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Abstract

This paper tests whether the conditional CAPM accurately prices assets utilizing data from the Istanbul Stock Exchange (ISE) over the time period from February 1997 to April 2008. In our empirical analysis, we closely follow the methodology introduced in Lewellen and Nagel (2006). Our results show that the conditional CAPM fairs no better than the static counterpart in pricing assets. Although market betas do vary significantly over time, the intertemporal variation is not nearly large enough to drive average conditional alphas to zero.

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1. Introduction

The Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) has long been the cornerstone of theoretical and empirical asset pricing literature. The model stipulates a linear relationship between the expected return on an asset and its systematic risk, as measured by beta. Even though it has been avidly taught by academics and widely used by practitioners, the empirical evidence in favor of the model is, at best, mixed. Our goal in this paper is to test a conditional version of the CAPM utilizing data from the Istanbul Stock Exchange (ISE).

There is a long list of empirical regularities which are at odds with the CAPM, which constitutes the basis of the so-called anomalies literature. Most notably, CAPM does not capture any of the size, book-to-market, past return and illiquidity effects.[1] The failure of the unconditional CAPM in explaining various asset pricing anomalies has led researchers to consider dynamic versions of the model. Dyvbig and Ross (1985), and Jagannathan and Wang (1996) show that, in a setting where the conditional CAPM holds, the unconditional version may nevertheless commit serious pricing errors. The theoretical support for the conditional CAPM is coupled by a significant number of empirical studies recognizing the importance of modeling systematic variation in beta[2]. Ghysels (1998) argues that the conditional model outperforms the unconditional version, as long as the dynamics of beta are appropriately captured. On the other hand, the conditional model can commit larger pricing errors than the unconditional version if the beta risk is inherently misspecified.

Despite growing evidence in favor of the conditional CAPM, Lewellen and Nagel (2006) (LN, hereafter) argue that the conditional model performs as poorly as the unconditional version in explaining various asset pricing anomalies. To avoid using specific conditioning information, LN perform time-series intercept tests using high frequency data over short windows. Their evidence documents large conditional alphas (i.e., intercepts) in favor of rejecting the conditional CAPM. Although market betas do vary significantly over time, LN show that intertemporal variation is not nearly large enough to explain asset pricing anomalies like B/M or momentum effects.

Within the scope of emerging markets, asset pricing tests become more complicated. Harvey (2001) argues that the lack of complete market integration is the main reason why emerging markets do not obey classical asset pricing paradigms. Pereiro (2002) states that several other factors, such as imperfect diversification and lack of transparency in final prices, make the use of CAPM controversial in emerging markets. Furthermore, relatively uncertain financial, economic and institutional environments in emerging economies lead researchers to take into account various other factors such as political risk and stability. Yet, over the years, the Istanbul Stock Exchange has become a significant emerging market with a growing number of companies, market capitalization and trading volume - making it a distinct test ground to provide either corroborative or contradictory evidence for asset pricing models.

As a prelude, our evidence shows that a conditional version of the CAPM which allows beta to vary over time commits large pricing errors. We follow the approach used in LN in our empirical tests, and first perform market model regressions every quarter, using daily returns from February 1997 to April 2008. We then use the time-series of estimated alphas to test whether the average conditional alpha is zero. In addition, we test the joint hypothesis that conditional alphas obtained for each portfolio are equal to zero in whole by performing an F-test. In these short window regressions, we do not specify any conditioning variable, but rather assume that betas are relatively stable within a given quarter. Usually, macroeconomic variables such as the aggregate dividend yield, default spread, term spread or short term interest rates are used to model the time variation in betas in conditional asset pricing tests [Cochrane (2001)]. However, given the lack of transparency or lack of certain types of data in emerging markets, the difficult task of specifying conditioning variables becomes problematic. For this reason, the assumption of stable betas within a quarter underlying short window regressions seems a reasonable compromise, and avoids the need to identify conditioning variables.

Our primary aim in this paper is to test the asset pricing performance of the conditional CAPM. We choose to work at the portfolio level rather than at individual stock level and rely on portfolio formation procedures of the anomalies literature to group stocks into portfolios - which also gives us the chance to see to what extent asset pricing anomalies are present in the Istanbul Stock Exchange. We perform quarterly short window regressions using daily portfolio returns based on size, book-to-market, past return and illiquidity sorts. For size and B/M portfolios, average conditional alphas are statistically significant. We construct three types of momentum/contrarian portfolios, varying in the length of formation and holding periods. The average conditional alpha is significantly different from zero in some of the decile portfolios for all three types of momentum/contrarian portfolios. We consider two types of illiquidity based portfolios, differing in time horizon: For both the 1-month and 12-month illiquidity portfolios average conditional alphas are significantly different from zero for some of the decile portfolios as in momentum/contrarian portfolios. In addition, we test the joint hypothesis that conditional alphas obtained for each portfolio are equal to zero by looking at F-statistics. Very low p-values for all types of portfolios is evidence against the null hypothesis. To summarize, we show that the conditional CAPM displays a bad pricing performance in the Istanbul Stock Exchange as well.

LN show that, as long as the conditional CAPM holds, a stock’s unconditional alpha depends on covariances between its beta and the market risk premium, and between its beta and the market volatility. In the second part of our empirical analysis, we compare the unconditional alpha from the CAPM regression to that predicted by the analytical results stated above. Our results show that, despite significant intertemporal variation in betas, the pricing error due to time variation seems to be too small to explain the aggregate pricing error.

In Section 2, we discuss the related literature on the ISE and other emerging markets. The main characteristics of the Istanbul Stock Exchange are summarized in Section 3. Section 4 describes the data and the methodology used in conditional CAPM tests. We present empirical results in Section 5, and present our conclusions in Section 6.

2. Related Literature on ISE and Other Emerging Markets

Investor interest in emerging markets has exploded in recent years. Harvey (1995) states several reasons for this interest. First, emerging markets exhibit higher returns, albeit having higher volatility. Second, emerging market returns are not highly correlated with developed markets, giving investors a chance to further diversify their portfolios.

Several studies have reported on the implications of the conditional CAPM within the framework of emerging markets. For example, Bonomo and Garcia (2001) employ Generalized Method of Moments (GMM) based tests for Brazil, covering the period between 1976 and 1992. Their results show that the conditional CAPM explains returns well for size based portfolios. Using ten emerging countries, Garcia and Ghysels (1998) test two types of conditional CAPM: the world and the local versions. The world conditional CAPM assumes that emerging markets are integrated with world markets, and CAPM is tested between each country index and the world market portfolio, represented by the Morgan Stanley Capital International (MSCI) value-weighted index. The local conditional CAPM analyzes the relation between size portfolios and local market returns. They show that the world conditional CAPM gives unstable parameters, whereas the local conditional CAPM parameters are stable and support the conditional CAPM theory in most of the emerging markets analyzed. Furthermore, following Jagannathan and Wang (1996), Durack et al. (2004) test the conditional CAPM in the Australian stock market. Their results show that the conditional CAPM performs better than alternative asset pricing models such as the APT and the Fama French three-factor model. They also document a significant size factor in Australia. As for the evidence in Asian markets, Soydemir (2001) and Yakob and Delpachitra (2006) show that the conditional CAPM prices market risk, unlike the static CAPM.

There are a few empirical studies testing asset pricing models in Turkey. Akdeniz et al. (2001) use a methodology similar to that of Fama and French (1992) for the time period between 1992 and 1998. They find that size and B/M explain stock returns, whereas market beta has no explanatory power. Gokgoz (2007) tests the unconditional CAPM and the Fama-French three-factor model using 2001-2006 data. He performs both time-series and cross-sectional regression tests and concludes that both models are significant, evidenced by high F-values and statistically significant t-statistics. Regarding the conditional CAPM and time-varying betas, Odabasi (2002) investigates time variation of betas in the Istanbul Stock Exchange from 1992 to 1999 and demonstrates that betas in Turkey are highly time-varying over four and eight year estimation periods. Furthermore, Karatepe et al. (2002) show that returns estimated by the conditional CAPM are quite close to actual returns.

In this study, our goal is to test the pricing performance of the conditional CAPM. While testing the conditional CAPM, we work at the portfolio level rather than individual asset level. We rely on portfolio formation procedures of the anomalies literature based on size, B/M, past return and illiquidity, which also helps us see to what extent these anomalies are present in the Istanbul Stock Exchange..

3. Istanbul Stock Exchange (ISE) and its Characteristics

The ISE was formally inaugurated on December 26, 1985. The stock exchange developed rapidly since and has increasingly attracted foreign institutional investors. In 1989, all barriers to foreign investment were lifted, in accordance with Turkey's liberalization program. In October 1993, the U.S. Securities and Exchange Commission (SEC) recognized the ISE as a "Designated Offshore Securities Market". On May 9 1995, the Japan Securities Dealers Association (JSDA) officially designated the ISE as an "appropriate foreign investment market for private and institutional Japanese investors."

In the period following the 2001 currency crisis in Turkey, the macroeconomic situation has improved significantly, as result of fiscal, monetary and institutional reform packages. Between 2002 and 2007 Turkey displayed an average growth rate of 7%[3]. A favorable international environment and progress towards EU-facilitated foreign direct investment also increased interest in ISE. Some of the ISE member banks and public companies were partially acquired by foreign investors. In line with these developments, 22 years after its foundation, numbers show that the Istanbul Stock Exchange has successfully attracted large numbers of foreign investors. By the end of 2007, the share of foreign portfolio investors in the free float increased to 72%.

Table 1 documents the rapid development of the Exchange over the years[4]. The number of companies listed on the ISE increased from 80 in 1986 to 319 by the end of 2007. Total market capitalization of the listed companies increased from 938 million U.S. dollars to 290 billion over the same time period. The total annual trading volume increased from a mere 13 million U.S. dollars in 1986 to 300 billion in 2007, whereas the daily average volume increased approximately to 1.2 billion U.S. dollars by 2007. By the end of 2007, in terms of total annual trading volume, Turkey became the 7th largest among 20 emerging markets, following China, South Korea, Taiwan, India, Brazil and South Africa while, in terms of total market capitalization, Turkey ranked 9th.

4. Data and Empirical Methodology

The basic data consist of daily returns, market capitalization, book value of equity, and lagged returns for a sample of common stocks traded on ISE, and spans the time period from February 1997 to April 2008. Our data provider is Rasyonet[5], a trustable Turkish data vendor and financial services company. We use the ISE-All Index, a value-weighted portfolio of all listed companies on the exchange, as a proxy for the market portfolio in market model regressions[6]. We form various value-weighted portfolios, and track their performance over time[7].

We first consider market capitalization (size) and book-to-market value of equity (B/M) double-sort portfolios. Due to the availability of financial statement data, we start forming intersection portfolios on July 1997. We form portfolios every 3 months, as financial statement data is published quarterly and size data is available monthly. We form 9 size-B/M portfolios every 3 months (3 by 3 independent sorts)[8] similar to those in Fama and French (1993). Size and B/M cutoff points are determined every 3 months, based on all stocks in the sample with available data on the first trading day of the portfolio formation month. Size is defined as the market capitalization (in TL) on the last trading day of the previous month, whereas B/M is defined as the ratio of the book value of equity as of the previous fiscal quarter to the market value of equity on the last trading day of the previous month. We then track the value-weighted returns on the resulting 9 portfolios over the following three months. The term "Small" stock portfolio is defined as the equally-weighted average of the three low market capitalization portfolios, whereas "Big" stock portfolio is the average of the three high market capitalization portfolios. The long/short portfolio Small-minus-Big, "S-B" is defined simply as their difference. A growth portfolio is constructed in a similar fashion as the average of the three low B/M portfolios, whereas "Value" is the average of the three high B/M portfolios. "V-G" is the Value-minus-Growth portfolio and is defined as the difference between the two.

Three momentum/contrarian portfolios, differing in the length of formation and holding periods, are considered. At the beginning of every month, we sort stocks into deciles in ascending order (P1 to P10), based on past one-month, three-month or six-month cumulative returns. We hold the one-month portfolio for a month, and the three- and six-month portfolios for overlapping periods of 3 and 6 months, respectively. For each trading day, we calculate the average of the corresponding overlapping returns, which we assign to be the portfolio return for that day. The "Winner-minus-Loser" momentum portfolio is then constructed by differencing the returns on the highest past return portfolio (P10) and the lowest past return portfolio (P1). Following Cooper et al. (2005), we allow for a one month gap between formation and holding periods for three- and six-month portfolios, in order to minimize the bid-ask bounce effect. Another reason to allow a one month gap for three- and six-month portfolios, is that it helps us analyze the medium term momentum[9] effect documented by Jegadeesh and Titman (1993) separate from the influence of the one-month reversal[10] effect documented by Zarowin (1989), Jegadeesh (1990) and Chang et al. (1995).

We form two types of illiquidity portfolios based on the Amihud (2002) illiquidity measure (Illiquid *i*), given below in equation (1), over the past one month or twelve months.

$$\text{Illiquid}\, i = (1/\text{N})^* \sum_{T=1}^{N} \frac{|R_{iyd}|}{Vol_{iyd}} \qquad (1)$$

where $|R_{iyd}|$ is the absolute value of the return on stock i, on day d of period y – where y is either the prior 1-month or the 12-month period. Vol_{iyd} is the corresponding trading volume (in TL). *N* represents the number of days stock *i* trades within one month or over a period of twelve months. Given the difficulty of finding long time-series of reliable data in emerging markets, the Amihud illiquidity measure is easier to construct than finer measures of liquidity requiring microstructure data. To construct one-month illiquidity portfolios, starting from February 1997, we sort all stocks which traded for more than 14 days during the previous month into deciles in ascending order (P1 to P10), based on the Amihud measure. For the 12 month illiquidity portfolio, we sort all stocks with more than 200 trading days during the previous year into deciles. We then hold the resulting value-weighted portfolios for a month in either case. The long/short "Illiquid-Liquid" portfolio is constructed by subtracting the returns on the lowest decile portfolio (P1-liquid) from the returns on the highest decile portfolio (P10-illiquid).

As indicated previously, we report all our results in this study on value-weighted portfolios. Results on equally-weighted portfolios do not alter our conclusions. Furthermore, for any grouping, we calculate breakpoints using all the stocks considered in a particular test. For robustness analysis, we repeat our empirical tests using breakpoints based on the largest 100 stocks on ISE with similar conclusions - which are not reported here to conserve space. Concerning delistings and new stocks portfolios at each time are constructed with trading stocks at that time so that our portfolio formation and updating procedure automatically includes new stocks and excludes non trading stocks.

4.1 Methodology

For each portfolio strategy considered, we run time-series CAPM regressions following the approach in LN. These regressions are run quarterly, using daily excess returns, net of daily overnight interest rate. To increase the precision of our estimates, we use overlapping quarters, as we do not have a very long time-series at hand. Since each consecutive quarter has 2 months of overlap, we report Newey-West (1987) heteroscedasticity and autocorrelation consistent standard errors in all of our tables[11]. As a robustness check, we also run CAPM regressions using a dummy variable for economic crisis periods in Turkey, but come to similar conclusions.

Lo and MacKinlay (1990) demonstrate that nonsynchronicity can result in substantially biased inferences for the temporal behavior of asset returns. To circumvent this problem, our tests focus on value-weighted returns. We also follow Dimson (1979) to include both contemporaneous and lagged market returns in time-series regressions. In our quarterly regressions utilizing daily returns, we include four lags of market returns, imposing the constraint that lags 2 through 4 have the same slope, in order to reduce the number of parameters to be estimated, as shown in Equation (2):

$$R_{j,t} = \alpha_j + \beta_{j0} R_{M,t} + \beta_{j,1} R_{M,t-1} + \beta_{j2} \left[\left(R_{M,t-2} + R_{M,t-3} + R_{M,t-4} \right) / 3 \ \right] + \varepsilon_{j,t} \qquad (2)$$

where $R_{j,t}$ is the excess daily return net of the overnight interest rate on portfolio j at time *t*, and $R_{M,t}$ is the market excess return at time *t*. The CAPM beta is defined as the sum of the three estimated betas in Equation (2). These short window regressions do not need any conditioning variable to be specified, but assume that betas are rather stable within a given quarter. We believe that this is a reasonable assumption and particularly useful in our scenario, as it avoids the problem of specifying the appropriate set of conditioning variables, which tends to be a more problematic task in emerging markets. The time-series average of estimated alphas and betas in equation (2) then provide the final estimates in the first part of our empirical analysis to test whether the average conditional alpha is zero. In addition to testing whether the average conditional alpha is zero for each decile portfolio, we test the joint hypothesis that conditional alphas obtained for each decile portfolio are equal to zero by performing an F-test.

In the second part of our empirical analysis, we rely on the analytical expression derived again in LN for unconditional alpha, α^u:

$$\alpha^u = \left[1 - \frac{\gamma^2}{\sigma_M^2} \right] \mathrm{cov}(\beta_t, \gamma_t) - \frac{\gamma}{\sigma_M^2} \mathrm{cov}\left[\beta_t, (\gamma_t - \gamma)^2 \right] - \frac{\gamma}{\sigma_M^2} \mathrm{cov}(\beta_t, \sigma_t^2) \qquad (3)$$

where the stock's conditional beta at time *t* is denoted by β_t. The market's conditional risk premium and excess return volatility are denoted by γ_t and σ_t^2, whereas γ and σ_M^2 represent the corresponding unconditional statistics. Equation (3) provides a general framework for the unconditional pricing error.

From February 1997 to April 2008, the market's unconditional risk premium γ is 0.73% per month, whereas the market's unconditional excess return standard deviation σ_M is

14.7% per month. This gives a very small and negligible market's squared Sharpe ratio, $\frac{\gamma^2}{\sigma_M^2}$, of 0.00247. Furthermore, the expression in the second term $(\gamma_t - \gamma)^2$ in equation (3), is also very small, given γ and the decreasing effect of squaring. Likewise, given that $\frac{\gamma}{\sigma_M^2}$ in the second expression is 0.34, the second expression decreases further in value, which helps simplify Equation (3) into Equation (4):

$$\alpha^u \approx \text{cov}(\beta_t, \gamma_t) - \frac{\gamma}{\sigma_M^2}\text{cov}(\beta_t, \sigma_t^2) \tag{4}$$

Equation (4) states that if the conditional CAPM holds, unconditional alpha depends both on the covariance between beta and the risk premium, and the covariance between beta and market volatility. In the second part of our empirical analysis, we calculate the unconditional alpha implied by equation (4) and compare it with the unconditional alpha suggested by CAPM regressions.

5. Empirical Results

This section consists of two main sub-sections. First, we test whether the average conditional alpha is zero for size-B/M intersection, momentum and illiquidity portfolios. Second, we analyze whether portfolio betas co-vary sufficiently with the market risk premium or market volatility to account for the documented pricing errors.

5.1 Conditional Alphas

5.1.1 Size-B/M Intersection Portfolios

Table 2 reports the results for size-B/M intersection portfolios from July 1997 to April 2008. In this and the following tables, we report excess returns and alphas as daily figures multiplied by 21, i.e. in percent per month for ease of exposition. Panel A shows average excess returns, net of the overnight interest rate. In size portfolios, excess returns do not display the cross sectional pattern suggested by the size anomaly. Although large stocks on

ISE actually seem to earn a higher return than small stocks (1.12% vs. 0.71%), this return difference fails to be significant with a t-statistic of -0.69. This finding counters Gonenc et al. (2003), Akdeniz et al. (2001) and Bildik and Gulay (2007), who find a significant anomaly. However, value effect seems to be very significant among ISE stocks during the time period analyzed. High B/M (value) stocks earn 1.42% on average, whereas low B/M (growth) stocks earn only 0.10% and the difference is significant with a t-statistic of 3.68.

Panel B reports alphas and betas from unconditional CAPM regressions. The unconditional alpha for the small stock portfolio is close to zero, whereas that for the large stock portfolio is 0.53% with a t-statistic of 2.19. High B/M (value) stocks perform better than the unconditional CAPM would suggest, with an alpha of 0.87% (t-statistic of 2.15). In contrast, the growth stocks (low B/M) seem to be correctly priced by the model, with a statistically zero unconditional alpha of -0.38%. The value minus growth long/short spread has an unconditional alpha of 1.25% with a significant t-statistic of 3.56, which shows that the B/M effect is significant even after risk is accounted for by the unconditional CAPM.

Panel C reports alphas and betas from conditional CAPM regressions. Alphas for both Small and Big portfolios are large and statistically significant. As in unconditional tests, the B/M anomaly is very significant, given that V-G has an average conditional alpha of 1.18% with a t-statistic of 3.68.

An interesting feature of the results in Table 2 concerns betas. Unlike the pattern reported in the U.S. studies, both conditional and unconditional Big stock betas are higher than Small stock betas (unconditional betas of 1.06 vs. 0.82 and average conditional betas of 1.02 vs.0.75). Gonenc et al. (2003) document a similar pattern, whereas Akdeniz et al. (2001) document roughly equal betas across size portfolios in ISE. One of the potential reasons for this pattern in betas is that Big stocks constitute approximately 92% of the total market capitalization in the ISE, whereas Small stocks constitute just 1.44% [12].

5.1.2 Momentum/Contrarian Portfolios

Table 3 reports summary statistics for three types of momentum/contrarian portfolios, differing in length of formation and holding periods. The letter J represents length of the formation period, whereas K represents length of the holding period (in months). To illustrate, in the three-month J3-K3 portfolios, stocks are selected on the basis of their cumulative returns over the previous 3 months and held for 3 months. 1 month portfolios differ from 3 and 6 month portfolios in terms of the formation period. For 3 and 6 month portfolios, we skip a month between the formation and holding periods, whereas for 1 month portfolios we do not. There are two reasons for this: First, following Cooper et al. (2005), we aim to minimize the bid-ask bounce effect for 3 and 6 month portfolios. Second, skipping a month assists analysis of medium term momentum effect separate from the influence of one-month reversal. We sort all stocks in the sample every month into deciles in ascending order (P1 to P10) on the basis of their formation period returns, and hold the resulting portfolios for 1 month and for overlapping 3 or 6 month periods. A Long/Short spread portfolio “P10-P1” is constructed by subtracting the returns on the worst performing portfolio (P1) from the returns on the best performing portfolio (P10).

The evidence reported in Panel A of Table 3 is not in favor of momentum/contrarian profits for all three types of portfolio formation strategies. The raw return spread is -1.06% per month for the 1-month formation portfolios, and -1.31% and -0.68% for 3- and 6-month portfolios, respectively. However, they fail to be significant at the 5% significance level. Our results counter Bildik and Gulay (2007), who report evidence of contrarian profits over a wide range of holding periods, varying from 1 month to 36 months.

Panel B reports alphas and betas from unconditional CAPM regressions. In one-month portfolios J1-K1 and three month portfolios J3-K3, both past losers (P1) and past winners (P10) seem to be correctly priced: Alphas are not significantly different from zero. In three-month portfolios J3-K3, P1 is correctly priced, whereas alpha for P10 has a t-statistic of -1.92, which is significant at 10% significance level. Betas in the unconditional model do not vary significantly across decile portfolios in any formation procedure, ranging from a minimum of 0.92 to a maximum of 1.04.

In Panel C, the evidence is against the conditional CAPM in one-month and three-month portfolios. The Long/Short spread portfolio (P10-P1) has a significant average conditional alpha of -1.61% and -1.46%, respectively (corresponding t-statistics of -2.24 and -1.76). These results suggest that the conditional CAPM fails to correctly price contrarian portfolios in the Turkish case. On the other hand, it appears that the conditional CAPM leaves no pricing error for the six-month F6-H6 portfolio. We cannot reject the hypothesis that the average conditional alpha for the Long/Short spread portfolio is zero in this case. Another interesting observation for Long/Short momentum/contrarian portfolios is that both the average conditional alphas and their t-statistics decrease in absolute value as formation and holding period lengths increase. As we move from F1-H1 to F6-H6, the magnitude of average conditional alpha for P10-P1 decreases from 1.61 to 0.85 (t-statistic of -2.24 and -1.25). It appears that contrarian portfolios in ISE are more profitable over the short-run than the longer run. The pattern in unconditional betas does not show much variation across decile portfolios either, ranging from 0.91 to 1.00.

5.1.3 Illiquidity Portfolios

We form two types of portfolios based on the Amihud (2002) illiquidity measure over the past one month and twelve months, as previously explained. Table 4 shows raw returns and risk-adjusted returns, based on both the unconditional and conditional CAPM. There is weak evidence for the positive return-illiquidity relationship proposed by Amihud and Mendelson (1986) in Panel A of Table 4. The spread in the raw return is 0.74% per month for the 12-month (12M) illiquidity portfolio, but is almost zero (0.09% per month) for the 1-

month portfolio. While the former is economically robust, neither are statistically significant. In Panel B, it can be seen that unconditional alpha is higher for more illiquid portfolios. Even though there is an illiquidity premium present, the difference as given by the spread P10-P1 is statistically zero for both the 1M and the 12M portfolios with t-statistics of 0.42 and 1.15, respectively. However, the tendency is for the more illiquid portfolios to have higher unconditional alphas. For example, for the 12M portfolios, deciles P9 and P10 have unconditional alphas of 0.91% and 1.20%, respectively.

In Panel C, it is clear that more illiquid portfolios have much higher conditional alphas than the more liquid ones. Contrary to the case with unconditional CAPM, the most liquid portfolio P1 is correctly priced for both portfolio formation procedures. Portfolios which are more illiquid (deciles P8, P9 and P10) are mispriced by the conditional CAPM for both portfolio types. Average conditional alphas are large for P8, P9 and P10 (1.21%, 1.56% and 1.26% for 1M, and 1.09%, 1.55% and 1.73% for 12M) with conventionally high t-statistics.

5.2 Conditional Betas

In this section, we first focus on the intertemporal variation of portfolio conditional betas. We then compare unconditional alphas implied by the conditional CAPM [Equation (4)] to those obtained directly from unconditional CAPM regressions. Tables 5 and 6 report conditional beta statistics for size versus book-to-market double-sort, and momentum and illiquidity portfolios, respectively. In both tables, Panel A shows the standard deviation of the time-series of estimated betas, and panel B reports the unconditional alpha implied by Equation (4).

As can be clearly observed, there is significant intertemporal variation in conditional betas for all portfolio strategies that we consider. For instance, in Table 5 Panel A, the standard deviation of estimated beta for the small-minus-big spread portfolio S-B is 0.23. Similarly, the value-minus-growth spread portfolio V-G has a standard deviation of 0.15. The beta of small stock portfolio is, on average, more volatile than the beta of big stock portfolio (0.25 vs. 0.09). On the other hand, the time-series variations in the betas of value and growth stock portfolios are of the same magnitude (0.21 vs. 0.16).

The momentum portfolio beta also displays significant time variation. In Table 6 Panel A, the Winner-minus-Loser portfolio (P10-P1) estimated beta has a standard deviation of 0.43, 0.33 and 0.33 respectively for 1, 3 and 6 month momentum strategies. The decile portfolios based on past performance (P1 through P10) also have highly volatile beta estimates. For instance, portfolios based on the prior month return (J1-K1) have a standard deviation of estimated beta ranging from 0.16 to 0.33. The betas of extreme losers or winners tend to be more volatile than the betas of average performance groups; the standard deviation displays a U-shaped curve from Losers (P1) through Winners (P10).

Conditional betas also fluctuate significantly in illiquidity portfolios. In Table 6 Panel A, the illiquidity spread portfolio (P10-P1) estimated beta has a rather high standard deviation of 0.29 and 0.32 for 1M and 12M strategies, respectively. Besides the most liquid portfolio P1, the rest of the decile portfolios display significant time variation in estimated betas. For example, for the strategy based on the prior month illiquidity measure (1M), portfolios P2 through P10 have a standard deviation of estimated betas of at least 0.19. In contrast, the most liquid portfolio P1 beta has a standard deviation of 0.09, suggesting that, on average, betas of illiquid stocks on the ISE are much more volatile than the betas of more liquid stocks.

Figure 1 displays the intertemporal variation in Long/Short spread portfolios discussed in detail above. As Figure 1 shows, there is substantial variation in betas over time. The natural question that follows is whether the volatility in betas is enough to account for the evidence on mispricing. As discussed previously, Equation (4) states that, assuming conditional CAPM holds, a stock's unconditional alpha can be expressed as a sum of covariances of the stock's beta with excess market return and with the market volatility.

Evidence from Panel B of Tables 5 and 6 shows that unconditional alphas implied by Equation (4) are far from those obtained directly from unconditional CAPM regressions. Implied unconditional alphas are often wrong in sign or smaller. In Table 5 Panel B, implied size spread (S-B) and value spread (V-G) unconditional alphas are -0.94 and 0.09, whereas the unconditional counterparts in Table 2 Panel B are -0.28 and 1.25. In Table 6 Panel B, implied Winner-Loser (P10-P1) unconditional alphas for 1, 3, and 6 month momentum portfolios are 0.61, 0.31 and 0.09, respectively. However, the corresponding actual unconditional alphas in Table 3 are -1.05, -1.28 and -0.65. In Table 6 Panel B, implied illiquid-liquid (P10-P1) unconditional alphas for 1M and 12M illiquidity portfolios are -0.78 and -0.65, respectively. However, the corresponding actual unconditional alphas are 0.30 and 0.86, as observed in Table 4. Overall, we see that implied alphas are far from predicting unconditional alphas.

6. Conclusions

We show that a conditional version of the CAPM which allows beta to vary over time commits significant pricing errors in the Istanbul Stock Exchange (ISE) over the time period from February 1997 to April 2008. We follow the approach used in Lewellen and Nagel (2006) in our empirical tests, and perform market model regressions every quarter, using daily returns. For size and B/M portfolios, average conditional alphas are statistically significant. Moreover, the average conditional alpha is significantly different from zero in most decile portfolios for all three types of momentum/contrarian portfolios. We consider two types of illiquidity based portfolios, differing in time horizon: For both the 1-month and 12-month illiquidity portfolios average conditional alphas are significantly different from zero for some decile portfolios as in momentum/contrarian portfolios. In summary, the conditional CAPM performs no better than the unconditional version in pricing portfolios we consider. Despite the significant intertemporal variation in betas, the pricing error due to time variation seems to be too small to explain the risk-adjusted returns.

We hope to add to the debate going around the conditional CAPM in the academic circles, bringing forward evidence from an emerging market. In a period where the interest in emerging markets such as the Istanbul Stock Exchange is increasing globally, more detailed analyses are needed on the performance of asset pricing models. The conclusion following from such work will be of substantial value for both local and foreign investors.

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Table 1. Development of the Istanbul Stock Exchange: 1986-2007

This table reports number of companies, market capitalization and traded value statistics for the Istanbul Stock Exchange (ISE) over the period from 1986 to 2007. Figures are taken from ISE's website (http://www.ise.org/Data/StocksData.aspx).

	Number of companies	Market capitalization	Traded Value	
			Total	Daily Average
Year		Million US$	Million US$	Million US$
1986	80	938	13	0.05
1987	82	3,125	118	0.47
1988	79	1,128	115	0.45
1989	76	6,756	773	3
1990	110	18,737	5,854	24
1991	134	15,564	8,502	34
1992	145	9,922	8,567	34
1993	160	37,824	21,770	88
1994	176	21,785	23,203	92
1995	205	20,782	52,357	209
1996	228	30,797	37,737	153
1997	258	61,879	58,104	231
1998	277	33,975	70,396	284
1999	285	114,271	84,034	356
2000	315	69,507	181,934	740
2001	310	47,689	80,400	324
2002	288	34,402	70,756	281
2003	285	69,003	100,165	407
2004	297	98,073	147,755	593
2005	304	162,814	201,763	794
2006	316	163,775	229,642	919
2007	319	289,986	300,842	1,194

Table 2. Size and Book-to-Market intersection portfolios: July 1997- April 2008

This table reports summary statistics for size-B/M intersection portfolios. Panel A reports average excess returns net of the daily overnight interest rate and t-statistics for S-B and V-G portfolios. Panel B reports alphas and betas from unconditional CAPM regressions, whereas Panel C reports alphas and betas from conditional CAPM regressions. Conditional CAPM regressions are run quarterly in overlapping form using daily returns. Excess returns and alphas are expressed in percent monthly. Daily figures are multiplied by 21 to report in monthly form. Newey-West corrected standard errors are used to calculate t statistics.

Value-weighted portfolio returns are constructed as follows. Every month starting in July 1997, we form 9 size-B/M portfolios (3 by 3 independent sorts). Size and B/M breakpoints are based on all stocks considered. Size is the market capitalization on the last trading day of the previous month, whereas B/M is defined as the ratio of the book value of equity as of the prior fiscal quarter to the market value of equity on the last trading of the previous month. "Small" stock portfolio is defined as the equally-weighted average of the three low market capitalization portfolios, whereas "Big" stock portfolio is the average of the three high market capitalization portfolios. The long/short portfolio Small-minus-Big, "S-B", is defined as their difference. Growth portfolio is constructed as the equally-weighted average of the three low B/M portfolios, whereas "Value" is the average of the three high B/M portfolios. V-G is the Value-minus-Growth portfolio and is defined as the difference between the two.

		Small	**Big**	**S-B**	**Value**	**Growth**	**V-G**
Panel A: Portfolio Characteristics							
Excess R.	Mean (%)	0.71	1.12	-0.41	1.42	0.10	1.32
	t-stat			-0.69			3.68
Panel B: Unconditional estimates							
Alpha	Est.(%)	0.25	0.53	-0.28	0.87	-0.38	1.25
	t-stat	0.52	2.19	-0.60	2.15	-1.11	3.56
Beta	Est.	0.82	1.06	-0.23	0.99	0.87	0.12
	t-stat	47.65	120.16	-13.53	67.51	69.25	9.49
Panel C: Conditional estimates							
Alpha	Est.(%)	1.10	0.55	0.55	1.26	0.08	1.18
	t-stat	1.94	3.45	0.92	3.20	0.23	3.68
Beta	Est.	0.75	1.02	-0.27	0.90	0.81	0.08
	t-stat	23.53	82.22	-9.30	31.71	39.15	4.36

Table 3. Momentum/Contrarian portfolios, 1997- 2008

The table reports summary statistics for 3 types of momentum/contrarian portfolios represented by letters J and K. J represents length of formation period, whereas K represents length of holding period (in months). To minimize bid-ask bound effect for 3 and 6 month portfolios, at the end of each month t, the formation period consists of prior 3 and 6 months excluding month t. To illustrate, J3-K3 means that stocks are selected on the basis of returns over the prior 3 months and they are held for 3 months. However, for 1 month portfolios the formation period consists of month t. Panel A reports average excess return net of average daily overnight interest rate and t-statistic for P10-P1 portfolios for all types of momentum/contrarian portfolios. Panel B reports alphas and betas from unconditional CAPM regressions, whereas Panel C reports alphas and betas from conditional CAPM regressions. Conditional CAPM regressions are run quarterly in overlapping form using daily returns. Excess returns and alphas are expressed in percent monthly. Daily figures are multiplied by 21 to report in monthly form. Newey-West corrected standard errors are used to calculate t statistics.

The portfolios are all value weighted. We sort all stocks in the sample every month into deciles in ascending order (P1 to P10) on the basis of their formation period returns and hold the stocks for overlapping 1,3 and 6 months. An eleventh portfolio "P10-P1" is constructed for all types of portfolios by subtracting the returns of the lowest decile portfolio (P1) from the returns of the highest decile portfolio (P10).

		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Panel A: Portfolio Characteristics												
J1-K1-Excess R.	Mean (%)	0.60	0.60	1.14	1.27	1.50	0.54	1.08	0.40	0.49	-0.45	-1.06
	t-stat											-1.05
J3-K3-Excess R.	Mean (%)	1.15	0.65	0.87	1.30	1.25	1.03	0.64	0.88	0.80	-0.17	-1.31
	t-stat											-1.78
J6-K6-Excess R.	Mean (%)	0.32	0.69	0.50	0.85	0.92	1.24	0.28	0.94	0.48	-0.36	-0.68
	t-stat											-1.10
Panel B: Unconditional statistics												
J1-K1-Alpha	Est.(%)	0.07	0.08	0.61	0.72	1.02	0.06	0.59	-0.09	0.01	-0.98	-1.05
	t-stat	0.10	0.14	1.14	1.48	1.95	0.12	1.27	-0.17	0.02	-1.39	-1.04
J3-K3-Alpha	Est.(%)	0.47	-0.05	0.20	0.62	0.59	0.37	-0.04	0.21	0.14	-0.80	-1.28
	t-stat	0.86	-0.11	0.54	1.66	1.75	1.06	-0.14	0.64	0.41	-1.59	-1.74
J6-K6-Alpha	Est.(%)	-0.22	0.15	-0.04	0.30	0.38	0.67	-0.27	0.41	-0.05	-0.87	-0.65
	t-stat	-0.46	0.39	-0.11	1.03	1.18	2.46	-1.07	1.64	-0.17	-1.92	-1.06

Table 3 (Continued)

		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
J1-K1-Beta	Est.	1.04	1.02	1.03	1.05	0.94	0.93	0.95	0.95	0.92	1.02	-0.02
	t-stat	41.68	51.23	52.11	58.37	49.28	53.04	55.44	51.45	50.83	39.25	-0.54
J3-K3-Beta	Est.	1.00	1.04	1.00	1.01	0.99	0.98	1.02	0.99	0.98	0.95	-0.05
	t-stat	49.81	69.38	73.35	74.45	80.36	78.18	88.92	81.56	79.50	51.28	-2.02
J6-K6-Beta	Est.	0.99	1.00	1.00	1.01	1.00	1.03	1.01	0.98	0.96	0.95	-0.04
	t-stat	56.82	71.50	71.89	94.23	85.69	103.02	109.68	108.92	95.02	57.31	-1.95
Panel C: Conditional statistics												
J1-K1-Alpha	Est.(%)	0.66	0.42	0.74	1.10	0.77	0.32	0.59	0.20	-0.19	-0.95	-1.61
	t-stat	1.27	0.90	1.24	2.89	1.76	0.86	1.69	0.47	-0.39	-1.76	-2.24
J3-K3-Alpha	Est.(%)	0.82	0.27	0.64	0.71	0.65	0.36	-0.18	0.23	0.25	-0.63	-1.46
	t-stat	1.71	0.78	2.25	3.00	2.24	1.55	-0.71	1.13	0.85	-1.14	-1.76
J6-K6-Alpha	Est.(%)	0.12	0.39	0.10	0.52	0.40	0.69	-0.18	0.49	0.20	-0.73	-0.85
	t-stat	0.26	1.31	0.31	2.31	1.95	3.21	-0.84	2.76	0.82	-1.60	-1.25
J1-K1-Beta	Est.	0.97	0.98	0.98	1.00	0.94	0.93	0.94	0.93	0.94	0.93	-0.04
	t-stat	30.08	40.11	36.04	40.41	42.57	43.76	50.25	37.14	47.37	22.57	-0.77
J3-K3-Beta	Est.	0.95	0.97	0.95	0.98	0.97	0.96	0.99	0.99	0.96	0.93	-0.02
	t-stat	31.03	36.47	42.29	53.81	52.32	59.40	71.46	53.90	57.68	38.56	-0.55
J6-K6-Beta	Est.	0.92	0.93	0.94	0.97	0.99	0.99	1.00	0.98	0.94	0.91	-0.01
	t-stat	29.52	34.17	37.54	54.97	66.55	58.27	80.16	60.23	75.97	32.49	-0.24

Table 4. Illiquidity portfolios, 1997- 2008

The table reports summary statistics for 2 types of illiquidity portfolios differing in past period horizon and represented by 1M and 12M. 1M represents 1 month, whereas 12M represents 12 months. Panel A reports average excess return net of average daily overnight interest rate and t-statistic for P10-P1 for both types of illiquidity portfolios. Panel B reports alphas and betas from unconditional CAPM regressions, whereas Panel C reports alphas and betas from conditional CAPM regressions. Conditional CAPM regressions are run quarterly in overlapping form using daily returns. Excess returns and alphas are expressed in percent monthly. Daily figures are multiplied by 21 to report in monthly form. Newey-West corrected standard errors are used to calculate t statistics.

The portfolios are all value weighted. We construct two types of illiquidity portfolios differing in past period horizon: 1 month and 12 month. For the 1 month illiquidity portfolio, starting from February 1997, on the first trading day of each month, we sort all stocks in ISE in ascending order (P1 to P10), which traded more than 14 days in the previous month, based on the Amihud illiquidity measure (2002). Then we hold the ten portfolios for exactly one month. For the 12 month illiquidity portfolio, we sort all stocks in ISE, which traded more than 200 days in the previous 12 months, based on the Amihud illiquidity measure. Then we hold the ten portfolios for exactly one month. An eleventh portfolio "Illiquid-liquid" is constructed by subtracting the returns of the lowest decile portfolio (P1) from the returns of the highest decile portfolio (P10).

		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Panel A: Portfolio Characteristics												
1M-Alpha	Est.(%)	0.91	0.59	0.71	-0.02	0.06	0.79	-0.14	1.20	1.56	0.99	0.09
	t-stat											0.08
12M-Alpha	Est.(%)	0.61	0.20	-0.09	0.02	0.37	0.22	0.25	0.64	1.11	1.36	0.74
	t-stat											0.75
Panel B: Unconditional statistics												
1M-Alpha	Est.(%)	0.37	0.09	0.20	-0.50	-0.40	0.33	-0.57	0.78	1.20	0.67	0.30
	t-stat	1.73	0.19	0.40	-1.01	-0.81	0.59	-1.03	1.29	1.94	1.06	0.42
12M-Alpha	Est.(%)	0.34	-0.06	-0.34	-0.23	0.13	-0.03	0.03	0.44	0.91	1.20	0.86
	t-stat	1.66	-0.11	-0.75	-0.47	0.27	-0.05	0.05	0.70	1.27	1.77	1.15
1M-Beta	Est.	1.04	0.98	0.99	0.94	0.89	0.89	0.85	0.82	0.70	0.63	-0.41
	t-stat	130.97	59.77	55.09	51.64	48.88	43.53	41.69	37.18	30.82	27.00	-15.82
12M-Beta	Est.	1.04	0.98	0.96	0.92	0.88	0.94	0.83	0.76	0.73	0.60	-0.43
	t-stat	139.41	52.89	57.39	52.65	48.68	39.28	33.28	32.95	27.87	24.42	-15.79

Table 4 (Continued)

Panel C: Conditional statistics

		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
1M-Alpha	Est.(%)	0.10	0.23	0.61	0.03	-0.10	0.80	0.02	1.21	1.56	1.26	1.16
	t-stat	0.47	0.59	1.63	0.08	-0.28	1.68	0.06	2.31	3.25	2.14	1.62
12M-Alpha	Est.(%)	0.16	0.00	0.01	0.27	0.69	0.25	0.61	1.09	1.55	1.73	1.56
	t-stat	1.03	0.00	0.02	0.76	1.83	0.49	1.28	2.14	2.77	2.76	2.14
1M-Beta	Est.	1.07	0.95	0.92	0.88	0.83	0.80	0.75	0.71	0.63	0.53	-0.54
	t-stat	96.05	37.54	38.26	37.23	34.16	31.60	25.23	21.80	21.20	16.62	-14.87
12M-Beta	Est.	1.07	0.92	0.89	0.86	0.81	0.86	0.75	0.72	0.57	0.55	-0.52
	t-stat	101.92	33.33	38.95	30.39	27.77	23.78	22.09	18.92	15.56	14.53	-12.32

Table 5. Conditional Betas for size-B/M intersection portfolios, July 1997- April 2008

The table reports conditional betas statistics for size-B/M intersection portfolios between July 1997 and April 2008. We obtain time-series of estimated betas by running quarterly CAPM regressions in overlapping form using daily returns. Panel A reports the standard deviation of the time-series of estimated betas from short-window regressions. Panel B reports the unconditional alpha implied by Equation (4). Please see table 2 on the formation of size and book-to-market portfolios.

		Small	Big	S-B	Value	Growth	V-G
Panel A: Standard Deviation of Estimated Betas							
		0.25	0.09	0.23	0.21	0.16	0.15
Panel B: Unconditional alphas implied by conditional CAPM							
Alpha	Est.(%)	-0.94	0.00	-0.94	-0.40	-0.49	0.09

Table 6. Conditional Betas for Momentum/Contrarian portfolios and Illiquidity portfolios, 1997- 2008

The table reports summary statistics for 3 types of momentum/contrarian portfolios represented by letters J and K and 2 types of illiquidity portfolios differing in past period horizon and represented by 1M and 12M. J represents length of formation period, whereas K represents length of holding period.(in months). To minimize bid-ask bound effect for 3 and 6 month portfolios, at the end of each month t, the formation period consists of prior 3 and 6 months excluding month t. To illustrate, J3-K3 means that stocks are selected on the basis of returns over the prior 3 months and they are held for 3 months. However, for 1 month portfolios the formation period consists of month t. For illiquidity portfolios, 1M represents 1 month, whereas 12M represents 12 months. We obtain time-series of estimated betas by running quarterly CAPM regressions in overlapping form using daily returns. Panel A reports the standard deviation of the time-series of estimated betas from short-window regressions. Panel B reports the unconditional alpha implied by Equation (4).

Please see table 3 (4) on the formation of momentum/contrarian (illiquidity) portfolios.

		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Panel A: Standard deviation of estimated betas												
Momentum/Contrarian												
J1-K1		0.26	0.20	0.21	0.19	0.18	0.18	0.16	0.20	0.16	0.33	0.43
J3-K3		0.23	0.20	0.17	0.14	0.14	0.13	0.11	0.14	0.14	0.20	0.33
J6-K6		0.24	0.20	0.19	0.13	0.11	0.13	0.10	0.12	0.10	0.21	0.33
Illiquidity												
1M		0.09	0.20	0.19	0.20	0.20	0.20	0.23	0.25	0.24	0.25	0.29
12M		0.08	0.20	0.18	0.22	0.21	0.26	0.26	0.27	0.27	0.28	0.32
Panel B: Unconditional alphas implied by conditional CAPM												
Momentum/Contrarian												
J1-K1-Alpha	Est.(%)	-0.66	-0.37	-0.03	-0.30	0.29	-0.27	0.02	-0.31	0.02	-0.05	0.61
J3-K3-Alpha	Est.(%)	-0.42	-0.24	-0.47	0.01	-0.02	-0.03	0.09	-0.09	-0.14	-0.11	0.31
J6-K6-Alpha	Est.(%)	-0.29	-0.15	-0.02	-0.22	-0.07	0.02	-0.02	-0.16	-0.19	-0.21	0.09
Illiquidity												
1M-Alpha	Est.(%)	0.21	-0.10	-0.39	-0.56	-0.20	-0.35	-0.51	-0.35	-0.44	-0.57	-0.78
12M-Alpha	Est.(%)	0.18	0.02	-0.38	-0.52	-0.52	-0.07	-0.67	-0.61	-0.59	-0.47	-0.65

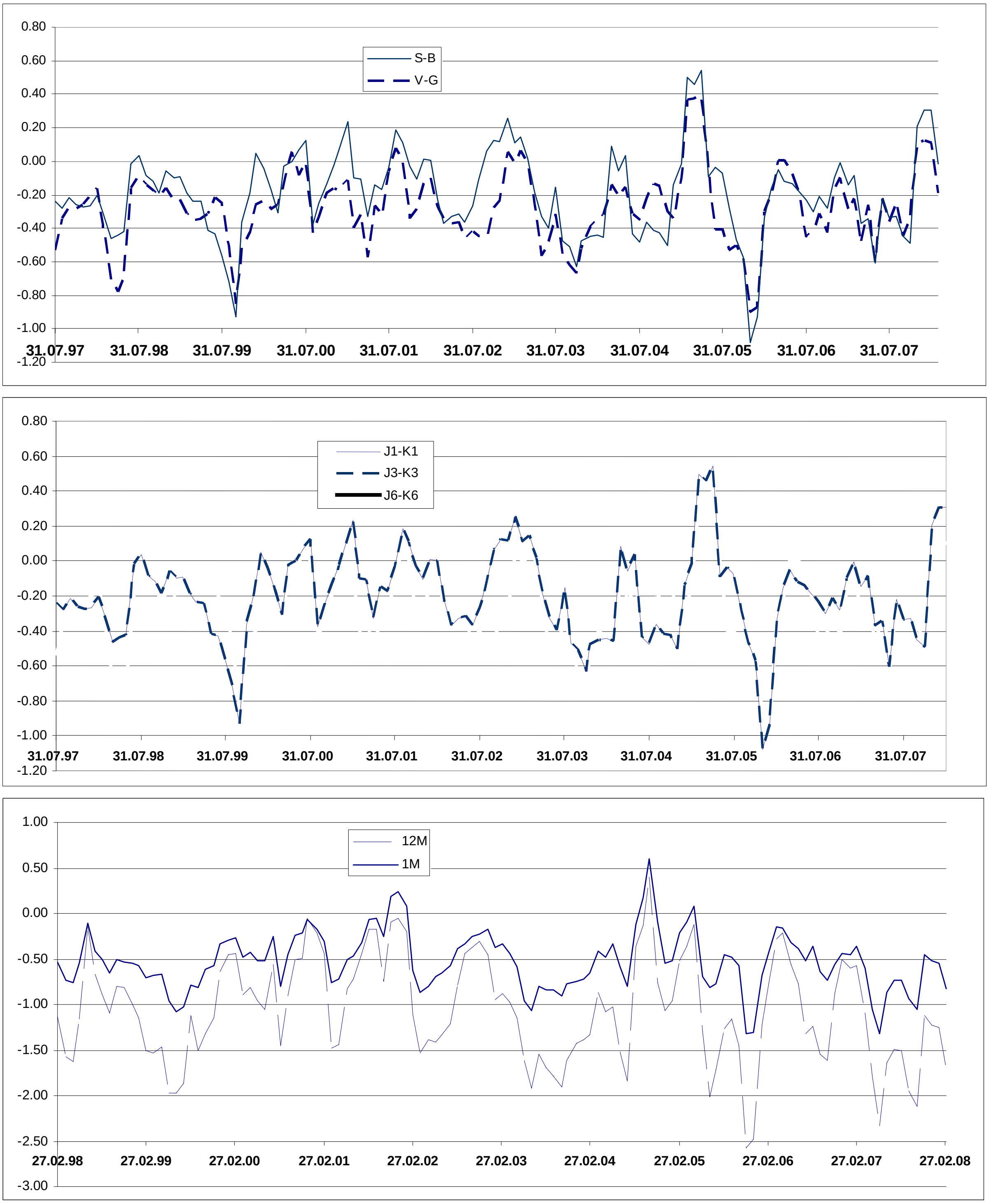

Figure 1. Conditional betas. The figure shows time varying betas for size, book-to-market, momentum and illiquidity Long/Short portfolios. Size and book-to-market differences are represented by S-B and V-G, respectively. J1-K1, J3-K3, and J6-K6 represent long/short momentum portfolios of 1,3, and 6 months formation and holding periods, respectively. 1M and 12M represent long/short illiquidity portfolios at 1 month and 12 months horizon, respectively.

[1]Influential studies of the anomalies literature are: Banz (1981) on size anomaly, Rosenberg, Reid and Lanstein (1985), and Fama and French (1992) on book-to-market (B/M) anomaly, Jegadeesh and Titman (1993) and De Bondt and Thaler (1985,1987) on past return continuity and reversal, Amihud and Mendelson (1986), and Brennan and Subrahmanyam (1996) on positive relationship between average returns and illiquidity both across stocks and over time.

[2] A partial list includes Harvey (1989), Ferson and Harvey (1991,1993), Cochrane (1996), Jagannathan and Wang (1996), and Lettau and Ludvigson (2001).

[3] 2008 OECD Economic Survey of Turkey.

[4] Please see ISE's website (http://www.ise.org/Data/StocksData.aspx).

[5] Please see http://www.rasyonet.com/_eng/index.html.

[6] We also consider alternative market indices, such as the ISE 100 index, and obtain qualitatively similar results.

[7] Using equally-weighted portfolio returns does not change our conclusions. These results are available from the authors upon request.

[8] We also analyze either way dependent sorts, which provide similar conclusions.

[9] Jegadeesh and Titman (1993) document that the momentum based trading strategy of buying recent winners and selling recent losers over a medium term of 3-12 months provides economically large and statistically significant payoffs.

[10] Zarowin (1989) and Jegadeesh (1990) report a pattern of return reversal, where losers outperform winners in the subsequent 1 month for U.S. markets. Chang et al. (1995) report the same for Japanese markets.

[11] We also perform non-overlapping quarterly regressions, with similar conclusions.

[12] To measure these percentages, we calculate the average market capitalization of both Small and Big stock portfolios and divide them by the aggregate average market capitalization over the time period from February 1997 to April 2008.