci.com/world.

[22]The index captures large and mid-cap representation across 23 emerging markets with 837 constituent stocks. The index covers approximately 85% of the free float-adjusted market capitalization in each country. For more information, see https://www.msci.com/emerging-markets.

2.3.2 Turn-of-the-Month Period

The turn-of-the-month (ToM) is typically defined as the period that spans the last few days of each month and the first few days of the subsequent month (e.g. Ogden (1990) and Lakonishok and Smidt (1988)). We examine the performance of alternative ToM definitions and label these based on the number of trading days included from the month that ends ($L_{\#}$) and the month that begins ($F_{\#}$). L_1F_2, for instance, refers to the period that covers the last trading day of the month that ends and the first two trading days of the subsequent month. As our analysis also features a month-by-month analysis of the ToM effect, it is important to clarify how the ToM periods for different months are labeled. We refer to each ToM period with the name of month that begins with it: for instance, the period that encompasses the last few days of December and the first few days of January is referred to as the January ToM.

Table 15 reports the mean daily returns over the last six days (t–6 to t–1) and the first six days (t+1 to t+6) of the month over the period from January 1998 to December 2015. We observe that the mean returns are particularly high from day t–4 to day t+1, and notably lower outside of this period. For instance, the mean daily return in the U.S. is high on days t–4, t–3, t–2, and t+1 (0.16%, 0.10%, 0.10%, and 0.18%) compared to a full sample mean of 0.03%. Similarly, the mean daily return in the U.K. is high on days t–5, t–4, t–3, t–1, and t+1 (0.10%, 0.14%, 0.12%, 0.10%, and 0.22%) compared to a full sample mean close to zero.[23] The concentration of high returns around the month-end is also evident in Canadian, German, French, Italian, and Japanese markets. Effectively, the mean return for MSW is high on

[23]Note that the index returns here do not include dividend yields. The price indices track variation in price levels without explicitly adjusting for the effect of dividends.

days t–4, t–3, and t+1 (0.12%, 0.11%, and 0.14%), while that for MSE is somewhat high on days t–3 and t–2 (0.08% and 0.09%) and extremely high on days t–1 and t+1 (0.27% and 0.21%).

In our analysis, we focus on the ToM definition that maximizes the average spread between the mean return in the ToM period with respect to that in the remaining days of the month. We refer to this spread as the excess ToM return. Based on the evidence above, we choose the period that spans the period from trading day t–4 to t+1, i.e. the L_4F_1 definition as a uniform ToM period for all markets under investigation, and use this definition in our further analysis.

2.3.3 Conditional Volatility

We start by writing the realized excess return on the market as:

$$r_{M,t} = \lambda_0 + \lambda_1 \sigma_t^2 + \theta_1 \epsilon_{t-1} + \epsilon_t \tag{19}$$

where $r_{M,t}$ is the market return in day t, σ_t is the conditional standard deviation of market return in day t, and ϵ_t is a random shock that is normally distributed with mean zero and variance σ_t^2. We use an exponential generalized autoregressive conditional heteroskedasticity (e-GARCH) model in the spirit of Nelson (1991) to extract the conditional variance of r_M as:

$$ln(\sigma_t^2) = \alpha_0 + \beta_1 ln(\sigma_{t-1}^2) + \alpha_1[\theta_2 \psi_{t-1} + \gamma(|\psi_{t-1}| - (2/\pi)^{1/2})] \tag{20}$$

The conditional variance of the market in any period is thus a function of (i) its conditional variance in the previous period, (σ_{t-1}^2); (ii) the standardized unit-variance return shock from the previous period, $\psi_{t-1} = \epsilon_{t-1}/\sigma^2_{t-1}$; and (iii) the deviation of the absolute value of this lagged return shock, ψ_{t-1}, from its mean absolute value of $(2/\pi)^{1/2}$. Applying the conditional mean and conditional variance equations given above to daily log index returns, we extract a daily time-series for its conditional volatility for each index.

2.4 Results and Discussion

2.4.1 Return Behavior around the Turn-of-the-Month Period

Table 16 reports the mean daily returns for the turn-of-the-month (ToM) period that spans the last four trading days of the month and the first trading day of the month. The table also reports the mean daily returns for the rest-of-the-month (RoM) period and the mean excess ToM return, i.e. the difference between mean daily ToM and RoM returns.

Panel A of Table 16 reports the results for the full sample period. The mean daily ToM and RoM returns are 0.11% and 0.01% in the U.S., 0.11% versus –0.02% in Canada, 0.12% versus –0.04% in the U.K., 0.16% versus –0.02% in Germany, 0.16% versus –0.04% in France, 0.12% versus –0.04% in Italy, and 0.09% versus –0.02% in Japan. These figures suggest a mean excess ToM return of 0.10% in the U.S., 0.13% in Canada, 0.16% in the U.K., 0.18% in Germany, 0.20% in France, 0.17% in Italy, and 0.11% in Japan, all of which are statistically significantly greater than zero at conventional significance levels. For broader developed and emerging market indices, we observe mean daily ToM and RoM period returns of 0.09% versus –0.01% for MSW and 0.13% versus –0.02% for MSE, The mean excess ToM return in both markets are strongly significant, measured at 0.10% for MSW and 0.15% for MSE.

The window dressing and information risk hypotheses described in Section 2.2 invoke the possibility that the ToM effect may exert a stronger presence in months that coincide with financial reporting deadlines or, more generally, with periods of increased information arrival rates. To address this possibility, we examine how ToM and RoM period returns vary across the months of the year and present the mean excess returns conditional on the month of the year in Table 17.[24] To conserve space, we do not report the mean ToM and RoM returns.

Our results from this monthly decomposition suggest that the mean excess ToM returns of G7 countries are consistently higher in January, May, June, July, and November. In the order of declining magnitude, the January mean excess ToM return (*per day*) is 0.71% in Germany, 0.68% in France, 0.55% in Italy, 0.51% in Canada, 0.49% in the U.K., 0.30 in Japan, 0.23% in the U.S., and statistically significant in all cases. In July, the mean excess ToM return is statistically significant in most of the G7 markets: 0.40% in Italy, 0.39 in France, 0.37% in Japan, 0.35% in Germany, and 0.26% in the U.S., while insignificant only in the U.K. at 0.21% and Canada at 0.19%. In May, the mean excess ToM return is strongly significant at 0.42% in Italy, 0.40% in Germany, 0.39% in France, 0.26% in the U.K., and 0.24% in the U.S., and statistically insignificant (but economically meaningful) at 0.18% and 0.17% in Canada and Japan. The mean excess ToM returns are also high in November: 0.41% and 0.36% in the U.K. and the U.S., respectively. In the remaining five countries, the mean excess ToM returns range from 0.36% in Germany to 0.21% in Italy. In June, the mean excess ToM return is statistically significant at 0.28% in Canada and, while reasonably high in economic magnitude, statistically insignificant at 0.25% in France, 0.23% in the U.K., 0.22% in Germany, 0.20% in Italy, 0.19% in the U.S., and 0.17% in Japan.

The last two columns of Table 17 show that returns on broader indices follow a very similar monthly decomposition of the ToM effect. Here, we observe that the mean excess ToM return for the broad developed and emerging market indices

[24]Although these tests suffer from low statistical power due to sample size limitations, they are nevertheless informative as the patterns that survive even under these circumstances are likely to be important ones.

(MSW and MSE) are 0.19% and 0.25% in January, 0.21% and 0.14% in May, 0.17% and 0.25% in June, 0.25% and 0.31% in July, and 0.33% and 0.48% in November. All of the reported spreads are strongly significant at conventional significance levels with the exception of that for May in emerging markets.

The consistency in the ToM pattern in different countries suggests that it must be associated with a systematic factor. The superior returns around July and January month-ends coincide with the second and fourth quarter-ends. The fact that these periods mark the fiscal year-end for most companies resonates with the information risk and window dressing hypotheses.[25] Further, if there is a lag between the fiscal year-end and these deadlines (see, for instance, Soltani, 2002; Ashton et al., 1987; Zeghal, 1984), the superior ToM returns in May and November may coincide with the deadlines for annual or quarterly financial reports.

Subperiod Analysis

It is of importance whether the ToM pattern persists over different subperiods. The effect will persist across subperiods if it arises due to systematic causes (either rational or behavioral), and disappear in certain subperiods if it is an artifact of data mining. To address this issue, we investigate ToM returns over two nine-year subperiods: from 1998 to 2006 (the early period) and from 2007 to 2015 (the late period). As before, we compute the mean daily ToM and RoM returns, as well as the mean excess ToM returns for all indices included in our sample. Panel B of Table 16 reports the results.

Going from the early period to the late period, the mean excess ToM return across all months increases from 0.09% to 0.11% in the U.S. and from 0.08% to

[25] For instance, the U.S. equity market fiscal year ends in December for 70%, in June for 6%, in September for 5%, and in March for 5% of the companies (WRDS CRSP database).

0.17% in Canada, while it declines from 0.19% to 0.12% in the U.K., from 0.21% to 0.15% in Germany, from 0.24% to 0.16% in France, from 0.17% to 0.16% in Italy, and from 0.12% to 0.10% in Japan. The mean excess ToM return for the emerging markets index increases from 0.10% in the early period to 0.21% in the late period, suggesting a strengthening of the effect in emerging markets.

It is also appealing to learn whether the ToM effect varies based on market performance. Jacobs (2015), for instance, studies the link between different stock market anomalies and popular proxies for time-varying investor sentiment. He finds that many of the anomalies can be explained by the market-level sentiment, in particular on the short side of the portfolios. To control for market-level performance, we divide our sample into two as up-market and down-market states based on the performance of the market index over the month that leads to a given ToM period. In doing so, we define an up (down) market state as one where the mean return in the month leading to a given month turn is higher (lower) than the mean market return over the full sample. Panel C of Table 16 presents our results for up and down markets.

In up-market states, the mean excess ToM return is strongly significant in all countries: 0.10% in the U.S., 0.16% in Canada, 0.24% in the U.K., 0.25% in Germany, 0.30% in France, 0.26% in Italy, and 0.22% in Japan. In down-market states, the spread between the mean daily ToM and RoM returns is statistically insignificant at 0.02% in the U.S., 0.09% in Canada, 0.08% in the U.K., 0.12% in Germany, 0.11% in France, 0.07% in Italy, and 0.00% in Japan. MSW records a positive and significant excess ToM return of 0.13% in up-market states and a statistically insignificant 0.03% in down-market states. MSE, on the other hand, records a positive and significant excess ToM return of 0.23% in up market states, and insignificant but economically meaningful 0.09% during down market states. The mean excess ToM return of 0.09% during down-markets, however, is mostly due to the negative RoM return of –0.08%.

The finding that the mean daily ToM returns are statistically and economically significantly greater than those in the rest of the month in both subperiods strengthens the case for the argument that the ToM effect arises due to systematic causes and weakens the case for the argument that it is due to data mining. The result that the high mean excess ToM returns are specific to up-market months suggests that that the hitherto undefined systematic factor that drives the ToM effect must be significant only around month-turns that succeed up-market months (i.e. months with above-average market returns) and insignificant following down-market months. To our knowledge, this last finding is novel to this literature.

2.4.2 Other Calendar Anomalies

This section investigates ToM effect and its interaction with other calendar anomalies. The list of anomalies we control for include the day-of-the-week, turn-of-the-year, and January effects.[26] The day-of-the-week (DoW) effect refers to the significant and persistent differences in mean equity market returns realized on

[26]Rozeff and Kinney (1976) were one of the first authors to document the January effect. Gultekin and Gultekin (1983) confirm existence of January effect in 16 different countries. Keim (1983), Blume and Stambaugh (1983), and Roll (1983) show that the January effect is driven by small-cap stocks. Keim (1983) and Reinganum (1983) and Ritter (1988) find that high returns realized by small-cap stocks occur mostly during the first two weeks of January, relabeling this seasonal pattern as the ToY effect. Reinganum (1983) and Roll (1983) attribute this effect to tax-loss-selling around the year-end. Poterba and Weisbenner (2001) study the ToY effect as the period spanning the last day of December and the first five days of January. More recently, Gu (2003) reports a decline in the effect for the U.S. market for both small and large stocks over the period from 1988 to 2000.

different days of the week.[27] January and the turn-of-the-year (ToY) effects are closely related: the former refers to a pattern of distinctly high returns during the first two weeks of the year while the latter includes the first four weeks.

As the ToM may overlap with other calendar anomalies, it is important to see which anomaly prevails. To investigate the presence of January, ToY, and DoW effects in the G7 countries, we regress their stock market returns on dummy variables that correspond to each of these anomalies. We first study each of the anomalies separately, and then test all effects jointly to see whether they co-exist in G7 equity market returns. Table 18 presents our results for:

$$r_t = \alpha_0 + \beta_1 ToM_t + \epsilon_t \quad (21)$$

$$r_t = \alpha_0 + \beta_1 Mon_t + \beta_2 Tue_t + \beta_3 Wed_t + \beta_4 Thu + \beta_5 Fri_t + \epsilon_t \quad (22)$$

$$r_t = \alpha_0 + \beta 1 ToY_t + \epsilon_t \quad (23)$$

$$r_t = \alpha_0 + \beta 1 Jan_t + \epsilon_t \quad (24)$$

$$r_t = \alpha_0 + \beta_1 ToM_t + \beta_2 Mon_t + \beta_3 Tue_t + \beta_4 Thu_t + \beta_5 Fri_t + \beta_6 ToY + \beta_7 Jan_t + \epsilon_t (25)$$

where r_t is the daily index return, ToM is a dummy variable that equals 1 within the ToM period and 0 otherwise, Mon to Fri are dummy variables that correspond to each of the five trading days of the week, ToY is a dummy variable that takes the value of 1 during the last ten trading days in December and the first five trading days in January and 0 otherwise. Finally, Jan is a dummy variable that equals 1 during January and 0 in other months.

[27]French (1980) documents that average returns of S&P composite index are significantly negative on Mondays and positive on the remaining days of the week over the 1953–1977 period. Harris (1986), Lakonishok and Smidt (1988), and Keim (1987) study the interaction of DoW effect with both size and month effects. Cadsby (1989) identifies a Monday effect for the Canadian stock market. Jaffe and Westerfield (1985) and Lee et al. (1990) show that Japanese stock market records negative returns on Tuesday. Negative Monday return is also observed on the London Stock Exchange (Theobald and Price, 1984) and the Paris Bourse (Hamon and Jacquillat, 1990; Solnik and Bousquet, 1990). In the Italian equity market, negative returns are observed on Monday and Tuesday (Barone, 1990). Kohers et al (2004) study the DoW effect in world's largest equity markets over a more recent 1980–2002 period, and find that the effect has faded away in the 1990s.

Consistent with our results from the univariate analyses in the previous sections, the results reported in Panel A indicate that the coefficient estimate on ToM is positive and strongly significant in all countries, estimated at 0.20% in France, 0.18% in Germany, 0.17% in Italy, 0.16% in the U.K., 0.13% in Canada, 0.11% in Japan, and 0.10% in the U.S. The results from the day-of-the-week analysis reported in Panel B point to a lack of strong intraweek patterns in international index returns, except for a statistically significantly negative Monday dummy for the Italian market.[28] Our simple regressions examining the ToY effect, reported in Panel C, reveal that the coefficient on ToY is a statistically significant 0.36% for France, 0.32% for Italy and Germany, 0.30% for Canada, 0.24% for the U.K., 0.16% for the U.S., 0.15% for developed markets (MSW), and 0.21% emerging markets (MSE) and a positive but statistically insignificant 0.15% for Japan.[29] Finally, Panel D reports our simple regression results for the January dummy. These results indicate no presence of the January effect. The coefficient on Jan is negative and statistically insignificant in all of the G7 countries. Collectively, these initial results suggest existence of strong ToM and ToY effects in stock market indices of G7 countries, while we find no evidence of the DoW or January effects.

After studying each effect separately, we next look for their possible counterfeiting effects on stock market returns in a multiple regression setting. The results reported in Panel E suggest that the coefficient on ToM is positive and statistically significant at 0.19% in France, 0.16% in Germany, 0.15% in Italy, 0.14% in the U.K.,

[28] We also observe slightly higher mean returns on Tuesday and Thursday and slightly lower mean returns on Friday across all markets, but none of the coefficients are significantly different than zero. These findings are in line with the evidence reported in Kohers et al. (2004) about the disappearance of the day-of-the-week effect in developed markets after the 1990s.

[29] We define the turn-of-the-year as the period spanning the last ten trading days of December and the first trading day of January as this definition maximizes the mean daily ToY return. This suggests a backwards shift in the span over which the ToY effect is defined when compared to the earlier findings of the literature.

0.11% in Canada, 0.10% in Japan, 0.09% in the U.S., and 0.14% and 0.09% for the MSCI emerging and developed market indices. The coefficient estimate on ToY is positive and significant at 0.32% in France, 0.29% in Italy, 0.28% in Germany, 0.27% in Canada, and 0.21% in the U.K., and positive but insignificant at 0.14% in Japan and the U.S. The ToY coefficient is also positive and significant for MSE at 0.17% and MSW at 0.13%. The fact that the coefficients on ToM and ToY remain almost identical in simple and multiple regression tests suggests that these two anomalies co-exist in the international equity market index returns, and are distinct from one another. As in our univariate analysis, we do not observe significant day-of-the-week and January effects in the returns of G7 stock market indices.

2.4.3 Comovement of the Indices of the G7 Equity Markets

In the previous sections, a strong and remarkably consistent pattern of high returns around month-turns across the seven G7 equity markets is documented. In this section, we further investigate the comovement of the returns of these equity markets using an international CAPM framework. We start by estimating the following model over the ToM period:

$$r_{ToM,t} = \alpha_0 + \beta_1 US_{ToM,t} + \epsilon_t \tag{26}$$

where dependent variable is the total return during the five ToM days, and the independent variable is the total return of the U.S. stock market over the same period.[30] Next, we estimate a similar model for two five-day periods around the ToM period:

$$r_{t-9\ to\ t-5\ period,t} = \alpha_0 + \beta_1 US_{t-9\ to\ t-5\ period,t} + \epsilon_t \tag{27}$$

$$r_{t+2\ to\ t+6\ period,t} = \alpha_0 + \beta_1 US_{t+2\ to\ t+6\ period,t} + \epsilon_t \tag{28}$$

where t-9 to t-5, and t+2 to t+6 refer to the two five-day periods immediately before and after the turn-of-the-month. These models are estimated over five-day periods to ensure unbiased comparison with the model estimated over the ToM period. Finally, we estimate the model over the full sample period:

$$r_t = \alpha + \beta_1 US_t + \epsilon_t \tag{29}$$

Panel A of Table 19 reports the country betas estimated using the ToM period returns. These beta estimates vary from 0.84 in the U.K to 1.04 in Canada, suggesting a strong link between the U.S. and other equity market indices. The beta for Japan, however, is only 0.49, indicating a comparably weaker link with the U.S. We next compare the ToM period betas to those estimated in the 5-day period prior to ToM (Panel B). The results suggest that coefficients during the ToM period are lower than those during the 5-day period preceding ToM: 1.04 versus 1.13 in Canada, 0.84 versus 0.90 in the U.K., 1.01 versus 1.04 in Germany, 0.98 versus 1.01 in France, 0.93 versus 1.03 in France, and 0.49 versus 0.68 in Japan. ToM period betas are

[30] This study defines turn-of-the-month as five-day period spanning the last four *trading* days of each month and the first *trading* day of the following month. As these five trading days do not necessarily fall on the same calendar days in different countries, in this section of the study we define turn-of-the-month as five-day period spanning the last four *calendar* days of each month and the first *calendar* day of the following month. This ensures that the dependent and independent variables in our regressions correspond to identical time periods.

also lower than those estimated for the 5-day period after ToM days (Panel C): 1.04 versus 1.07 in Canada, 0.84 versus 0.96 in the U.K., 1.01 versus 1.16 in Germany, 0.98 versus 1.12 in France, 0.93 versus 1.08 in Italy, and 0.49 versus 0.69 in Japan.

Finally, we compare the link between the G7 countries during the ToM period with that for the full sample (Panel D). With the exception of Canada where the two coefficients are equal, the link between the country-pair returns is weaker during the turn-of-the-month period than during the full period. The last row of the table includes the p-values of the null hypothesis that the two coefficients are equal. The hypothesis is rejected for four out of six countries, assuming a 90% significance level.

To further explore the comovement dynamics of international index returns, we estimate an international CAPM over rolling 5-day windows. We start with the 5-day window coinciding with the ToM period, and continue by shifting the window by one calendar day backwards and one calendar day forwards. We construct seven rolling windows prior to the ToM and seven rolling windows after the ToM. Figure 2 plots the beta coefficients corresponding to the fifteen rolling-window regressions for the six countries in our dataset. These plots indicate that the beta coefficients decline prior to month-ends, and reach their minimum over the t-6 to t-2 period – shortly before the ToM period starts, and then rise again.

The finding that CAPM betas are lower during the ToM period suggests that month-turns are associated not only with higher returns but also with lower level of risk. This is consistent with our findings about conditional volatility patterns around month-ends. Both of the findings provide support for the *information-risk hypothesis* that suggests the resolution of uncertainty that coincides with month-ends leads to a reduction in expected risk premiums, sending equity valuations up.

Additionally, lower betas during month-ends are indicative of additional benefits to holders of internationally diversified portfolios during those periods.

2.4.4 Conditional Volatility around the Turn-of-the-Month Period

Section 2.4.1 is suggestive of a distinctive pattern of high returns in stock markets around month ends. This section investigates whether this pattern is driven by a reduction in conditional volatility around the same period. To analyze how the expected volatility behaves around the month-turn, we extract the daily time-series of conditional volatility using the e-GARCH model described in Section 2.3.3. We first average conditional volatility over a 10-day window around each month-end in the sample period and plot its behavior in Figure 3.

The figure reveals that the turn-of-the-month (ToM) periods of all countries see a decline in conditional volatility. Specifically, the local minimums of the volatility series are reached around the end of the ToM period. In the U.S., for instance, the conditional volatility declines in the last five days of the month and the first four days of the subsequent month, after which it starts increasing. Similarly, in Canada, the last six and the first two days of the month see a reduction in expected volatility. A broadly consistent pattern is observed in other equity markets in our sample, suggesting that the ToM effect that we consistently observe in different subperiods and different stock market indices might be a byproduct of a reduction in the risk that is faced by equity market investors.

Next, we formally investigate the dynamics of the decline in conditional volatility over the course of a month. In doing so, we compare the average level of volatility in the RoM with the lowest level of volatility reached during the ToM period. The full sample results reported in Panel A of Table 20 suggest a significant decline in volatility during the ToM period. The conditional volatilities during the ToM and RoM periods are 15.7% versus 17.3% in the U.S., 18.1% versus 19.4% in Canada, 17.9% versus 19.5% in the U.K., 22.3% versus 24.2% in Germany, 21.6% versus 23.5% in France, 23.0% versus 24.8% in Italy, and 21.6% versus 23.6% in Japan. The differences are statistically significant in all countries except Canada, confirming our observation that volatility tends to decline around the ToM periods.

Panel B of Table 18 replicates the same analysis for the two nine-year subsamples. The results are consistent with the full sample results, although due to lower power of the tests some of the differences in volatility are not statistically significant. In the early sample, conditional volatilities during ToM and RoM periods are 15.5% and 17.0% in the U.S., 16.7% and 17.9% in Canada, 16.6% and 18.0% in the U.K., 22.1% and 23.7% in Germany, 19.9% and 21.4% in France, 19.7% and 21.0% in Italy, and 22.6% and 24.7% in Japan. Conditional volatility is also lower in ToM days during the late sample: 15.9% versus 17.7% in the U.S., 19.4% versus 20.9% in the Canada, 19.1% versus 21.1% in U.K., 22.4% versus 24.8% in Germany, 23.2% versus 25.5% in France, 26.2% versus 28.6% in Italy, and 20.4% versus 22.4% in Japan.

Last, Panel C reports the results for up- and down-market states separately. Several interesting findings arise. First, by comparing volatility dynamics in up- and down-markets, we see that the volatility is significantly lower during the latter. Specifically, while the ToM volatility during up markets ranges between 17.1% in the U.S. to 24.9% in Italy, down-market volatility ranges between 14.7% in the U.S. and 21.9% in Italy. Second, focusing on down markets, we observe statistically significant declines in volatility during the ToM period in the U.S. (17.1% versus 18.8%), the U.K. (19.0% versus 20.6%), Germany (24.2% versus 26.0%), France

(23.3% versus 25.2%), and Japan (22.4% versus 24.4%), while the difference is not statistically significant in Canada and Italy. Third, focusing on up markets, the differences in volatility between ToM and RoM periods are statistically significant in all seven countries: 14.7% versus 15.9% in the U.S., 16.4% versus 18.2% in Canada, 16.1% versus 18.0% in the U.K., 21.1% versus 22.7% in Germany, 19.2% versus 22.0% in France, 21.9% versus 23.9% in Italy, and 20.7% versus 22.8% in Japan.

These results resonate most with an information risk story, wherein uncertainty regarding firm fundamentals is gradually resolved around financial reporting deadlines, pushing expected risk premia down and equity prices up.

2.5 Conclusion

This chapter investigates the turn-of-the-month (ToM) effect in G7 markets over the period from January 1998 to December 2015. Our results indicate that the effect is strongly significant, with a mean daily return of 0.16% in Germany and France, 0.12% in the U.K. and Italy, 0.11% in the U.S. and Canada, and 0.09% in Japan over the 5-day period that covers the last four trading days of each month and the first trading day of the following month. By contrast, the mean daily return during the rest-of-the-month is 0.01% in the U.S., –0.02% in Canada, Germany, and Japan, and –0.04% in France, Italy, and the U.K.

The existence of a monthly seasonal in stock market returns is difficult to reconcile with the efficient markets view. To further test the robustness of this effect, we divide our sample into an early and a late subperiod and conduct sub-period tests to observe the evolution of the month-end seasonal over time. Our ex-ante expectation is to see the ToM effect disappear in more recent periods. Our evidence points to a strengthening in the effect in the U.S. and Canada, while it diminished in the remainder of the G7 countries.

The consistency of the ToM effect across different markets suggests that it must be associated with a systematic factor (rational or behavioral) in the behavior of investors. To shed light on possible alternative stories for the existence of the ToM effect, we conduct a monthly decomposition of returns and show that the ToM effect is particularly strong in January and July, which coincide with the second and the last quarter end, but also in May, June, and November. In addition, dividing the sample into up- and down-markets, we show that the turn-of-the-month effect is strong following market upturns and insignificant following market downturns.

The findings above resonate best with an information risk story, where gradual resolution of uncertainty in the days that lead to the month-end tilts equity returns upwards, the more so the better the news in the period that leads to the ToM period. To further address this explanation, we estimate a daily time-series for the conditional volatility of the G7 equity market indices using an exponential generalized autoregressive heteroskedasticity (e-GARCH) model in the spirit of Nelson (1991) and show that the conditional volatility of the index tends to decline in the period that leads to the month-end. Additionally, we estimate an international-CAPM model separately for periods during and outside month-turns, and find that returns during month-ends are associated with lower levels of risk implied by the CAPM beta, providing additional support to the information risk story.

2.6 Chapter II Figures and Tables

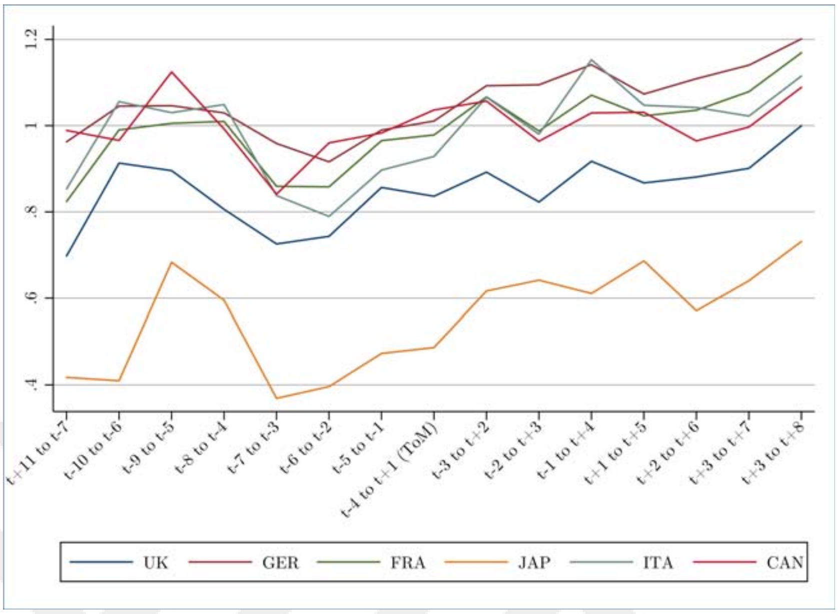

Figure 2: Evolution of International-CAPM Beta Throughout a Calendar Month

This figure plots the regression coefficients from an International CAPM model estimated over 15 five-day rolling windows. We start by the five-day period that coincides with turn-of-the-month days, and continue by shifting the five-day rolling window one calendar day backwards and one calendar day forwards. For sake of brevity, we omit the plots of the two MSCI indices coefficients as they follow a very similar pattern.

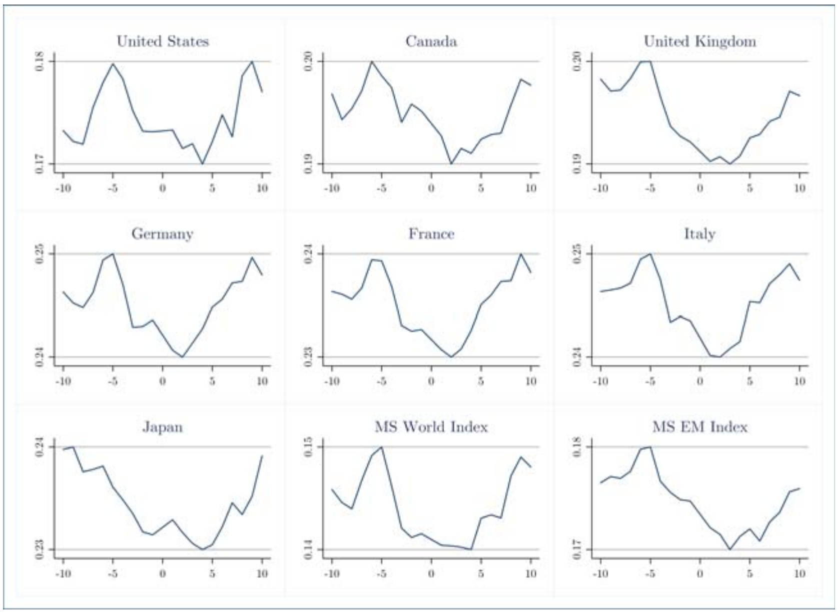

Figure 3: Conditional Volatility around Month End

This figure plots the mean (annualized) conditional standard deviation of the G7 equity market indices over a twenty-day window around the month-end. In doing so, the conditional volatility of the index is extracted from daily return data using the exponential GARCH(1,1) model in Nelson (1991), and the resulting daily time series is used to calculate the mean conditional volatility across all months in the sample on each trading day that falls within the twenty-day window around the month-turn.

Table 14: Country Indices, Data Sources and Spans, and Market Capitalizations

Country	Index	Abbrev.	Source	Start date	Market cap.
United States	CRSP VW Index	US	CRSP	Jan 1, 1926	27,840
Canada	S&P's Toronto SE Comp.	CAD	Thomson Reuters	Jan 31, 1950	1,220
United Kingdom	FTSE 100	UK	Thomson Reuters	Jan 31, 1978	2,527
Germany	DAX 30 Performance	GER	Thomson Reuters	Dec 31, 1964	1,148
France	France CAC 40	FRA	Thomson Reuters	Jul 9, 1987	1,368
Italy	FTSE MIB Index	ITA	Thomson Reuters	Dec 31, 1997	320
Japan	Nikkei 225 Stock Average	JAP	Thomson Reuters	Apr 3, 1950	2,903
Developed Markets	MSCI World U.S. Dollar	MSW	Thomson Reuters	Dec 31, 1969	-
Emerging Markets	MSCI EM U.S. Dollar	MSE	Thomson Reuters	Dec 31, 1987	-

The time period ends on Dec 31, 2015 for each country. Market capilaizations are reported in USD billion. The total market capitalization of all indices included in the study is USD 37,326 billion as of 2015 year-end (MSCI indices excluded).

Table 15: Mean Daily Returns around Month-End

t	USA	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
-6	-0.10	-0.10	-0.07	-0.07	-0.08	-0.16	-0.12	-0.10	-0.16*
-5	0.00	0.09	0.10	0.13	0.18	0.13	0.09	0.04	0.03
-4	0.16*	0.09	0.14*	0.26**	0.18**	0.16*	0.08	0.12**	0.01
-3	0.10	0.02	0.12	0.14	0.20	0.13	0.05	0.11	0.08
-2	0.10	0.06	0.01	-0.06	-0.03	-0.03	0.06	0.02	0.09
-1	0.01	0.19**	0.10	0.20*	0.23**	0.17*	0.03	0.03	0.27***
1	0.18*	0.17	0.22*	0.25**	0.22*	0.17	0.21*	0.14*	0.21**
2	0.05	0.09	0.05	-0.05	-0.05	-0.05	0.00	0.09	0.30***
3	0.03	-0.04	0.06	0.14	0.01	0.09	-0.24**	0.02	-0.04
4	0.01	0.02	-0.19*	-0.20*	-0.17	-0.25*	0.02	-0.05	0.03
5	-0.03	-0.08	0.02	-0.03	-0.06	-0.04	0.08	-0.06	0.03
6	-0.03	-0.08	-0.12	-0.09	-0.13	-0.03	-0.34***	0.00	-0.08
RoM	0.02	-0.02	-0.05	-0.02	-0.04	-0.04	0.02	-0.01	-0.05*
Total	0.03**	0.01	0.00	0.02	0.01	0.00	0.01	0.01	0.01

This table presents mean daily returns for the last six days (t–6 to t–1) and the first six days (t+1 to t+6) of the month over the period from Jan 1998 to Dec 2015, along with the asterisks from a *t*-test for the null hypothesis that these means are equal to zero. *RoM* is the mean daily return over the rest of the month and *Total* is the mean daily return over the full sample. Return variables are reported as percentages. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Table 16: ToM Effect Over Different Subsamples

Panel A: Full Sample									
	USA	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
ToM	0.11***	0.11***	0.12***	0.16***	0.16***	0.12**	0.09*	0.09***	0.13***
SD	1.27	1.38	1.37	1.63	1.60	1.68	1.54	1.01	1.19
RoM	0.01	-0.02	-0.04	-0.02	-0.04	-0.04	-0.02	-0.01	-0.02
SD	1.25	1.40	1.40	1.68	1.63	1.74	1.61	1.03	1.26
Diff	0.10**	0.13***	0.16***	0.18***	0.20***	0.17***	0.11**	0.10***	0.15***
Panel B: Subsamples									
	USA	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
					1998–2006				
ToM	0.10**	0.10*	0.16***	0.18***	0.22***	0.16***	0.10	0.10***	0.11**
SD	1.13	1.20	1.14	1.53	1.39	1.36	1.56	0.86	1.03
RoM	0.01	0.02	-0.03	-0.02	-0.03	-0.01	-0.02	-0.01	0.01
SD	1.14	1.16	1.16	1.59	1.39	1.36	1.66	0.89	1.11
Diff	0.09	0.08	0.19***	0.21***	0.24***	0.17**	0.12	0.11***	0.10*
					2007–2015				
ToM	0.11*	0.12*	0.08	0.13*	0.11	0.09	0.08	0.07	0.15***
SD	1.40	1.53	1.56	1.73	1.79	1.95	1.51	1.14	1.33
RoM	0.01	-0.05	-0.04	-0.02	-0.05	-0.08	-0.02	-0.01	-0.05
SD	1.35	1.60	1.59	1.78	1.84	2.04	1.56	1.15	1.39
Diff	0.11	0.17**	0.12	0.15*	0.16*	0.16*	0.10	0.08	0.21***
Panel C: Market States									
	USA	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
					Down				
ToM	0.03	0.05	0.04	0.07	0.04	0.01	-0.03	-0.01	0.01
SD	1.54	1.56	1.51	1.78	1.75	1.76	1.68	1.20	1.35
RoM	0.01	-0.04	-0.05	-0.04	-0.07	-0.06	-0.03	-0.04	-0.08**
SD	1.50	1.64	1.67	1.97	1.99	2.03	1.76	1.27	1.47
Diff	0.02	0.09	0.08	0.12	0.11	0.07	0.00	0.03	0.09
					Up				
ToM	0.12***	0.16***	0.22***	0.25***	0.29***	0.23***	0.20***	0.14***	0.26***
SD	0.99	1.16	1.14	1.44	1.43	1.53	1.35	0.81	0.98
RoM	0.01	0.00	-0.03	0.00	-0.01	-0.03	-0.02	0.01	0.03
SD	1.02	1.15	1.06	1.39	1.25	1.42	1.45	0.77	1.02
Diff	0.10**	0.16***	0.24***	0.25***	0.30***	0.26***	0.22***	0.13***	0.23***

This table presents mean daily ToM and RoM returns for L_4F_1definition of the ToM period, along with the asterisks from a t-test for the null hypothesis that these means are equal to zero. *Diff* is the difference between ToM and RoM returns under each ToM definition. The standard t-test of mean difference being equal to zero takes into account the fact that number of observations used to calculate mean ToM returns is significantly lower than that for mean RoM returns. Return and standard deviation variables are reported as percentages. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Table 17: Tom Effect by Months of the Year

		USA	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
Jan	Diff	0.23*	0.51***	0.49***	0.71***	0.68***	0.55***	0.30*	0.19**	0.31***
	t-stat	1.83	3.32	3.43	3.63	4.00	3.10	1.79	2.41	3.28
Feb	Diff	0.17	0.23*	0.15	0.27	0.25	0.13	0.01	0.14	0.09
	t-stat	1.26	1.66	1.00	1.54	1.53	0.81	0.08	1.31	0.67
Mar	Diff	-0.13	-0.04	-0.22	-0.25	-0.21	-0.24	0.04	-0.14	-0.07
	t-stat	-0.91	-0.22	-1.31	-1.26	-1.13	-1.18	0.18	-1.18	-0.49
Apr	Diff	-0.06	-0.13	-0.04	-0.15	-0.05	-0.05	-0.28	-0.04	0.01
	t-stat	-0.47	-0.92	-0.23	-0.78	-0.31	-0.27	-1.50	-0.41	0.08
May	Diff	0.24*	0.18	0.26*	0.40**	0.39**	0.42**	0.17	0.21**	0.14
	t-stat	1.93	1.31	1.89	2.36	2.26	2.00	0.92	2.22	1.05
Jun	Diff	0.19	0.28*	0.23	0.22	0.25	0.20	0.17	0.17*	0.25*
	t-stat	1.39	1.97	1.61	1.34	1.56	1.26	1.07	1.67	1.73
Jul	Diff	0.26**	0.19	0.21	0.35*	0.39**	0.40**	0.37**	0.25**	0.31**
	t-stat	2.17	1.38	1.40	1.97	2.04	1.99	2.25	2.45	2.33
Aug	Diff	0.03	-0.03	0.26	0.19	0.25	0.15	0.02	0.10	0.17
	t-stat	0.19	-0.22	1.58	0.97	1.27	0.78	0.10	0.81	1.24
Sep	Diff	-0.04	0.00	0.13	0.00	0.17	0.11	0.10	0.02	0.10
	t-stat	-0.21	0.02	0.76	0.01	0.84	0.55	0.50	0.18	0.66
Oct	Diff	-0.12	-0.07	-0.03	-0.14	-0.07	0.04	-0.09	-0.08	-0.07
	t-stat	-0.62	-0.32	-0.16	-0.63	-0.30	0.17	-0.42	-0.48	-0.41
Nov	Diff	0.36*	0.33	0.41*	0.36	0.34	0.21	0.26	0.31*	0.48**
	t-stat	1.93	1.49	1.97	1.37	1.30	0.75	1.09	1.96	2.43
Dec	Diff	0.09	0.10	0.02	0.17	0.05	0.06	0.24	0.03	0.13
	t-stat	0.47	0.49	0.11	0.79	0.26	0.27	1.33	0.19	0.92

This table presents mean daily ToM and RoM returns for L_4F_1 definition of the ToM period, along with the asterisks from a t-test for the null hypothesis that these means are equal to zero. *Diff* is the difference between ToM and RoM returns under each ToM definition. The standard t-test of mean difference being equal to zero takes into account the fact that number of observations used to calculate mean ToM returns is significantly lower than that for mean RoM returns. Return variables are reported as percentages. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Table 18: Co-existence of Calendar Anomalies in G7 Countries

Panel A: Turn-of-the-Month Effect									
	USA	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
Intercept	0.01	-0.02	-0.04	-0.02	-0.04	-0.04	-0.02	-0.01	-0.02
ToM	0.10**	0.13***	0.16***	0.18***	0.20***	0.17***	0.11*	0.10***	0.15***
Panel B: Day-of-the-Week Effect									
	USA	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
Intercept	0.05	0.00	-0.05	-0.02	-0.02	0.04	0.05	0.01	0.04
Mon	-0.07	-0.05	0.01	0.05	-0.01	-0.14*	-0.08	-0.03	-0.08
Tue	0.00	0.01	0.08	0.06	0.05	0.00	-0.05	0.02	-0.04
Thu	0.00	0.04	0.08	0.06	0.08	-0.02	0.00	0.02	-0.04
Fri	-0.01	0.07	0.06	0.02	0.03	-0.05	-0.09	0.00	0.02
Panel C: Turn-of-the-Year Effect									
	USA	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
Intercept	0.03	0.00	-0.01	0.01	-0.01	-0.02	0.00	0.01	0.01
ToY	0.16*	0.30***	0.24**	0.32***	0.36***	0.32**	0.15	0.15*	0.21**
Panel D: January Effect									
	USA	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
Intercept	0.04*	0.02	0.01	0.03	0.01	0.00	0.01	0.02	0.02
Jan	-0.05	-0.04	-0.09	-0.09	-0.08	-0.01	-0.06	-0.06	-0.03
Panel E: All Calendar Anomalies									
	USA	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
Intercept	0.02	-0.04	-0.08*	-0.06	-0.07	-0.01	0.02	-0.01	0.00
ToM	0.09**	0.11**	0.14***	0.16***	0.19***	0.15**	0.10*	0.09**	0.14***
Mon	-0.07	-0.04	0.02	0.04	-0.01	-0.14*	-0.09	-0.03	-0.08
Tue	0.00	0.01	0.08	0.06	0.05	0.00	-0.05	0.02	-0.04
Thu	0.01	0.04	0.08	0.06	0.08	-0.02	0.00	0.02	-0.04
Fri	-0.01	0.07	0.06	0.01	0.03	-0.06	-0.09	0.00	0.02
ToY	0.14	0.27***	0.21**	0.28**	0.32***	0.29**	0.14	0.13*	0.17*
Jan	-0.05	-0.04	-0.09	-0.09	-0.08	-0.01	-0.07	-0.06	-0.03
N	4529	4525	4547	4571	4593	4566	4421	4696	4696

This table reports the results from time-series regressions of the G7 equity market returns on a set of dummy variables. ToM is a dummy variable that is 1 within the ToM period (assuming L_4F_1 ToM definition) and 0 otherwise, Mon to Fri are dummies that correspond to the days of the week, ToY is a dummy that is 1 during the last 8 trading days in December and the first trading day in January and 0 otherwise, and $January$ is a dummy variable that is 1 during the first month of the year, and 0 otherwise. Wen dummy is omitted to avoid multi-collinearity. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Table 19: Comovement of the Indices of the G7 Equity Markets

Panel A: ToM (t-4 to t+1)

	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
Coeff	1.04	0.84	1.01	0.98	0.93	0.49	0.86	0.98
Obs	216	216	216	216	216	216	216	216
Rsq	0.73	0.59	0.59	0.57	0.46	0.18	0.89	0.56

Panel B: preToM (t-9 to t-5)

	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
Coeff	1.13	0.90	1.04	1.01	1.03	0.68	0.94	1.08
Obs	216	216	216	216	216	216	216	216
Rsq	0.70	0.64	0.58	0.58	0.47	0.34	0.92	0.65

Panel C: afterToM (t+2 to t+6)

	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
Coeff	1.07	0.96	1.16	1.12	1.08	0.69	0.94	1.02
Obs	216	216	216	216	216	216	216	216
Rsq	0.73	0.77	0.74	0.74	0.61	0.38	0.95	0.71

Panel D: Full sample

	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
Coeff	1.06	0.90	1.09	1.05	1.04	0.63	0.92	1.01
Obs	864	864	864	864	864	864	864	864
Rsq	0.71	0.66	0.65	0.65	0.54	0.30	0.92	0.61
P-values	0.35	0.18	0.00	0.06	0.03	0.02	0.00	0.12

This table presents estimates from an international CAPM model that uses U.S. equity market return as the independent variable and the returns of the remaining countries as dependent variables. The estimates are reported for ToM period (Panel A) as well as for the two five-day periods immediately before and after the ToM days. Panel E reports the estimates for the full sample. The last row of the table reports the p-values corresponding to the test of equality of the coefficients during the ToM period and the full sample.

Table 20: Volatility Estimates for ToM & RoM Periods Over Different Subsamples

	USA	CAN	UK	GER	FRA	ITA	JAP	MSW	MSE
Panel A: Full Sample									
ToM	0.1570	0.1811	0.1790	0.2235	0.2159	0.2303	0.2158	0.1334	0.1605
RoM	0.1735	0.1938	0.1953	0.2424	0.2347	0.2480	0.2357	0.1444	0.1741
Diff	-0.0165**	-0.0127	-0.0163**	-0.0189**	-0.0188**	-0.0177*	-0.0198***	-0.0110*	-0.0136**
Panel B: Subsamples									
					1998–2006				
ToM	0.1546	0.1674	0.1657	0.2213	0.1988	0.1970	0.2266	0.1270	0.1528
RoM	0.1697	0.1788	0.1792	0.2367	0.2141	0.2101	0.2474	0.1362	0.1638
Diff	-0.0151*	-0.0114	-0.0135*	-0.0154	-0.0153	-0.0132	-0.0207***	-0.0092	-0.0109
					2007–2015				
ToM	0.1586	0.1940	0.1913	0.2245	0.2318	0.2620	0.2042	0.1393	0.1677
RoM	0.1773	0.2088	0.2114	0.2482	0.2554	0.2858	0.2240	0.1526	0.1844
Diff	-0.0187	-0.0148	-0.0201	-0.0237*	-0.0236*	-0.0238	-0.0198*	-0.0133	-0.0167
Panel C: Market States									
					Down				
ToM	0.1708	0.1937	0.1904	0.2420	0.2331	0.2491	0.2243	0.1495	0.1783
RoM	0.1879	0.2051	0.2064	0.2604	0.2522	0.2659	0.2443	0.1756	0.2006
Diff	-0.0171*	-0.0115	-0.0160*	-0.0184*	-0.0191*	-0.0168	-0.0201**	-0.0262***	-0.0223**
					Up				
ToM	0.1467	0.1641	0.1607	0.2115	0.1926	0.2195	0.2075	0.1214	0.1460
RoM	0.1593	0.1825	0.1805	0.2270	0.2200	0.2386	0.2282	0.1181	0.1493
Diff	-0.0126*	-0.0184**	-0.0198***	-0.0156*	-0.0274***	-0.0191**	-0.0207***	0.0032	-0.0033

This table presents mean daily ToM and RoM return volatilities for L_4F_1 definition of the ToM period, where volatility is the annualized standard deviation extracted from an exponential-GARCH model as in Nelson (1991). *Diff* is the difference between ToM and RoM return volatilities, reported along with asterisks from a t-test for the null hypothesis that the difference equals zero. The standard t-test takes into account the fact that number of observations used to calculate mean ToM return volatilities is significantly lower than that for mean RoM return volatility. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Chapter III

TURN-OF-THE-MONTH EFFECT: NEW EVIDENCE FROM AN EMERGING STOCK MARKET[†††]

3.1 Introduction

The turn-of-the-month (ToM) effect is a widely recognized empirical pattern characterized by high returns around the month-ends. This pattern is first documented by Ariel (1987) in an analysis of an advice, voiced by several popular equity market analysts (e.g. Merrill, 1966; Hirsch, 1968; and Fosback, 1976), that sales should be deferred to the latter half of the month and the purchases should be made prior to month-ends to expropriate unusually high returns accrued in the early days of the month. Lakonishok and Smidt (1988) show that the four-day period that begins with the last trading day of a month and ends with the third trading day of the subsequent month accounts for all positive return to the DJIA over 1897–1986. McConnel and Xu (2008) adopt the same methodology over an extended sample from 1897 to 2005 and confirm that the ToM pattern is alive and well over the more recent 1987–2005 period.

The ToM effect is also observed in international equity markets. Among others, Cadsby and Ratner (1992) study international index returns over 1962–1989 and show that the mean daily return in the ToM period is significantly higher than that in other days in 6 out of 10 indices examined. Similarly, Kunkel et al. (2003) analyze a large cross-section of international index returns over 1988–2000 and find

[†††]This chapter is a result of my work with my thesis advisor, N. Volkan Kayaçetin, and was published in *Finance Research Letters* Journal in 2016, volume 18, p142–157.

that the ToM pattern exists in 15 out of 19 countries studied, with ToM period returns on average accounting for 87% of the monthly index returns. In addition to these multi-country studies, several papers provide detailed analyses of the ToM effect in various stock exchanges across the globe.[32] Our analysis falls into this latter category.

This chapter provides a detailed investigation of the ToM pattern in the Turkish equity market. Studying daily BIST100 index[33] returns over 1988–2014, we document that the effect is highly significant with a mean daily return of 0.46% in the ToM period, and 0.09% in the rest of the month. In subperiod analysis, we show that the mean ToM return is 0.60% over 1988–1996, 0.56% over 1997–2005, 0.20% over 2006–2014, and strongly significant in each case. While the mean ToM return is lower in the latest subsample, the fraction of total returns accounted for by the ToM period displays a secular increase from 39% over 1988–1996 to 49% over 1997–2005 and to 86% over 2006–2014, suggesting a strengthening in the ToM effect. Conditioning on the month of the year, we demonstrate that the mean daily return in ToM days exceeds that in the remaining days in all months except September, and is particularly high in April (1.13%), January (1.03%), December (0.62%), and June (0.51%) over the full sample period. In subperiod analysis, we find that April is the only month in which the mean daily return in the ToM period is consistently higher than that in remaining days in all three subperiods. Last, we extract the conditional volatility of the index via an exponential GARCH model in the spirit of Nelson (1991) and uncover a link between the ToM period returns and the dynamics

[32]Notable examples include Compton et al. (2013), Maher and Parikh (2013), Jacobsen and Zhang (2013), Depenchuk et al. (2010), Raj and Kumari (2006), Lucey and Whelan (2004), and Booth et al. (2001).

[33]BIST100 is a value-weighted index of the largest 100 stocks trading in Borsa Istanbul (BIST). The stocks that comprise the index account for over 85% of the total market capitalization of the Turkish equity market.

of expected volatility in the days leading to month-turns. In particular, we show that the change in expected volatility from the previous month-end to the current month-end explains a statistically and economically significant portion of the ToM period returns. These results favor a story where 'liquid funds' created by wage and interest/dividend income, which are deterred from equity assets during high information risk periods, are released back into equities once information uncertainty is resolved in the aftermath of such periods.

What should one make of the evidence on the ToM effect in Borsa Istanbul returns? First, the evidence that the effect manifests itself consistently in almost all months of the year and in different sub-periods is consistent with Ogden (1990), who argues that re-investment of liquid funds created by wages and interest and dividend income at the month-ends drives equity prices up. The finding that ToM returns are strongest in month-turns that mark the ends of the first and last quarters of the year is in line with both window-dressing by fund managers prior to reporting deadlines as in Haugen and Lakonishok (1987) and Ritter (1988) and with early voluntary disclosure of good news and suppression of bad news as in McNichols (1988). The novel finding that the conditional volatility of returns declines as the turn-of-the-month draws closer supports a risk-based explanation in which uncertainty regarding equity fundamentals is gradually resolved towards month-ends, pushing risk premiums down and equity prices up.

Our study adds to a list of papers that study the ToM effect in the Turkish stock market (e.g. Bildik, 2004; and Oguzsoy and Guven, 2006).[34] Our analysis

[34]Bildik (2004) confirms the existence of the ToM effect in BIST100 over the period from 1988 to 1999, in addition to a distinct mid-month effect that coincides with the payment day customs of governmental institutions in Turkey. Oguzsoy and Guven (2006) study BIST30 index components over the same period and document starkly higher returns in the ToM period and drastically lower in the days surrounding the ToM period.

updates their results using a more recent sample period, conducts subperiod tests, provides a monthly decomposition of the ToM effect, and incorporates conditional volatility dynamics around month-turns as an alternative explanation to the turn-of-the-month pattern. To our knowledge, this latter finding is novel.

The rest of the chapter is organized as follows. Section 3.2 summarizes the extant research on the ToM effect and lays out several possible explanations for the existence and persistence of this pervasive seasonal pattern. Section 3.3 describes our data and methodology. Section 3.4 presents and discusses our empirical findings. Section 3.5 concludes.

3.2 Literature Review

Ariel (1987) is the first to document a seasonal pattern in equity returns at the turn of the month in his analysis of an advice voiced by several popular stock market analysts that their clients should make anticipated sales in the latter half of the month and anticipated purchases before the month-ends to expropriate unusually high returns observed in early days of the month. The author finds that the mean daily return in the ten-day period including the last trading day of the month and the first nine trading days of the subsequent month is high and positive, while the mean return in the remaining days of the month is negative. Ariel also documents that removing disclosure months exacerbates the effect rather than eliminating it.

Lakonishok and Smidt (1988) refer to the four-day period beginning with the last trading day of the month and ending with the third trading day of the next month as the turn-of-the-month (ToM) period and show that ToM period returns account for all positive return to the DJIA from 1897 to 1986: the mean daily return during the ToM period is 0.47% compared to 0.35% over the full sample. In later work, Hensel and Ziemba (1996) show that a portfolio strategy that invests in the S&P500 in the ToM period and in T-bills otherwise outperforms a buy-and-hold strategy on S&P500 by 0.6% per year in the period from 1928 to 1993. More recently, McConnel and Xu (2008) confirm the results in Lakonishok and Smidt (1988) that the ToM effect accounts for all positive return to the U.S. stocks for the extended 1897–2005 period, and show that the ToM effect in U.S. equity returns persists in the period from 1897 to 2005.

A large literature investigates the ToM effect for international index returns.

Among others, Cadsby and Ratner (1992) study daily index returns from 1962 to 1989 and show that the ToM effect is significant in six out of the ten countries included in their sample. Similarly, Kunkel, Compton, and Beyer (2003) examine daily index returns from 1988 to 2000 and find that the ToM effect exists in fifteen out of the nineteen countries studied, accounting on average for 87% of monthly stock returns in these countries. For Turkish stocks, Bildik (2004) confirms the existence of the ToM effect in Borsa Istanbul (BIST) index returns in addition to a mid-month effect that may relate to institutional differences in payment date customs. Oguzsoy and Guven (2006) examine BIST returns over 1988–1999 and document high returns in the ToM period and drastically lower returns in days surrounding the ToM period. Georgantopoulos and Tsamis (2008) examine calendar anomalies in BIST returns and demonstrate that the ToM effect is strongly significant over the nine-year period from 2000 to 2008. Other studies on the turn-of-the-month effect include Eken and Uner (2010) and Guler and Cimen (2014), who confirm the existence of the ToM effect over alternative periods.

What could possibly drive the turn-of-the-month effect? Jacobs and Levy (1988) argue that such calendar anomalies occur at turning points in time that may invoke special patterns of behavior despite having little economic significance. Thaler (1987) lays out three plausible stories for the existence of seasonal patterns observed in stock returns. The first story, which we refer to as the *liquid funds hypothesis*, relates to payment day customs that influence fund flows in and out of the equity market. Following this thread, Ogden (1990) argues that regularity in payment dates of wages and interest/dividend income would create a supply of 'liquid funds' at month-ends and the flow of these liquid funds into the market push equity prices up, resulting in a monthly seasonal characterized by higher mean returns at the turn of the month. The second story, which we refer to as the *window dressing hypothesis*, suggests that fund managers adjust their portfolios to close out embarrassing positions in advance of reporting deadlines and the fund flows generated as these managers return to their prior portfolio compositions after the reporting dates may result in a seasonal pattern characterized by high returns around reporting dates (Haugen and Lakonishok, 1987; Ritter, 1988). The third story, which we refer to as the *news clustering hypothesis*, relates to systematic patterns in the dissemination of good and bad news. McNichols (1988) shows that firms tend to disseminate good news voluntarily in early days of the month and suppress bad news until reporting deadlines. This induces a clustering of good news and positive return shocks in early days of the month, which may explain the high equity returns accrued at the turn of the month. Lastly, it is plausible to assume that investors face greater information risk around the turn-of-the-month due to an increase in the arrival frequency of key macroeconomic (Ross, 1989) and firm-specific information during month-ends. An increase in information arrival frequency will drive information uncertainty and expected volatility up until the information is finally released and the uncertainty is resolved. The gradual resolution of uncertainty in the days that lead to month-turns would lead to a reduction in expected risk premiums, sending equity valuations up. We refer to this risk-based story as the *information risk hypothesis.*

Our study provides an explorative investigation of the ToM effect in Borsa Istanbul returns. In addition to updating the evidence on the current state of this pervasive seasonal pattern, we offer new evidence by analyzing mean returns in the ToM period conditional on the month of the year and market states, and by investigating how expected volatility, extracted through fitting an exponential GARCH model in the spirit of Nelson (1991) to index returns, behaves around the ToM period. Though we do not aim for a direct test of the alternative hypotheses above, the results from these parts of our analysis are likely to provide suggestive evidence.

3.3 Data and Variables

3.3.1 The Setting

Borsa Istanbul (BIST) is an order-driven, multiple-price, continuous auction market with no market makers or specialists.[35] Founded in 1986, the exchange managed to attract a great deal of attention among international investors through rapid development and high performance. As of 2014, the total market capitalization of Borsa Istanbul is TRY626.43 billion, with about 64% of the free-floating shares quoted on the exchange held by international investors. BIST is a very dynamic market, with average daily volume of TRY3.47 billion. Trading activities are carried out through a computerized trading system. Trading days are Monday to Friday, organized in two daily sessions from 09:15 until 12:30, and from 14:00 to 17:40.

3.3.2 Index Characteristics

BIST100 Index is used as the main index for Borsa Istanbul Equity Market. It consists of 100 stocks selected among the stocks of companies traded on the National Market and the stocks of real estate investment trusts and venture capital investment trusts traded on the Collective Products Market. The index price is calculated as free-float market capitalization weighted average. To become eligible for inclusion in BIST100, a stock should have been traded on Borsa Istanbul for at least 60 days as of the end of the review period. Then, stocks are selected for

[35]For different types of stocks, trading in the Equity Market of Borsa Istanbul can be carried out with continuous auction, continuous auction with market maker, or single price trading methods. However, stocks included in BIST100 index are traded only under the continuous-auction method with no market makers or specialists.

inclusion (exclusion) in the BIST100 based on their ranking in terms of the free-float market capitalization and the daily average trading volume during the review period.

3.3.3 Index Returns

We obtain daily closing levels of the BIST100 price index for the period between January 1988 and December 2014 from the Borsa Istanbul website.[36] These closing levels are then used to calculate daily log returns as represented by the formula below:

$$r_t = ln(P_t/P_{t-1}) \tag{30}$$

where P_t and P_{t-1} are the closing prices of the BIST100 index at the end of trading days t and t-1, and r_t is the log index return from day t-1 to day t.

3.3.4 Turn-of-the-Month Period

The turn-of-the-month (ToM) is typically defined as the period spanning the last few days of each month and the first few days of the subsequent month. In Section 3.4.1, we examine the performance of alternative ToM definitions and label these based on the number of trading days included from the month that ends ($L_\#$) and the month that begins ($F_\#$). L_1F_2, for instance, refers to the period that covers the last trading day of the month that ends and the first two trading days of the month that begins with the turn of the month. In our analysis, we focus on the two ToM definitions that yield (i) the maximum mean daily return in the ToM period and (ii)

[36]The price index is not adjusted for cash dividend payment so that the returns calculated from the index exclude dividend distributions. Using the total return index that is only available over a shorter sample period (from 1997 to 2014) results in qualitatively and quantitatively similar conclusions.

the minimum mean daily return in the remaining trading days of the month. As our analysis also features a month-by-month analysis of the ToM effect, it is important to clarify how the ToM periods for different months are labeled. We refer to each ToM period with the name of month that it leads to, rather than the month that it ends. The period that encompasses the last few days of December and the first few days of January, for instance, will be referred to as the January ToM period rather than the December ToM period.

3.3.5 Conditional Volatility

We start by writing the realized excess return on the market as:

$$r_{M,t} = \lambda_0 + \lambda_1 \sigma_t^2 + \theta_1 \epsilon_{t-1} + \epsilon_t \qquad (31)$$

where $r_{M,t}$ is the market return in day t, σ_t is the conditional standard deviation of market return in day t, and ϵ_t is a random shock that is normally distributed with mean zero and variance σ_t^2. We use an exponential generalized autoregressive conditional heteroskedasticity (e-GARCH) model in the spirit of Nelson (1991) to extract the conditional variance of r_M as:

$$ln(\sigma_t^2) = \alpha_0 + \beta_1 ln(\sigma_{t-1}^2) + \alpha_1[\theta_2 \psi_{t-1} + \gamma(|\psi_{t-1}| - (2/\pi)^{1/2})] \qquad (32)$$

The conditional variance of the market in any period is thus a function of (i) its conditional variance in the previous period, (σ_{t-1}^2); (ii) the standardized unit-variance return shock from the previous period, $\psi_{t-1} = \epsilon_{t-1}/\sigma_{t-1}^2$; and (iii) the deviation of the absolute value of this lagged return shock, ψ_{t-1}, from its mean absolute value of

$(2/\pi)^{1/2}$.

We apply the conditional mean and conditional variance equations given above to the daily log returns of the BIST100 index and extract a daily time-series for its conditional volatility. The parameter estimates from this model are presented in the Appendix Table A1, along with some important descriptive statistics, which are not discussed here in favor of brevity.

3.4 Results and Discussion

3.4.1 Defining the Turn-of-the-Month Period

We launch our analysis off by investigating mean daily returns around month-ends. Figure 4 plots mean daily returns over the last ten days (t-10 to t-1) and the first ten days (t+1 to t+10) of the month over the period from January 1988 to December 2014. As the daily returns are particularly high from day t-2 to day t+4, and notably lower outside of this period, we examine alternative definitions for the turn-of-the-month period within t-2 and t+4, and label these based on the days included at the end of each month as defined in Section 3.3.4.

Table 21 reports the mean daily returns under alternative definitions of the turn-of-the-month (ToM) period. The mean daily return in the ToM period varies between 0.46% for L_1F_1 and L_1F_2 and 0.35% for L_2F_3 and L_2F_4, while the mean daily return in rest-of-the-month (RoM) ranges from 0.11% for L_1F_1 to 0.05% for L_2F_4. The mean daily return in the ToM period is strongly significant under all eight definitions, while that in the RoM is insignificant under L_2F_4, marginally significant under L_2F_3 and L_1F_4, and significant under the remaining five definitions. The difference between mean daily ToM and RoM returns varies between 0.37% for L_1F_2 and 0.28% for L_2F_3, and is strongly significant under all eight definitions.[37]

In the last column of the table, we report the fraction of overall index returns generated over the ToM period. This fraction is computed as the total return generated over the ToM period divided by the overall index return over the full

[37]Note that the number of observations is significantly lower for the turn-of-the-month period than for the rest of the month under all eight definitions. This is accounted for by the standard t-test that is applied to test the null hypothesis that the mean daily return is the same in the ToM and RoM periods.

sample period.[38] Despite the relatively short length (2 to 6 days) of the ToM, it can be observed that the returns accrued during this period account for a large share of the overall index returns. In particular, the ToM period returns account for 47% of the overall index returns under the three-day L_1F_2 definition and 72% of the overall index returns under the six-day L_2F_4 definition for the turn-of-the-month period.

Based on these results, we choose L_1F_2 and L_2F_4 as the two turn-of-the-month definitions that we focus on in the remainder of our analysis. L_1F_2 is selected as it maximizes the mean daily return (0.46%) generated over the turn-of-the-month period, and L_2F_4 is selected because it minimizes the mean daily return generated in the remaining days of the month (0.05%).

3.4.2 Turn-of-the-Month Effect over Different Subperiods

It is of theoretical and empirical importance whether the ToM pattern persists over different subperiods. The effect should persist in all subperiods studied if it arises due to systematic causes (rational or behavioural), and disappear in certain subperiods if it is an artefact of data mining. To address this question, we investigate ToM returns over three nine-year subperiods: 1988–1996, the early period; 1997–2005, the interim period; and 2006–2014, the late period. As before, we compute the mean daily ToM and RoM returns under both ToM definitions, L_1F_2 and L_2F_4, and test whether the mean return in the ToM period is statistically significantly greater than the mean return in the RoM. Table 22 reports the results from these tests, along with the standard deviation of daily returns during the ToM and RoM

[38] If the mean return over the ToM is positive and that over the RoM is negative or zero, we set *Frac* equal to unity to indicate that all positive index returns are generated over ToM period. Similarly, if the mean daily return over the ToM is negative and that over the RoM is positive, we set *Frac* equal to zero to indicate that all positive returns are generated over the RoM.

periods.

The early period results are presented in Panel A of Table 22. The mean daily ToM return generated over the early period is a statistically and economically significant 0.60% under L_1F_2 and 0.38% under L_2F_4. These figures are notably higher than the mean daily return generated over the remaining days of the month, which is computed as 0.16% under both L_1F_2 and L_2F_4. The difference between the mean daily ToM return and the mean daily RoM return is a strongly significant 0.45% under L_1F_2 and a marginally significant 0.22% under L_2F_4. Despite the significantly higher mean returns generated during the ToM period, the fact that the standard deviation of returns in the turn-of-the-month days and in the remaining days of the month are roughly equal rules out a standard risk-based explanation. Finally, the fraction of total returns accounted for by the ToM period is 39% under L_1F_2 and 49% under L_2F_4.

Panel B of Table 22 presents the interim period results. The mean daily ToM period return in this subperiod is a strongly significant 0.56% under L_1F_2 and 0.53% under L_2F_4. The former figure is similar in magnitude, while the latter is slightly greater in comparison to the early period counterparts, 0.60% and 0.38%. The mean daily return generated over the rest of the month, on the other hand, is a statistically insignificant 0.10% under L_1F_2 and 0.02% under L_2F_4. The difference between the mean ToM and RoM period returns is strongly significant at 0.46% under L_1F_2 and at 0.51% under L_2F_4. The standard deviations of daily returns in the ToM and RoM periods are computed as 2.9% and 3.1% under L_1F_2 and as 3.2% and 3.1% under L_2F_4. As with the early period results, the standard deviations do not appear to support a standard risk-based explanation for the statistically significantly greater returns during the ToM period. Lastly, the fraction of total index returns accounted for by the ToM period is 49% under L_1F_2 and 92% under L_2F_4. Both of these figures are greater in comparison to 39% accounted for under L_1F_2 and 49% accounted for under L_2F_4 in the early period.

The late period results are reported in Panel C of Table 22. The mean daily ToM return is 0.20% under L_1F_2 and 0.15% under L_2F_4 in this subperiod, both statistically significant at a 10% confidence level. These figures are starkly lower compared to the early and interim period means presented above (0.60% and 0.58% under L_1F_2 and 0.38% and 0.53% under L_2F_4). This final subperiod, however, includes the financial turmoil around the subprime mortgage crisis, so the mean RoM return is significantly lower as well, computed as a statistically insignificant 0.01% under L_1F_2 and –0.01% under L_2F_4. The spread between the mean daily ToM and RoM returns is 0.20% under L_1F_2 and 0.16% under L_2F_4, statistically significant at a 10% confidence level. The fraction of total index returns accounted for by the ToM period is 86% under L_1F_2 and in excess of 100% under L_2F_4, reflecting the finding that the mean index return outside of the L_2F_4 period is negative in the late period.

The secular increase in the fraction of total index returns accounted for by the relatively few days at the turn-of-the-month suggests that, in spite of a decline in the magnitude of the mean returns in the late sample, the ToM period return has become a more significant determinant of overall index returns in more recent periods. The finding that the mean daily returns in these few days are statistically and economically significantly greater than those in the rest of the month in all subperiods strengthens the case for the argument that the ToM effect arises due to systematic causes and weakens the case for the argument that it is due to data mining.

It is also appealing to learn whether the ToM effect varies based on market performance. Besides examining chronologically separated subperiods, we also divide our sample into two as up market and down market states based on the performance of the BIST100 index over the month that leads to a given ToM period. In doing so, we define an up (down) market state as one where the mean return in the month leading to a given turn-of-the-month is higher (lower) than the mean market return over the full sample period. Panels D and E of Table 22 present our results for up and down markets.

In up-markets, the mean daily ToM return is strongly significant at 0.63% under L_1F_2 and at 0.53% under L_2F_4, compared to mean daily RoM returns of 0.05% and 0.01% under L_1F_2 and L_2F_4, and the difference between these means is a strongly significant 0.57% under L_1F_2 and 0.52% under L_2F_4. In down-markets, the mean daily ToM return is 0.29% under L_1F_2 and 0.18% under L_2F_4, compared to a mean RoM return of 0.12% under L_1F_2 and 0.09% under L_2F_4, and the difference between the two means is not significant. The fraction of index returns accounted for by the ToM period is 68% during turn-of-the-month periods that follow up-market states and 30% during turn-of-the-month periods that follow down-market states. Collectively, these results suggest that the hitherto undefined systematic factor that drives the excessively high returns during the turn-of-the-month period must be more significant in months following up-markets than in those following down-markets.

3.4.3 Turn-of-the-Month Effect by Year Months

The window dressing and information risk hypotheses (see Section 3.2) invoke the possibility that the ToM effect is driven by superior returns accrued at month-ends that coincide with financial reporting deadlines. To address this issue, we study how ToM returns vary across the months of the year. Panel A of Table 23 reports our results under the L_1F_2 definition. The results under L_2F_4 are qualitatively very similar to those under L_1F_2, and are thus not reported here for sake of brevity. (See Table A2 in the Appendix.)

Over the full sample, the mean daily ToM return is the greatest at 1.13% in April, followed by 1.03% in January, 0.62% in December, 0.51% in June, and 0.41% in February. The mean excess ToM return, i.e. the spread between the mean daily return in the ToM period and that in the rest of the month (RoM), on the other hand, is the greatest at 0.93% in April, followed by 0.83% in January, 0.48% in May, 0.44% in August, and 0.40% in June. Although the null hypothesis that mean excess ToM return is statistically significantly different from zero can only be rejected at conventional confidence levels for the months of January, April, and May, the mean excess ToM return is positive in all months except September. By contrast, the standard deviation of daily returns (untabulated) in the ToM period is lower than that for the remaining days of the month in all months except December, in which the standard deviation is 3.1% in the ToM period and 2.8% in the RoM. This suggests that the ToM period not only provides higher returns as compared to the rest of the month, but also is somewhat counterintuitively associated with lower realized volatility. (In Section 3.4.4, we provide a more detailed analysis of the expected volatility dynamics in the days leading to the month-turns.)

Next, we divide the sample into two as up-markets and down-markets, as defined in the previous section, and examine the mean daily ToM returns conditional on the performance of the market in the month that leads to these periods. The results from this analysis, presented in Panel B of Table 23, reinforce our findings from the previous section that the mean excess ToM period return is higher in up-markets than in down-markets. In January, for instance, the mean excess ToM period return is a strongly significant 1.2% in up-markets and a statistically insignificant 0.2% in down-markets. The mean excess ToM period returns are statistically significantly positive in only the up-market months during July (0.6%), August (0.7%), October (0.8%), November (0.6%), and December (0.8%), in only the down-market months during May (0.8%), and in both up-markets and down-market months (1.0% and 0.9%) during April. Thus, while high ToM returns in most months follow up-markets, the ToM effect in April is very strong following both downside and upside market swings.

As a final step, we investigate the turn-of-the-month effect conditional on the month of the year separately for the early, interim, and late subsamples. Panel C of Table 23 presents the mean daily ToM period returns, both raw and excess, in these subperiods and the significance statistics from a standard t-test of the null hypothesis that these means are equal to zero. Although these tests suffer from low statistical power, they are nevertheless informative as the patterns that survive even under these circumstances are likely to be important ones.

The results reveal significant variation in ToM period returns across the months of the year. In the order of declining economic significance, the mean daily ToM return is 1.6% in February (t=2.4), 1.4% in October (t=2.7), 1.4% in December (t=2.3), 1.1% in April (t=1.9), and 1.0% in January (t=1.6) in the early period; 1.9% in November (t=4.7), 1.7% in January (t=2.2), 1.3% in April (t=2.6), and 0.6% in August (t=1.8) in the interim period; and 1.0% in April (t=4.0), 0.6% in February (t=1.6), and 0.5% in December (t=1.3) in the late period. Similarly, the difference between the mean daily ToM and RoM return is 1.7% in October (t=3.0), 1.5% in February (t=2.0), 1.3% in December (t=2.0), and 1.1% in April (t=1.7) in the early period; 1.8% in November (t=3.6) and in January (t=2.2), 1.1% in August (t=2.6), 0.9% in April (t=1.5), and 0.7% in May (t=1.6) in the interim period; and 0.9% in April (t=3.1), 0.7% in February (t=1.9), 0.6% in May (t=1.5) and 0.4% in December (t=1.1) in the late period.

These figures reveal several interesting findings. First, ToM effect in January is statistically significant in the early and interim periods, but disappears in the late period. Second, ToM effects in February and December are high and significant in the early period, disappear in the interim period, and re-emerge in the late period. Third, ToM effect in May is non-existent in the early period and gains power in the interim and the late periods. Last and most important, ToM effect in April is consistently significant, economically and statistically, in all three subperiods in terms of both raw and excess ToM returns.

The prevalence of the ToM effect in different subperiods suggests that it must be associated with a systematic factor (rational or behavioral) in the behavior of investors. Given the fact that the annual financial statements of Turkish companies are regularly filed for public access by the end of March and the beginning of April (Turel, 2010), the finding that the ToM effect is particularly strong in April resonates best with the information risk story. Under this story, investors shy away from stocks in face of elevated information risk in periods that coincide with the release of key financial information. The gradual resolution of uncertainty following such periods pushes equity prices up, the more so the better the news in the period that leads to the ToM period.

A direct implication of the information risk hypothesis outlined above is that the information risk borne by investors should decline as the months that harbor the release of key financial information draw close to an end and the uncertainty associated with the information releases is gradually resolved. In the next section, we test this argument using the conditional volatility of the market, which we estimate from daily BIST100 index returns employing a variant of the exponential general autoregressive heteroskedasticity (e-GARCH) model in Nelson (1991), as a crude proxy for the information risk that is faced by investors.

3.4.4 Conditional Volatility around the Turn-of-the-Month Period

There are two ways in which conditional volatility dynamics may lead to high ToM returns. First, expected volatility may decline abruptly in the days around the month-turn, sending equity prices up. Alternatively, it may decline slowly as information uncertainty is gradually resolved in the days leading to the month-turn. In this scenario, a large pool of liquid funds, withheld from the equity market in previous periods due to greater risk, is released into the market at the month-turn and the abundance of liquidity will push equity valuations higher.

To analyze how the expected volatility of the BIST100 index behaves around the month-turn, we extract the daily time-series of conditional volatility using the e-GARCH model that is described in Section 3.3.5. We first average conditional volatility over a 10-day window around each month-end in the sample period and plot its behavior in Figure 5. The figure illustrates that the conditional volatility of the index declines prior to month-ends, reaches a minimum within the turn-of-the-month period, and jumps back in subsequent days. We then compute the mean conditional volatility on each calendar day of the year across all the years in our sample period and report our results in Figure 6. Here, we see that the conditional volatility of the index varies significantly across the months of a year. In particular, we observe significant declines in the conditional volatility of the index in the days leading to April and January.

Based on these observations, we define the pre-ToM period as the first six trading days that foreshadow the ToM period.[39] We compute the mean conditional volatility across the days that comprise these periods ($\bar{\sigma}_{ToM}$ and $\bar{\sigma}_{preToM}$) and denote the change in conditional volatility as we go from the pre-ToM period to the ToM period as $\Delta\bar{\sigma}^2_{a,t} = \bar{\sigma}^2_{ToM,t} - \bar{\sigma}^2_{preToM,t}$ and from the previous ToM to the current pre-ToM period as $\Delta\bar{\sigma}^2_{b,t} = \bar{\sigma}^2_{preToM,t} - \bar{\sigma}^2_{ToM,t-1}$. The ToM period returns should relate negatively to $\Delta\bar{\sigma}^2_{a,t}$ to support the story of an abrupt decline in conditional volatility driving the equity prices up. The second story of the gradual resolution of uncertainty driving the equity prices up assumes $\Delta\bar{\sigma}^2_{b,t}$ to be negatively related to the ToM period returns. Note that the two stories are not mutually exclusive, so $\Delta\bar{\sigma}^2_{a,t}$ and $\Delta\bar{\sigma}^2_{b,t}$ may be jointly insignificant.

Table 24 reports the monthly means for the volatility measures described above. The mean $\Delta\bar{\sigma}^2_{a,t}$ is negative in January (–2.6%), February (–0.7%), April (–0.8%), June (–1.0%), August (–0.5%), and October (–3.4%), and positive in March (0.8%), May (0.8%), July (0.1%), September (1.1%), November (0.1%), and December

[39]The decision of using a six day period is arbitrary, but altering the period length yields almost identical results.

(2.4%). The mean $\Delta\bar{\sigma}^2_{b,t}$, on the other hand, is positive in February (5.4%), March (2.7%), May (0.1%), June (0.6%), August (0.2%), September (0.8%), October (3.2%), November (2.4%), and December (2.0%), and negative only in January (–3.4%), April (–8.0%), and July (–3.1%). The latter three months coincide with reporting deadlines for annual and quarterly financial statements and the decline in conditional volatility from the previous ToM period to the current pre-ToM period during these months is consistent with the gradual resolution of uncertainty prior to the ToM periods.

As a final step, we estimate the following three regressions to formally quantify whether these two variables play a role in determining the ToM returns:

$$\bar{r}_t^{ToM} = \alpha + \beta\Delta\bar{\sigma}^2_{a,t} + \epsilon_t \quad (33)$$

$$\bar{r}_t^{ToM} = \alpha + \beta\Delta\bar{\sigma}^2_{b,t} + \epsilon_t \quad (34)$$

$$\bar{r}_t^{ToM} = \alpha + \beta\Delta\bar{\sigma}^2_{a,t} + \beta\Delta\bar{\sigma}^2_{b,t} + \epsilon_t \quad (35)$$

The first specification tests whether ToM period returns are driven by conditional volatility shifts that occur during the ToM period, while the second asks whether changes in conditional volatility from one month-turn to the other can predict ToM returns. The last specification includes the two variables in the same model to observe their marginal effect on ToM returns.

The results from these specifications are given in Table 25. The first column reports the coefficient estimate from the first specification. The coefficient on $\Delta\bar{\sigma}^2_{a,t}$ is positive, which contradicts our conjecture that a decline in the conditional volatility of the index during the ToM period leads to higher returns. The second column reports the estimates from the second specification. The coefficient estimate for $\Delta\bar{\sigma}^2_{b,t}$ is a strongly significant –0.013, suggesting that a decline in the conditional volatility from the previous ToM period to the current pre-ToM period predicts higher ToM returns. In economic terms, a one standard deviation decline in the conditional volatility of the index from the previous to the current ToM period forecasts an increase of 0.2% percent in the mean daily ToM return. Finally, the third specification in which $\Delta\bar{\sigma}^2_{a,t}$ and $\Delta\bar{\sigma}^2_{b,t}$ are used together results in a positive and significant coefficient of 0.019 on $\Delta\bar{\sigma}^2_{a,t}$ and a negative and significant coefficient of –0.011 for $\Delta\bar{\sigma}^2_{b,t}$.

The results here resonate most with a combination of the information risk and liquid funds hypotheses. As expected volatility dynamics within the ToM period does not seem to matter, the effect cannot be tracked back to information events that occur around month-turns. Rather, what seems to matter is how uncertainty evolves from one month-turn to the next. The starkest decline in uncertainty is observed after high information risk months that coincide with reporting periods. In this context, the month-turns are made special by the release of liquid funds that may or may not be channelled into the equity market. The resolution of uncertainty triggers a decline in risk and abundance of liquidity, pushing equity prices up.

3.4.5 Trading Volume Behaviour around the ToM Period

The 'liquid funds' hypothesis of Ogden (1990) suggests that the ToM seasonal may arise due to an inflow of funds created at month-ends into the equity markets. One way of testing this hypothesis is to examine whether the trading volume increases around month-ends. We thus analyze the total trading volume of the BIST100 index and present our results in Table 26.

We calculate the volume ratio (v_{ToM}) at each month-turn by dividing the mean trading volume in the ToM period by that in the rest of the month, and test whether it is significantly different from unity. The results reported in Panel A of Table 6 suggest that v_{ToM} is 0.99 (t=–0.73) in the full sample and 0.97 (t=–0.65), 0.97 (t=–0.79), and 1.01 (t=0.54) in the early, interim, and late subperiods. The null hypothesis that the trading volume in ToM days is roughly equal to the volume in other days cannot be rejected at conventional significance levels.

Panel B of Table 26 reports v_{ToM} in up markets and in down markets. The results suggest that v_{ToM} is 1.05 in up markets and 0.93 in down markets over the full sample period. The former figure is marginally significantly greater and the latter is significantly smaller than unity. This suggests that the trading volume during ToM is slightly higher in up markets and notably lower in down markets compared to the rest of the month. In subperiod analysis, however, v_{ToM} increases from 0.90 in early and interim periods to an insignificant 0.98 in the late period in down markets. For up markets, v_{ToM} is not significantly greater than unity in any subperiod.

Panel C presents the volume ratios conditional on the month of the year. Over the full sample period, v_{ToM} is significantly higher than unity in March (1.17), August (1.17), and December (1.12) and significantly lower than unity in January (0.78), September (0.78), and October (0.85). For other months, the null that the trading volume in the ToM period is similar to that in the rest of the month cannot be rejected. In subperiod analysis, we find that the high v_{ToM} in March is driven mostly by the early period. In December (January), v_{ToM} is significantly higher (lower) than unity in the early and late periods but not in the interim period, whereas v_{ToM}

is statistically significantly lower than unity in the interim and late periods but not in the early period in October. Lastly, v_{ToM} is significantly lower than unity over all three subperiods in September, while it is not significantly different from unity in any subperiod in August.

Although v_{ToM} displays significant variation across the months of the year, these results do not provide evidence that supports the conjecture that an inflow of liquid funds that is released into the market around the month-turns should be accompanied by higher trading volumes.

3.4.6 Turn-of-the-Month and Other Seasonal Effects

This section investigates the robustness of our findings through controlling for other patterns shown to exist in BIST returns, namely day-of-the-week (DoW) and turn-of-the-year (ToY) effects.[40] We first study each effect separately, and then test all effects jointly to see whether they co-exist in BIST100 returns. Table 27 presents our results for:

$$r_t = \alpha_0 + \beta_1 ToM_t + \epsilon_t \quad (36)$$

$$r_t = \alpha_0 + \beta_1 Mon_t + \beta_2 Tue_t + \beta_3 Wed_t + \beta_4 Thu_t + \beta_5 Fri_t + \epsilon_t \quad (37)$$

$$r_t = \alpha_0 + \beta_1 ToY_t + \epsilon_t \quad (38)$$

$$r_t = \alpha_0 + \beta_1 Mon_t + \beta_2 Wed_t + \beta_3 Thu_t + \beta_4 Fri_t + \beta_5 ToM_t + \beta_6 ToY_t + \epsilon_t \quad (39)$$

where r_t is the daily index return, ToM_t is a dummy variable that is 1 within the ToM period and 0 otherwise, Mon_t to Fri_t are dummy variables that correspond to each of the five trading days of the week, ToY_t is a dummy variable that takes the

[40] E.g. Balaban (1995), Oguzsoy and Guven (2003), Bildik (2004), and Abdioglu and Degirmenci (2013).

value of one during the last ten trading days in December and the first five trading days in January, and zero otherwise.

In the first model, the coefficient on ToM is positive and statistically significant at 0.37, confirming our earlier finding of significantly higher ToM returns. In the second model, the coefficient on Mon is an insignificant –0.05, while those on Thu and Fri are positive and significant at 0.23 and 0.32. This suggests returns generated over the end of the week are positive and economically large, which is in line with the extant evidence in the literature. In the third model, ToY has a positive and statistically significant coefficient of 0.52, confirming the findings in the literature that returns are higher around year-end.

In the fourth model, the coefficient estimate for ToM is a strongly significant 0.37. Looking at the day-of-the-week dummy variables, we observe that the Mon remains negative with a coefficient of –0.05, while Thu and Fri have positive and statistically significant coefficients at 0.26 and 0.32, respectively. Last, the coefficient estimate on ToY remains positive a statistically significant at 0.44. The fact that all the regression coefficients remain virtually unchanged in this specification suggests that the three anomalies co-exist in the Turkish equity market in our sample period, and that our findings on the ToM effect are robust to existence of other anomalies in BIST, namely DoW and ToY effects.

3.5 Conclusion

This study investigates the turn-of-the-month (ToM) effect in the Turkish equity market using daily return data for BIST100 index over the 27-year period from 1988 to 2014. Our results indicate that the effect is strongly significant, with a mean daily return of 0.46% in the three day period that covers the last trading day of each month and the first two trading days of the following month as compared to 0.09% in the remaining days of the month.

We show that the returns accrued during this three-day period account, on average, for 47% of the overall index returns over the full sample period. The existence of a monthly seasonal in stock market returns is difficult to reconcile with market efficiency. We divide the sample period into an early, an interim, and a late subperiod and conduct sub-period tests to observe the evolution of the month-end seasonal over time. Given the fast paced development of the Turkish equity market, the ex-ante expectation here is to see the ToM effect disappear in more recent periods. Our evidence, however, points to a strengthening rather than a reduction in the importance of the ToM effect, with the returns generated during the ToM period accounting for an increasingly larger share of overall returns as we go from the early to the late period.

The prevalence of the ToM effect across different subperiods and, as evidenced by the extant literature, across different markets suggests that it must be associated with a systematic factor (rational or behavioral) in the behavior of investors. To shed light on possible alternative stories for the existence of the ToM effect, we conduct a monthly decomposition of returns and show that the ToM effect is particularly strong in April, which incidentally is the month turn that follows the official release date of annual financial statements of Turkish firms. In addition, dividing the sample into up- and down-markets, we show that the turn-of-the-month effect is strong following market upturns and insignificant following market downturns.

The findings above resonate best with an information risk story, where gradual resolution of uncertainty in the days that lead to the month-end tilts equity returns upwards, the more so the better the news in the period that leads to the ToM period. To further address this explanation, we estimate a daily time-series for the conditional volatility of the BIST100 index using an exponential generalized autoregressive heteroskedasticity (e-GARCH) model in the spirit of Nelson (1991) and show that (a) the conditional volatility of the index tends to decline in the period that leads to the month-end, (b) the decline is particularly stark in January and April, and (c) the shift in the conditional volatility of the index from the end of the previous ToM to the beginning of the current ToM forecasts the average returns in the current ToM period.

3.6 Chapter III Figures and Tables

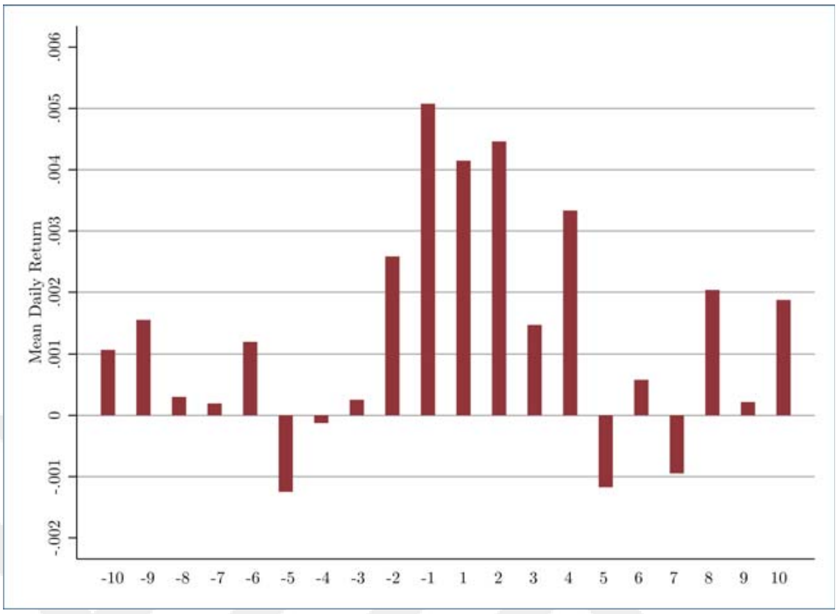

Figure 4: Mean Daily Returns around Month-End

This figure plots mean daily returns of BIST100 index over the last ten days (t-10 to t-1) and the first ten days (t+1 to t+10) of the month over the period from January 1988 to December 2014. Daily returns are calculated as $r_t = ln(P_t/P_{t-1})$, where P_t and P_{t-1} are the closing prices of the index at the end of trading days t and t-1. Note that the closing prices for BIST100 are not adjusted for cash dividend payments, so that the means plotted in the figure exclude dividend distributions.

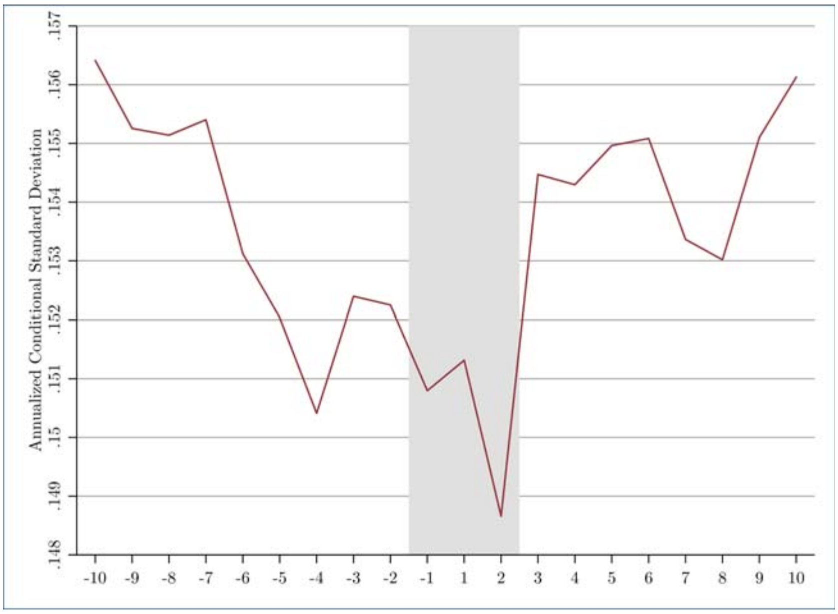

Figure 5: Conditional Volatility around the ToM Period

This figure plots the mean (annualized) conditional standard deviation of the BIST100 index over a twenty-day window around the month-end. In doing so, the conditional volatility of the index is extracted from daily return data using the exponential GARCH(1,1) model in Nelson (1991), and the resulting daily time series is used to calculate the mean conditional volatility across all months in the sample on each trading day that falls within the twenty-day window around the month-turn.

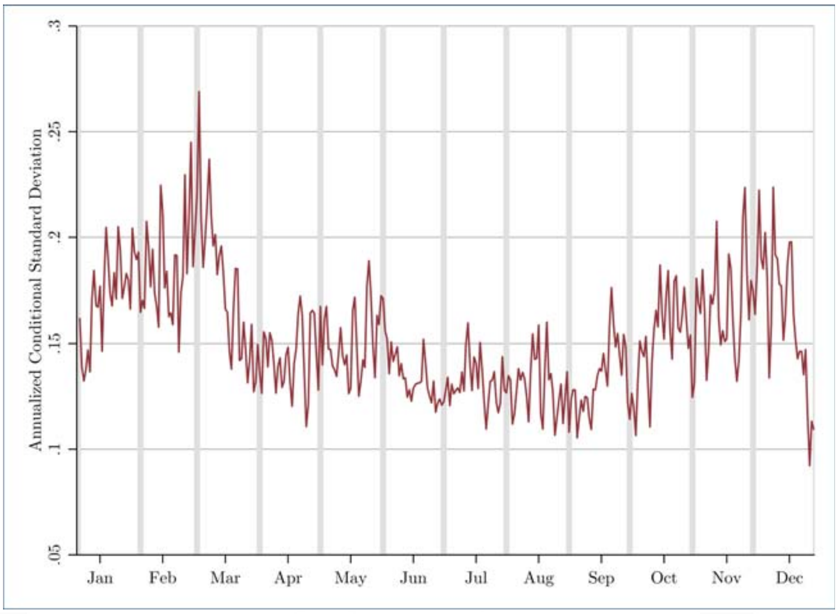

Figure 6: Conditional Volatility During the Calendar Year

The figure plots the mean (annualized) conditional standard deviation of the BIST100 index over a calendar year. The conditional volatility of the index is extracted from daily return data using the exponential GARCH(1,1) model in Nelson (1991), and the resulting daily time series is used to calculate the mean conditional volatility across all calendar days of the year.

Table 21: Alternative ToM Definitions

		ToM	*RoM*	*Diff*	*Frac*
Last 1 & First 1	Mean	0.46	0.11	0.35	0.32
	t-stat	4.27***	3.12***	3.13***	
Last 1 & First 2	Mean	0.46	0.09	0.37	0.47
	t-stat	5.31***	2.48**	3.97***	
Last 1 & First 3	Mean	0.38	0.08	0.30	0.52
	t-stat	5.01***	2.32**	3.53***	
Last 1 & First 4	Mean	0.37	0.07	0.30	0.64
	t-stat	5.49***	1.82*	3.93***	
Last 2 & First 1	Mean	0.39	0.10	0.30	0.41
	t-stat	4.51***	2.79***	3.14***	
Last 2 & First 2	Mean	0.41	0.08	0.33	0.56
	t-stat	5.47***	2.13**	3.99***	
Last 2 & First 3	Mean	0.35	0.07	0.28	0.61
	t-stat	5.27***	1.95*	3.68***	
Last 2 & First 4	Mean	0.35	0.05	0.30	0.72
	t-stat	5.73***	1.42	4.10***	

This table presents mean daily ToM and RoM returns of BIST100 index for different definitions of the ToM period, along with the t-statistics testing the null hypothesis that these means are equal to zero. *Diff* is the difference between ToM and RoM returns under each ToM definition. The standard t-test of mean difference being equal to zero takes into account the fact that number of observations used to calculate mean ToM returns is significantly lower than that for mean RoM returns. *Frac* is the fraction of total return generated during the ToM days, which is calculated by dividing the return generated during the ToM days with the overall return of the index. If the mean daily return over the ToM period is positive and that over the RoM is negative or zero, we set this ratio equal to unity to indicate that all positive index returns are generated over the ToM period. Similarly, if the mean daily return over the ToM period is negative and that over the RoM is positive, we set this this ratio equal to zero to indicate that all positive returns are generated over the RoM. Return variables are reported as percentages. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Table 22: Turn-of-the-Month Effect over Different Subsamples

	L_1F_2				L_2F_4			
Panel A: Subsample 1 (1988–1996)								
Day	ToM	RoM	Diff	Frac	ToM	RoM	Diff	Frac
Mean	0.60	0.16	0.45	0.39	0.38	0.16	0.22	0.49
SD	3.03	2.88			2.91	2.91		
t-stat	3.57***	2.38**	2.46**		3.30***	2.16**	1.63	
Panel B: Subsample 2 (1997–2005)								
Mean	0.56	0.10	0.46	0.49	0.53	0.02	0.51	0.92
SD	2.92	3.13			3.17	3.06		
t-stat	3.48***	1.38	2.62***		4.25***	0.23	3.48***	
Panel C: Subsample 3 (2006–2014)								
Mean	0.20	0.01	0.20	0.86	0.15	-0.01	0.16	1.00
SD	1.95	1.78			1.85	1.78		
t-stat	1.88*	0.14	1.72*		2.05**	-0.27	1.89*	
Panel D: Up Months								
Mean	0.63	0.05	0.57	0.68	0.53	0.01	0.52	0.95
SD	2.54	2.65			2.57	2.66		
t-stat	5.34***	1.01	4.50***		6.36***	0.23	5.17***	
Panel E: Down Months								
Mean	0.29	0.12	0.18	0.30	0.18	0.09	0.09	0.46
SD	2.80	2.68			2.82	2.67		
t-stat	2.32**	2.34**	1.30		2.00**	1.61	0.88	

This table presents mean daily ToM and RoM returns for BIST100 index over different subsamples. Panels A through C present the results for the three 9-year subsamples: 1988–1996, 1997–2005, and 2006–2014. Panels D and E present the results for up and down markets. An up (down) market is defined as one where the mean return in the month that leads to a given ToM period is higher (lower) than the mean market return over the full sample period. The left and right panels report the results for L_1F_2 and L_2F_4 definitions. The means are reported along with the t-statistics testing the null hypothesis of mean daily return being equal to zero. *Diff* and *Frac* are computed as reported in Table 21 notes. Return and standard deviation variables are reported as percentages. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.0$)

Table 23: Month-by-Month Analysis of the Turn of the Month Effect (L_1F_2)

		Panel A		Panel B				Panel C					
		Full Sample		Up Months		Down Months		1988–1996		1997–2005		2006–2014	
		R_{ToM}	*Diff*	R_{ToM}	*Diff*	R_{ToM}	*Diff*	R_{ToM}	*Diff*	R_{ToM}	*Diff*	R_{ToM}	*Diff*
Jan	Mean	1.03	0.83	1.58	1.22	0.29	0.22	1.04	0.57	1.69	1.79	0.30	0.45
	t-stat	3.17***	2.35**	3.67***	2.56**	0.61	0.42	1.63	0.81	2.22**	2.20**	0.92	1.25
Feb	Mean	0.41	0.38	0.45	0.49	0.37	0.27	1.55	1.46	-0.88	-1.07	0.56	0.73
	t-stat	1.25	1.04	0.96	0.96	0.78	0.52	2.35**	2.02**	-1.50	-1.61	1.60	1.93*
Mar	Mean	0.19	0.22	-0.05	0.05	0.38	0.35	0.65	0.72	0.20	0.41	-0.28	-0.47
	t-stat	0.46	0.50	-0.07	0.08	0.71	0.63	0.73	0.79	0.25	0.49	-0.72	-1.17
Apr	Mean	1.13	0.93	1.05	0.98	1.19	0.94	1.06	1.06	1.34	0.88	0.99	0.85
	t-stat	4.23***	3.15***	4.03***	3.22***	2.74***	2.00**	1.87*	1.71*	2.55**	1.50	4.02***	3.13***
May	Mean	0.31	0.48	0.04	0.12	0.64	0.77	0.20	0.18	0.37	0.68	0.35	0.57
	t-stat	1.16	1.67*	0.13	0.33	1.54	1.72*	0.33	0.26	0.98	1.59	1.02	1.54
Jun	Mean	0.51	0.40	0.96	0.61	0.32	0.35	0.78	0.20	0.58	0.67	0.15	0.28
	t-stat	2.00**	1.45	2.72***	1.54	0.97	0.99	2.38**	0.53	1.26	1.35	0.30	0.54
Jul	Mean	0.33	0.18	0.69	0.59	0.05	-0.13	0.05	0.07	0.55	0.41	0.40	0.08
	t-stat	1.33	0.67	2.11**	1.67*	0.13	-0.32	0.12	0.15	1.10	0.76	1.12	0.20
Aug	Mean	0.29	0.44	0.28	0.66	0.30	0.20	0.18	0.03	0.63	1.06	0.06	0.25
	t-stat	1.12	1.57	0.85	1.78*	0.72	0.45	0.28	0.05	1.77*	2.58***	0.19	0.76
Sept	Mean	0.15	-0.06	0.17	-0.33	0.14	0.13	-0.19	-0.62	0.20	0.13	0.44	0.31
	t-stat	0.67	-0.24	0.47	-0.83	0.48	0.39	-0.47	-1.38	0.45	0.26	1.32	0.83
Oct	Mean	0.25	0.14	0.83	0.84	-0.58	-0.96	1.43	1.69	0.13	-0.29	-0.81	-1.01
	t-stat	0.83	0.41	2.28**	2.13**	-1.18	-1.78*	2.71***	2.95***	0.25	-0.50	-1.85*	-2.15**
Nov	Mean	0.23	0.18	0.48	0.62	-0.13	-0.42	-0.89	-1.17	1.91	1.81	-0.32	-0.09
	t-stat	0.82	0.56	1.59	1.79*	-0.23	-0.71	-1.81*	-2.16**	4.68**	3.55***	-0.75	-0.19
Dec	Mean	0.62	0.34	1.11	0.83	0.29	0.04	1.37	1.26	0.00	-0.68	0.50	0.42
	t-stat	1.81*	0.93	2.48**	1.70*	0.58	0.07	2.28**	1.97**	0.00	-0.85	1.32	1.05

This table presents the mean daily returns for BIST100 index during the turn-of-the-month period (R_{ToM}) and the spread (*Diff*) between these means and the mean daily returns generated over the rest of the month (R_{RoM}) for different months of the year. Panel A reports the results for the full sample. Panel B reports the results for up and down months separately. Panel C reports the results for the three nine-year subsamples. Returns are reported along with the t-statistics testing the null hypothesis of mean daily return being equal to zero. The standard t-test of Diff being equal to zero takes into account the fact that number of observations used to calculate the mean for R_{ToM} is significantly lower than number of observations used to calculate the mean for R_{RoM}. Return variables are reported as percentages. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Table 24: Conditional Volatility around the Turn-of-the-Month

Month	Prior to ToM	ToM	$\Delta\bar{\sigma}_a^2$	$\Delta\bar{\sigma}_b^2$
January	0.397	0.372	-0.026	-0.034
February	0.434	0.425	-0.007	0.054
March	0.441	0.456	0.008	0.027
April	0.384	0.38	-0.008	-0.08
May	0.378	0.385	0.008	0.001
June	0.402	0.395	-0.01	0.006
July	0.354	0.357	0.001	-0.031
August	0.357	0.353	-0.005	0.002
September	0.352	0.352	0.011	0.008
October	0.388	0.356	-0.034	0.032
November	0.392	0.389	0.001	0.024
December	0.411	0.434	0.024	0.02

This table presents the sample means by month of the year for conditional volatility measures extracted from e-GARCH model. The first column reports the mean annualized conditional standard deviation over the six-day period prior to the ToM. The second column reports the mean annualized conditional standard deviation during the ToM period. $\Delta\bar{\sigma}_a^2$ is the mean change in conditional variance from the six-day pre-ToM period to the ToM period. $\Delta\bar{\sigma}_b^2$ is the mean change in conditional variance from the previous month's ToM period to the current pre-ToM period.

Table 25: Returns and Conditional Volatility around the Turn-of-the-Month

	(1)	(2)	(3)
$\Delta\bar{\sigma}_a^2$	0.021*		0.019*
	1.92		1.71
$\Delta\bar{\sigma}_b^2$		-0.013**	-0.011*
		-2.08	-1.89
Intercept	0.005***	0.005***	0.005***
	4.85	4.82	4.89
N	323	323	323

This table reports the results of regression analysis of BIST100 index returns on changes in conditional volatility of the index. Dependent variable is the mean daily return calculated for each month and for each pre-ToM and ToM period separately. Independent variables are $\Delta\bar{\sigma}_a^2$ and $\Delta\bar{\sigma}_b^2$. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Table 26: Trading Volume around the Turn-of-the-Month (L_1F_2)

Panel A: Trading Volume Ratio Over the Full Sample and the Three Nine-Year Subsamples					
		Full Sample	1988–1996	1997–2005	2006–2014
	Mean	0.99	0.97	0.97	1.01
	t-stat	-0.73	-0.65	-0.79	0.54

Panel B: Trading Volume Ratio During Down and Up Months					
		Full Sample	1988–1996	1997–2005	2006–2014
Down Months	Mean	0.93	0.90	0.90	0.98
	t-stat	-3.06***	-2.22**	-2.17**	-0.63
Up Months	Mean	1.05	1.05	1.04	1.05
	t-stat	1.67*	0.88	0.83	1.62

Panel C: Trading Volume Ratio by Year Months					
		Full Sample	1988–1996	1997–2005	2006–2014
Jan	Mean	0.78	0.65	0.89	0.78
	t-stat	-4.35***	-6.41***	-1.00	-3.14***
Feb	Mean	0.98	0.99	0.93	1.03
	t-stat	-0.27	-0.07	-0.56	0.77
Mar	Mean	1.17	1.43	1.06	1.02
	t-stat	1.87*	1.84*	0.74	0.23
Apr	Mean	0.92	0.88	0.86	1.02
	t-stat	-1.3	-1.23	-0.97	0.34
May	Mean	1.06	0.98	1.16	1.05
	t-stat	0.92	-0.19	1.04	0.92
Jun	Mean	1.06	0.86	1.18	1.15
	t-stat	1.02	-1.07	1.51	6.05***
Jul	Mean	0.96	0.96	0.95	0.98
	t-stat	-0.71	-0.34	-0.54	-0.36
Aug	Mean	1.17	1.15	1.22	1.14
	t-stat	2.42**	1.17	1.57	1.32
Sep	Mean	0.78	0.73	0.80	0.82
	t-stat	-5.43***	-3.53***	-2.29**	-4.56***
Oct	Mean	0.85	0.94	0.72	0.88
	t-stat	-2.77***	-0.65	-2.20**	-2.46**
Nov	Mean	0.97	0.86	0.93	1.10
	t-stat	-0.59	-1.35	-0.56	2.12**
Dec	Mean	1.12	1.22	0.97	1.16
	t-stat	2.09**	2.03**	-0.28	1.93*

This table presents the results of trading volume analysis during the ToM and RoM periods. First column reports the volume ratios for the full sample, while the next three columns report the ratios for the three nine-year subsamples. Panel B presents the results for down and up months separately. Panel C presents the results separately for each of the year months. Volume ratio is calculated by dividing average trading volume during the ToM days with the average trading volume during the RoM days. Table also reports the t-stats for the null hypothesis of ratio being equal to one. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Table 27: Robustness to Other Seasonal Patterns

	(1)	(2)	(3)	(4)
ToM	0.369***			0.365***
	4.00			3.92
Mon		-0.050		-0.050
		-0.48		-0.49
Wed		0.161		0.186*
		1.57		1.81
Thu		0.233**		0.256**
		2.26		2.50
Fri		0.317***		0.317***
		3.09		3.09
ToY			0.515***	0.441**
			2.93	2.50
Intercept	0.001**	0.000	0.001***	-0.001
	2.48	0.11	3.69	-0.94
N	6707	6707	6707	6707

This table reports the results from time-series regressions of daily BIST100 returns on a set of dummy variables. ToM is a dummy variable that is 1 within the ToM period (assuming L_1F_2 ToM definition) and 0 otherwise, Mon to Fri are dummies that correspond to the days of the week, and ToY is a dummy that is 1 during the last 10 trading days in December and the first 5 trading days in January, and 0 otherwise. Tue dummy is omitted to avoid multicollinearity. (* p<0.1;**p<0.05;*** p<0.01)

3.7 Appendix to Chapter III

Table A1: Estimation of Conditional Volatility

Panel A: Robust Standard Errors				
	Coefficient	StdEr	t-stat	p-value
λ_0	0.0009	0.0003	3.15	0.00
θ_1	0.0917	0.0149	6.17	0.00
λ_1	1.1292	0.4778	2.36	0.02
θ_2	-0.2203	0.0457	-4.82	0.00
α_1	-0.0173	0.0119	-1.46	0.14
β_1	0.9694	0.0062	155.62	0.00
γ_1	0.2820	0.0272	10.35	0.00
Log Likelihood				15656.34

Panel B: Sign Bias Tests	t-stat	p-value
Sign Bias	1.592	0.111
Negative Sign Bias	0.049	0.961
Positive Sign Bias	0.825	0.410
Joint Effect	3.568	0.312

Panel A of this table presents the coefficient estimates and robust standard errors from e-GARCH-M model, along with the respective significance statistics. The model jointly estimates:
$r_{M,t} = \lambda_0 + \lambda_1 \sigma_t^2 + \theta \epsilon_{t-1} + \epsilon_t$
$ln(\sigma_t^2) = \alpha_0 + \beta_1 ln(\sigma_{t-1}^2) + \alpha_1[\theta_2 \psi t - 1 + \gamma(|\psi_{t-1}| - (2/\pi)^{1/2})]$
using daily return data for the BIST100 index. In the equations above, $r_{M,t}$ is the return in day t and ϵ_t is a return shock that is assumed to be normally distributed with a zero mean and conditional variance σ_t^2.
Panel B of the table reports our results from Engle and Ng (1993) sign bias tests. These tests check whether the squared normalized residual (ψ^2) can be predicted by lagged variables that are not included in the volatility model, both separately and jointly for positive and negative realizations of the return shock. A rejection of the null hypothesis in these tests indicates that the volatility model is misspecified.

Table A2: Month-by-Month Analysis of the Turn of the Month Effect (L_2F_4)

		Panel A		Panel B				Panel C					
		Full Sample		Up Months		Down Months		1988–1996		1997–2005		2006–2014	
		R_{ToM}	*Diff*	R_{ToM}	*Diff*	R_{ToM}	*Diff*	R_{ToM}	*Diff*	R_{ToM}	*Diff*	R_{ToM}	*Diff*
Jan	Mean	0.9	0.68	1.41	1.04	0.21	0.02	1.18	0.74	1.02	1.03	0.31	0.43
	t-stat	3.79***	2.37**	4.68***	2.74***	0.56	0.04	2.66***	1.35	1.78*	1.58	1.23	1.40
Feb	Mean	0.14	0.12	0.46	0.68	-0.26	-0.46	0.78	0.69	-0.37	-0.52	0.03	0.17
	t-stat	0.65	0.42	1.58	1.80*	-0.78	-1.12	1.76*	1.24	-0.90	-0.93	0.10	0.57
Mar	Mean	0.01	-0.06	0.08	0.18	-0.04	-0.24	0.16	0.09	0.04	0.11	-0.15	-0.36
	t-stat	0.05	-0.20	0.20	0.40	-0.12	-0.63	0.28	0.15	0.07	0.19	-0.61	-1.26
Apr	Mean	0.73	0.61	0.65	0.4	0.80	0.75	0.76	0.84	0.86	0.54	0.59	0.44
	t-stat	3.52***	2.47**	2.85***	1.32	2.44**	1.99**	1.89*	1.75*	1.95*	1.05	2.96***	1.93*
May	Mean	0.19	0.36	0.31	0.49	0.05	0.25	0.21	0.19	0.25	0.57	0.12	0.32
	t-stat	0.92	1.49	1.04	1.41	0.16	0.75	0.48	0.38	0.65	1.27	0.52	1.13
Jun	Mean	0.22	0.16	0.35	0.08	0.16	0.31	0.35	-0.28	0.56	0.89	-0.26	-0.19
	t-stat	1.20	0.74	1.43	0.23	0.68	1.15	1.22	-0.78	1.65*	2.28**	-0.88	-0.55
Jul	Mean	0.30	0.22	0.74	0.74	-0.04	-0.25	0.10	0.21	0.54	0.47	0.27	-0.01
	t-stat	1.71*	1.04	3.06***	2.69***	-0.17	-0.82	0.29	0.53	1.60	1.16	1.15	-0.03
Aug	Mean	0.15	0.29	0.11	0.33	0.20	0.01	0.03	-0.19	0.32	0.82	0.09	0.28
	t-stat	0.89	1.38	0.50	1.19	0.76	0.03	0.09	-0.43	1.30	2.40**	0.39	0.96
Sept	Mean	0.22	0.00	0.14	-0.43	0.26	0.30	-0.22	-0.79	0.58	0.64	0.29	0.17
	t-stat	1.39	0.02	0.55	-1.37	1.32	1.09	-0.76	-2.17**	1.86*	1.52	1.51	0.63
Oct	Mean	0.31	0.23	0.77	0.93	-0.36	-0.72	0.86	1.23	0.21	-0.32	-0.14	-0.23
	t-stat	1.54	0.97	3.07***	3.08***	-1.12	-1.85*	2.53**	2.94***	0.52	-0.65	-0.52	-0.70
Nov	Mean	0.27	0.29	0.39	0.62	0.09	-0.15	-0.36	-0.63	1.19	1.24	-0.03	0.27
	t-stat	1.17	1.05	1.37	1.81*	0.24	-0.32	-1.08	-1.52	2.44**	2.09**	-0.09	0.76
Dec	Mean	0.78	0.71	0.81	0.76	0.76	0.74	0.74	0.72	1.00	0.74	0.59	0.65
	t-stat	2.95***	2.43**	2.43**	1.94*	1.98**	1.78*	1.73*	1.47	1.62	1.10	2.36**	2.32**

This table presents the mean daily returns for BIST100 index during the turn-of-the-month period (RToM) and the spread (Diff) between these means and the mean daily returns generated over the rest of the month (RRoM) for different months of the year. Panel A reports the results for the full sample. Panel B reports the results for up and down months separately. Panel C reports the results for the three nine-year subsamples. Returns are reported along with the t-statistics testing the null hypothesis of mean daily return being equal to zero. The standard t-test of Diff being equal to zero takes into account the fact that number of observations used to calculate the mean for RToM is significantly lower than number of observations used to calculate the mean for RRoM. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

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