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EXPOSURE TO LIQUIDITY RISK AND EQUITY RETURNS IN BORSA ISTANBUL

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Abstract: This study investigates the equity exposure to liquidity risk factors in Borsa Istanbul between 1992-2015. Stock level cross-sectional regression and univariate portfolio analysis are utilized to examine the predictive ability of liquidity risk in Turkish markets. The widest range of illiquidity proxies are used to test this effect. Cross-sectional regression analyses show that illiquidity betas predict expected equity returns. This relation remains robust when well-known priced factors are controlled for. The univariate portfolio analysis documents that equities that are more sensitive to illiquidity shocks generate 5% higher annualized returns than those that are less sensitive to liquidity shocks. Hence, these findings show that liquidity exposure is indeed priced for equity returns in Borsa Istanbul.

Keywords: *Liquidity risk, emerging markets, equity returns, asset pricing.*

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LİKİDİTE HASSASİYETİNİN BORSA İSTANBUL'DAKİ PAY SENETLERİNİN GETİRİLERİ ÜZERİNE ETKİSİ

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Bu çalışma, Sabancı Üniversitesi Sosyal Bilimler Enstitüsü Finans Anabilim Dalı tarafından 09/06/2016 tarihinde kabul edilen doktora tezinden türetilmiştir.

Öz: Bu makalede, likidite riskinin Borsa İstanbul'da işlem gören pay senetlerinin getirilerine olan hassasiyeti 1992–2015 yılları arası için incelenmiştir. Likidite riskinin Türkiye piyasalarında fiyatlanıp fiyatlanmadığını test edebilmek amacı ile kesitsel regresyon ve portföy analizleri yapılmıştır. Bu etkiyi test edebilmek amacı ile en kapsamlı likidite ölçütleri kullanılmıştır. Hisse bazında kesitsel regresyon sonuçları, likidite azlığı betası ve gelecek 1 aydan 6 aya kadar beklenen hisse senedi getirileri arasında istatistiksel olarak anlamlı pozitif bir ilişki olduğunu göstermektedir. Sonuçlar; piyasa, defter-piyasa değeri oranı ve momentum faktörleri kontrol edilerek desteklenmiştir. Tek değişkenli portföy analizi, likidite azlığına hassasiyeti yüksek hisse senetlerinin, likidite azlığına hassasiyeti düşük hisse senetlerine göre yıllık %5 daha fazla getiriye sahip olduğunu göstermektedir. Bu sonuçlara bakarak, Borsa İstanbul'da likidite riskinin gerçekten de hisse senedi getirileri için fiyatlandığı gösterilmiştir.

Anahtar Sözcükler: *likidite riski, gelişen piyasalar, pay senedi getirileri, varlık fiyatlama.*

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INTRODUCTION

In finance, according to the arbitrage pricing theory (APT), which is explained by Ross (1976), securities that are more sensitive to systematic risk factors must compensate investors with higher returns. The sensitivity of each security with respect to each risk factor is shown by a factor-specific beta coefficient. Although APT allows for the use of several risk factors that explain security returns, it does not have the ability to specify the factors ex ante. Illiquidity proxies are good candidates for the mentioned risk factors since unexpected variations in liquidity can affect firms' cash flows and investment opportunities.

Several studies in the literature have been dedicated to investigating the link between illiquidity and equity returns. There are two different ways that liquidity can affect asset returns. The first way is that liquidity being a characteristic of the asset returns. Secondly, liquidity can be thought of as a different and distinct risk factor. (e.g Sadka, 2006; Lee, 2011). In this study, I consider liquidity as a separate risk factor. Acharya and Pedersen (2005) introduce a new asset pricing model which is adjusted for liquidity and claim that if an equity's illiquidity moves inversely either with the market return or with the market liquidity, then that stock will have a significantly lower average return. The reason behind this conjecture is that investors are ready to pay a higher price for equities which are easier and less costly to exit when liquidity dries up in the market. Lee (2011) examines liquidity as a stock-specific attribute and as a separate risk factor at the same time in international equity markets and finds a positive link between illiquidity risk and expected equity returns in these different countries. Moreover, Asparouhova *et al*. (2010) stress the importance of illiquidity measure selection by showing that the sensitivity of future equity returns to different measures of illiquidity is biased towards finding a premium. Although prior literature investigates stock’s exposure to systematic liquidity risk in U.S. markets, the evidence in emerging markets, especially in Turkey, is still not complete.

This study aims to further understand the role of liquidity exposure in the Turkish stock market. I provide a better understanding of stocks' exposures to various illiquidity risk factors though estimated factor betas with respect to these illiquidity risk factors and investigate the role of these betas in predicting expected equity returns. Following Bali *et al.* (2011), I first estimate factor betas using monthly stock returns and then calculate the sensitivity of stock returns towards these factor betas. In other words, instead of the pricing capability of the factors, I test the pricing capability of the sensitivity coefficients on the factors. Therefore, if these financial factors indeed proxy for risk factors, stocks that are more sensitive to these factors ought to earn a compensation for risk in a risk-averse economy.

This paper has two main contributions to the literature. First, I prove that liquidity risk is priced in Turkish equities. Second, Liu (2006) and Subrahmanyam (2010) point out that results found in liquidity literature depend on the liquidity proxies used. Hence, to alleviate their concern, I gather an extended number of illiquidity metrics that can be utilized in Borsa Istanbul to fully comprehend the whole aspect of liquidity risk using daily data.

I find that the relationship between illiquidity betas and expected equity returns is significantly positive for different return horizons. The results are robust to the presence of size, value and momentum factor in regression analyses. Additionally, univariate portfolio level analysis documents that equities that are more sensitive to illiquidity generate higher returns than those that are low sensitive to illiquidity. Hence, I conclude that the sensitivity to illiquidity is actually priced in the Turkish stock market.

The article proceeds as follows. The second section details the methodology and data used in this study. The third section explains the findings. The fourth section concludes.

1. DATA AND METHODOLOGY

1.1. Illiquidity Variables

As in Amihud (2002), monthly illiquidity proxy, $Illiq_{it}$, is calculated as the monthly average of absolute daily equity return to the daily Turkish Lira trading volume for each equity. Specifically, $Illiq_{it}$ is defined as:

$$Illiq_{it} = 1/D_{it} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{VOL_{idt}} \quad (1)$$

where $|R_{idt}|$ is the absolute daily return on equity *i* on day *d* of month *t*, VOL_{idt} is the corresponding daily Turkish Lira trading volume and D_{it} is the number of non-missing return days for each equity. This ratio equals to the absolute price variation per local currency (Turkish Lira) of daily trading volume. This illiquidity proxy builds on the idea of price response when there is fluctuation in order flow.

Because illiquidity fluctuates dramatically over the sample period, the mean-adjusted equivalent of $Illiq_{it}$ is computed and utilized in the analyses. First, average market illiquidity is computed across equities for each month as:

$$Avilliq_t = 1/N_t \sum_{i=1}^{N_t} Illiq_{it} \quad (2)$$

where N_t is the number of distinct equities in each month. Second, the mean-adjusted illiquidity proxy is computed as:

$$IlliqMA_{it} = Illiq_{it} \,/\, Avilliq_t. \tag{3}$$

The main benefit of this illiquidity proxy is that it captures the relative illiquidity of each equity with respect to other equities that are traded in the markets.

Following Ben-Rephael et al. (2010), inflation-adjusted version of Amihud illiquidity proxy is calculated to adjust for inflationary pressure as:

$$IlliqRKW_{it} = 1/D_{it} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{VOL_{idt} \cdot inf_t} \tag{4}$$

where inf_t is the adjustment factor for inflation.[1]

To minimize the effects of extreme observations, following Karolyi et al. (2012), KLV_{it} measure is calculated and used in the analyses as:

$$KLV_{it} = 1/D_{it} \sum_{d=1}^{D_{it}} \left\{ ln\left(1+\frac{|R_{idt}|}{VOL_{idt}}\right) \right\} \tag{5}$$

Additionally, to eliminate the non-synchronous trading effect, Kang and Zhang (2014) proposed a modified Amihud measure by taking non-trading days into consideration as:

$$Illiqzero_{it} = \left[ln\left(\frac{1}{D_{it}} \sum_{1}^{D_{it}} \frac{|R_{idt}|}{VOL_{idt}} \right) \right] \times (1 + NT\%_{it}) \tag{6}$$

where $NT\%$ is the ratio of non-trading days to the total number of days in each month. Emerging markets, like Turkey, sometimes suffer from thin and infrequent trading, therefore Amihud proxy may not work perfectly for equities that have an abundance of non-trading days. In other words, $Illiqzero_{it}$ corrects for the biases associated with zero returns.

Lastly, Gamma measure is calculated using the following regression which is introduced by Pastor and Stambaugh (2003):

$$R^e_{i,d+1,t} = \theta_{it} + \phi_{it} R_{idt} + \gamma_{it} \text{sign}(R^e_{idt}) \times VOL_{idt} + \varepsilon_{i,d+1,t} \quad d=1,\ldots\ldots,D \tag{7}$$

where R^e_{idt} is the equity return in excess of the market portfolio on each day d, R_{idt} is the equity return on each day d, $R^e_{i,d+1,t}$ is the equity i's next day excess return, and VOL_{idt} is the trading volume. One-day-ahead excess stock return is used as the predictive variable since the *Gamma* variable detects the effect of contemporaneous order flow fluctuations on future daily stock returns. To proxy for illiquidity, the slope coefficient *Gamma* (γ_{it}) is multiplied by -1. This illiquidity proxy measures reciprocal of previous day's order flow impact. The absolute value of this illiquidity proxy moves in parallel with the implied price change. In other words, heavier volume-related return reversals are related to higher illiquidity.

1.2. Data and Empirical Methodology

All stock level information is provided by Stockground.[2] The sample is between January 1992 to December 2015. The sample includes all financial and non-financial firms in Borsa Istanbul. To avoid survivorship bias, I also keep all delisted stocks in the sample. Only common equities are retained in the sample. Stock level data, returns, prices and number of shares outstanding data are adjusted for stock splits, right offerings and dividend payments. I compound daily stock returns to calculate monthly returns. Widely used financial factors are constructed for Borsa Istanbul by using the non-parametric portfolio analysis. Market portfolio (*MKT*) is proxied by Borsa Istanbul-100 index. Fama and French (1993)'s size (*SMB*) and value (*HML*) factors are calculated by grouping equities into quintiles based on market capitalization and book-to-market ratios, respectively. Then, the monthly return spread between the extreme portfolios are calculated. Following Carhart (1997), the momentum factor (*UMD*) is estimated as the monthly return spread between 30 percent of equities with the highest past six-month cumulative returns (winders) and the 30 percent of equities with the lowest past six-month cumulative returns (losers). The portfolios are re-formed monthly.

The methodology of Fama and French (1992) is followed to match the accounting data with the return data. Specifically, monthly equity returns between July of each year and June of next year are matched with the accounting data from previous year ends to make sure that accounting information is revealed to the public before portfolios are formed. To be eligible for the tests in each year, I require that a stock must have a valid stock level information data as of December of the prior year. To calculate the sensitivity betas with respect to illiquidity proxies, I also require that an equity must contain at least 15 non-missing monthly returns during the past 24 months preceding July of each year. To eliminate the effect of outliers, illiquidity proxies are truncated at the 1% and 99% percentiles. Momentum is calculated as the cumulative past six-month stock return during months t-7 to t-2. By calculating momentum effect, the prior month is excluded since monthly stock returns exhibit strong monthly autocorrelation.

This article aims to investigate the significance of illiquidity exposure on the cross-section of expected equity returns. This goal can be reached by parametric tests and I conduct these analyses to investigate the predictive ability of liquidity betas. The test consists of two stages. In the first stage, I run univariate time-series monthly regression of equity returns on the risk factors using 24 months of data. In the second stage, future equity returns are regressed each month on factor betas found in first stage during the period 1994-2015. Put differently, from January 1992 to December 1993, I use the first two years of monthly equity returns to estimate the factor sensitivities for every individual stock during the sample period. I utilize a monthly rolling regression methodology with a 24 months of estimation window to estimate the monthly factor sensitivities using the following regression:

$$R_{i,t} = \alpha_{i,t} + \beta^{F}_{i,t} \,.\, F_t + \varepsilon_{i,t} \tag{8}$$

where $R_{i,t}$ is the monthly excess equity return and F_t is one of the 10 well-known financial and illiquidity risk factors each month *t.* $\alpha_{i,t}$ and $\beta^{F}_{i,t}$ are the alpha and the risk factor *F*'s beta for each stock, respectively. In Eq. (8), I consider 10 variables as risk factors, including *MKT, SMB, HML, UMD, Illiq, IlliqRKW, IlliqMA, KLV, Illiqzero,* and *Gamma.* In other words, Eq. (8) consists of 10 separate univariate regression equations. In each regression, I use a different risk factor.

In the second stage, one-, three-, and six-month forward individual stock returns are cross-sectionally regressed on the univariate different factor sensitivities utilizing the Fama-MacBeth (1973) methodology:

$$R_{i,t+n} = \omega_t + \lambda_t \,.\, \beta^{F}_{i,t} + \varepsilon_{i,t+n} \tag{9}$$

where $R_{i,t+n}$ is the cumulated excess return on stock *i* from month *t* to month *t*+*n* and $\beta^{F}_{i,t}$ is the risk factor *F*'s beta for stock *i* in each month *t* estimated using Eq. (8). ω_t and λ_t are the monthly alpha and coefficients from the previous cross-sectional regressions, respectively. Eq. (9) is also a collection of 10 regressions where each regression is estimated using each financial risk factor beta independently. I also perform statistical significance tests following Newey-West (1987) correction.[3] This second set of regression begin in January 1994.

2. Empirical Results

2.1. Descriptive Statistics

Table 1 reports stock-level summary statistics of firm-level stock returns and risk factors that are utilized in this paper. Panel A reports summary statistics for stock returns quoted in Borsa Istanbul for one-, three- and six-months holding periods. The mean monthly stock return is 3.8%, surpassing the median return of 1.01%. The standard deviation of the equity return is 20.01%. The return distribution is positively skewed and leptokurtic. Observe that similar patterns exist for 3- and 6-month return horizons. Panel A, Table 1 reveals that stock returns have non-normal distribution. Panel B of Table 1 reports the summary statistics for market, size, value and momentum factors as well as six illiquidity factors. I observe that the *SMB* and *HML* have positive means of 0.0086 and 0.0026, respectively echoing the results of Cakici et al. (2013) regarding the effect of size and value in international markets. *SMB* and *HML* exhibit slight negative skewness. *UMD* has a negative mean of -0.0085, revealing the existence of a reversal effect for equity returns in Borsa Istanbul. The Amihud illiquidity proxy (*Illiq*) and *KLV* measures have average values of 35.3603 and 35.4224, respectively. Both of the illiquidity proxies display highly leptokurtic characteristics. *IlliqRKW* has an average of 0.5282, implying that the average price variation per one million Turkish Lira trading volume equals to 53%. The mean-adjusted Amihud measure (*IlliqMA*) has an average of 0.8932. Illiqzero has a negative mean (-1.7013). *Gamma* has mean (median) values of 0.2972 (0.0006) and has a high kurtosis (37.7794).

2.2. Univariate Factor Betas in Cross-Sectional Regressions

Table 2 presents summary statistics for the factor betas estimated using the time-series univariate regressions of each factor on individual stock returns. β^{SMB} has a mean value of 0.1673 with a slightly positive skewness statistic of 0.3418. The mean value of β^{HML} is 0.4565 with a standard deviation of 0.9626. β^{UMD} has a negative mean of -0.8964, β^{MKT} has a mean of 0.8644 and both have almost symmetrical distributions since the mean and median values are close. This inverse momentum effect is in contrast with the U.S. studies which document that momentum is positively associated with stock returns. All univariate illiquidity factor betas have negative mean and median values with a negative skewness statistic. β^{Illiq}, $\beta^{IlliqRKW}$, β^{KLV} and $\beta^{Illiqzero}$ have negative mean values with negative 25th and 75th percentiles, indicating a robust negative relationship between these illiquidity betas and contemporaneous stock excess returns. For $\beta^{IlliqMA}$ and β^{Gamma}, 75th percentiles are slightly positive indicating that most of the values are still in the negative territory and therefore the negative relation between contemporaneous stock excess returns and *IlliqMA* together with *Gamma* betas still holds.

Table 3 reports average slope coefficients from Eq. (9) which uses the univariate factor betas as independent variables. In Panel A, the relationship between expected stock returns and four illiquidity betas are positive and significant when next month stock returns are used as the dependent variable, namely for β^{Illiq}, $\beta^{IlliqRKW}$, $\beta^{IlliqMA}$, β^{KLV}. The average slope coefficients for these factor betas are 0.0542, 0.0007, 0.0011 and 0.0543 and the corresponding t-statistics are 1.73, 2.00, 2.25 and 1.73, respectively. This finding proves that the relationship between expected equity returns and illiquidity betas is positive and significant, independent of the illiquidity measure selection. Note that the sensitivity of future stock returns to illiquidity betas is more pronounced when $\beta^{IlliqRKW}$ and $\beta^{IlliqMA}$ are used as explanatory variables.

In Table 3 Panel B, the significant relationship between illiquidity betas and future equity returns stays intact for four illiquidity proxies when the predicted variable is the three-month-forward stock returns. The slope coefficients of *Illiq* and *IlliqRKW* betas from these regressions are 0.2039 and 0.0024 with t-statistics of 2.02 and 2.18, respectively. Moreover, the average slope coefficient is significant at the 1% level when *IlliqMA* beta is used as the independent variable. Panel C of Table 3 shows the intercept terms and average slope coefficients from Eq. (9) using six-month ahead returns as the predicted variable. The results are consistent with the shorter time horizons. The average slope coefficients for the same four illiquidity betas (*Illiq*, *IlliqRKW*, *IlliqMA*, *KLV*) are positive and significant. The remaining six financial risk factor sensitivities, including *MKT*, *SMB* and *HML* do not have any explanatory ability over expected stock returns regardless of the return horizon.

2.3. Multivariate Factor Betas in Cross-Sectional Regressions

Previously, I document how strongly *Illiq*, *IlliqRKW*, *IlliqMA* and *KLV* betas predict the cross-sectional of future stock returns. Starting from this section, I exclude other insignificant illiquidity betas from my analysis and concentrate only on the significant ones and the widely used market, size, value and Carhart (1997)'s momentum factors.

In the first step, I again utilize a monthly rolling regression methodology with a fixed 24 months of estimation window to estimate the monthly multivariate factor sensitivities (betas) using the following regression:

$$R_{i,t}= \alpha_{i,t} +\beta_{i,t}^{MKT}.MKT_t+\beta_{i,t}^{SMB}.SMB_t+\beta_{i,t}^{HML}.HML_t+\beta_{i,t}^{UMD}.UMD_t+\beta_{i,t}^{ILLIQ}.ILLIQ_t+\varepsilon_{i,t} \quad (10)$$

where $R_{i,t}$ is the excess return on equity *i* in month *t*, $MKT_t, SMB_t, HML_t, UMD_t$ and $ILLIQ_t$ are the market, size, value, momentum factors and one of the four illiquidity proxies in month *t*, respectively. $\alpha_{i,t}$ is the alpha for equity *i* in month *t* and $\beta_{i,t}^{MKT}, \beta_{i,t}^{SMB}, \beta_{i,t}^{HML}, \beta_{i,t}^{UMD}$ and $\beta_{i,t}^{ILLIQ}$ are the market, size, value, momentum and illiquidity sensitivities for stock *i* in each month *t*, respectively.

In the second step, I run cross-sectional monthly regressions where the predicted variable is the future stock return and the explanatory variables are previously estimated factor betas for the following regression specification:

$$R_{i,t+n}=\omega_t+ \theta_t^{MKT}\beta_{i,t}^{MKT}+\theta_t^{SMB}\beta_{i,t}^{SMB}+\theta_t^{HML}\beta_{i,t}^{HML}+\theta_t^{UMD}\beta_{i,t}^{UMD}+\theta_t^{ILLIQ}\beta_{i,t}^{ILLIQ}+\varepsilon_{i,t+n} \quad (11)$$

where $R_{i,t+n}$ is the cumulative excess return on equity *i* from month *t* to month *t*+*n* and $\beta_{i,t}^{MKT}$, $\beta_{i,t}^{SMB}$, $\beta_{i,t}^{HML}$, $\beta_{i,t}^{UMD}$, $\beta_{i,t}^{ILLIQ}$ are, respectively the market, size, value, momentum and illiquidity betas for equity *i* in each month estimated from Eq. (10). θ_t^{MKT}, θ_t^{SMB}, θ_t^{HML}, θ_t^{UMD} and θ_t^{ILLIQ} are the regression coefficients from the previous cross-sectional regressions.

Table 4 exhibits the time-series means of the regression slopes from the cross-sectional regression of future stock returns on four-factor model and one of the illiquidity betas. Controlling for other factors, I observe no significant relationship between β^{Illiq} and future equity returns. $\beta^{IlliqRKW}$ exhibits a statistically significant predictive power for three- and six-month return horizons. Note that, there is a statistically significant relationship between $\beta^{IlliqMA}$ and expected stock returns and this positive and significant link persists regardless of the return horizon. The coefficient of *IlliqMA* beta changes between 0.0029 and 0.0104. The corresponding t-statistics range from 2.57 to 3.28. The mean slope of *HML* beta is always positive; however, signs of the mean slope coefficients of *SMB* and *UMD* betas alternate depending on the return horizon and the illiquidity proxies used. Moreover, aside from the illiquidity betas, only *HML* beta shows any significant predictive power and only when predicted variable is the next month equity return. All in all, Fama-MacBeth cross-sectional regressions document a significant positive relationship between *IlliqMA* beta and expected equity returns after local market, size, value and momentum factors are controlled for.

2.4. Univariate Portfolio Analysis of *IlliqMA* Beta

In the previous section, I show that the sensitivity of a stock's return towards mean-adjusted Amihud illiquidity proxy is a priced factor. An alternative method to test this significantly positive relation is to utilize univariate portfolio analyses. Stocks are grouped into terciles based on their illiquidity betas and next month portfolio returns are calculated each month to test whether the future return spread between extreme portfolios is statistically significant. More specifically, for each month between January 1994 and December 2015, equities are grouped into tercile portfolios based on their illiquidity beta, where low $\beta^{IlliqMA}$ portfolio contains equites with the lowest 30 percent illiquidity betas and high $\beta^{IlliqMA}$ portfolio contains equities with the highest 30 percent illiquidity betas. Next, I calculate next month's return for each tercile to examine whether the return spread between extreme terciles is statistically significant.

Table 5 reports average illiquidity betas and equal-weighted returns for each portfolio formed earlier. I should note that the average illiquidity beta of the low-beta portfolio is higher in absolute magnitude than the high-beta portfolio, yet it is considered as a low-beta portfolio due to its negative sign. I observe that the average illiquidity beta is negative for both low- and medium-beta portfolios whereas the high-beta portfolio has a mean of 1.9897. The mean next month returns of stocks in the low-beta and high-beta portfolios are 0.0344 and 0.0387, respectively. The difference between these two extreme terciles is equal to 0.0043 with a t-statistics of 4.44. This finding is also economically significant. Stocks in the high-beta portfolio yield about 5.16% higher annualized returns than those in the low-beta portfolio. Therefore, the results in Table 5 strengthen the previous findings that the sensitivity towards illiquidity is a priced in Turkish stock market.

CONCLUSION

This article investigates the predictive ability of liquidity risk in the Turkish stock market for the sample period January 1992 and December 2015 using univariate and multivariate estimates of factor sensitivities in univariate portfolio and regression analyses. This is the first study which investigates the impact of liquidity risk on future equity returns for the Turkish stock market.

I conduct two tests to study the effect of illiquidity factor loadings on future equity returns. First, I utilize a two-step methodology. In the first step, monthly factor sensitivities (betas) for each stock are computed using rolling time-series regressions of individual stock returns on 10 distinct risk factors (6 illiquidity factors). In the second step, parametric predictive cross-sectional regressions are estimated on the stock's univariate and multivariate factor sensitivities computed in the first step.

The univariate regression results reveal a robust and significant relationship between illiquidity betas and future equity returns when *Illiq*, *IlliqRKW*, *IlliqMA* and *KLV* are used as the illiquidity variables. Controlling for the betas associated with the market portfolio, size, value and momentum factors does not affect the explanatory ability of *IlliqMA* beta. Put differently, equities that are more sensitive to illiquidity shocks earn higher returns in the subsequent period. I also document that equities that are more susceptible to illiquidity, (i.e. that have high illiquidity beta), generate higher future returns than those that are less susceptible to illiquidity, (i.e. that have low illiquidity beta). I, therefore, conclude that the sensitivity to illiquidity is a priced risk factor in Borsa Istanbul.

Table 1. Descriptive Statistics for Equity Returns and Financial Factors

This table presents summary statistics for equity returns and risk factors used in the study. Panel A reports the mean, median, standard deviation, minimum, maximum, 25th and 75th percentile, skewness and kurtosis statistics for individual equity returns for periods of one, three and six months constructed with daily individual security data listed in Borsa Istanbul over the period from January 1992 to December 2015. Panel B reports the same statistics for different financial and illiquidity risk factors. Statistics are computed as the time-series averages of the cross-sectional means. *SMB* is the Fama-French (1993) size factor. *HML* is the Fama-French (1993) book-to-market factor. *UMD* is the Carhart (1997) momentum factor. *MKT* is the monthly excess return of BIST-100 index. *Illiq* is the average of the daily ratio of the absolute return to the trading volume. *IlliqRKW* is the average of the daily ratio of the absolute return to the trading volume adjusted for inflation. *IlliqMA* is the mean-adjusted value of the average of daily ratio of the absolute return to the trading volume. *KLV* is the natural logarithm of one plus the average of the daily ratio of the absolute return to the trading volume. *Illiqzero* is the natural logarithm of the average of the daily ratio of the absolute return to the trading volume adjusted for no-trading days in a month. *Gamma* is the return reversal coefficient estimated using daily returns and volume data in a month, as in Pastor and Stambaugh (2003).

Panel A: Individual Equity Returns

	Mean	Median	Std.Dev	Minimum	Maximum	25th Per	75th Per	Skewness	Kurtosis
1-month returns	0.0380	0.0101	0.2001	-0.4036	0.8214	-0.0755	0.1181	1.1495	5.7822
3-month returns	0.1273	0.0414	0.4180	-0.5714	1.9479	-0.1176	0.2649	1.7664	7.5710
6-month returns	0.2785	0.1010	0.7066	-0.6513	3.5500	-0.1380	0.4706	2.1738	9.1331

Panel B: Financial Factors

	Mean	Median	Std.Dev	Minimum	Maximum	25th Per	75th Per	Skewness	Kurtosis
SMB	0.0086	0.0079	0.0719	-0.2210	0.2157	-0.0316	0.0489	-0.0839	4.1547
HML	0.0026	0.0029	0.0606	-0.2069	0.1832	-0.0309	0.0346	-0.0661	4.7644
UMD	-0.0085	0.0012	0.0594	-0.2007	0.1272	-0.0346	0.0275	-0.8778	4.3893
MKT	0.0003	0.0072	0.1229	-0.3013	0.4445	-0.0828	0.0676	0.4280	4.6472
Illiq	35.3603	0.1120	209.0454	0.0005	1815.4210	0.0210	1.0788	7.4840	60.5323
IlliqRKW	0.5282	0.0350	2.1084	0.0003	16.5581	0.0100	0.1370	6.1358	42.8615
IlliqMA	0.8932	0.1412	2.4056	0.0006	16.8729	0.0304	0.6037	4.8658	28.8858
KLV	35.4224	0.1120	209.4906	0.0005	1820.7500	0.0210	1.0796	7.4892	60.6247
Illiqzero	-1.7013	-2.1921	3.1220	-7.5935	8.4309	-3.8638	0.0759	0.7854	3.7143
Gamma	0.2972	0.0006	6.9550	-35.1504	50.2308	-0.0073	0.0191	2.8200	37.7794

Table 2. Descriptive Statistics for Univariate Factor Betas

This table reports the mean, median, standard deviation, minimum, maximum, 25th and 75th percentile, skewness and kurtosis statistics for univariate monthly factor betas that are estimated using the univariate time-series regressions of individual equity returns on each financial factor for the sample period 1992-2015. The financial factors are described in Table 1.

	Mean	Median	Std.Dev	Minimum	Maximum	25th Per	75th Per	Skewness	Kurtosis
β^{SMB}	0.1673	0.1471	0.8349	-1.8544	2.8285	-0.3608	0.6440	0.3418	3.7261
β^{HML}	0.4565	0.4085	0.9626	-2.0729	3.2735	-0.1391	1.0100	0.2320	3.5344
β^{UMD}	-0.8964	-0.9124	1.1341	-3.9825	2.1718	-1.5799	-0.2015	-0.0023	3.3605
β^{MKT}	0.8644	0.8653	0.3818	-0.1472	1.8578	0.6275	1.1062	-0.0294	3.1840
β^{Illiq}	-2.6740	-0.1656	8.4253	-57.7780	5.3830	-1.2328	-0.0074	-4.7327	27.3956
$\beta^{IlliqRKW}$	-5.2221	-0.6397	15.1934	-103.5519	10.5542	-3.0249	-0.0759	-4.6140	26.4758
$\beta^{IlliqMA}$	-0.6287	-0.0348	3.1911	-22.6017	8.1018	-0.3041	0.0126	-4.4595	30.2739
β^{KLV}	-2.6634	-0.1656	8.3853	-57.4630	5.4728	-1.2325	-0.0074	-4.7234	27.3093
$\beta^{Illiqzero}$	-0.0599	-0.0558	0.0545	-0.2156	0.0930	-0.0919	-0.0257	-0.2180	3.5915
β^{Gamma}	-1.2872	-0.0357	16.5406	-96.0884	72.9145	-1.0679	0.2107	-1.5423	20.3107

Table 3. Univariate Fama-MacBeth Regressions of Stock Returns on Factor Betas

This table reports the time-series averages of the intercepts and slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of future individual stock returns on univariate factor betas for the sample period 1992-2015. In the first stage, monthly factor betas are estimated for each stock over a 24-month rolling-window period. In the second stage, the cross-section of one-month as well as three- and six-month-ahead stocks' excess returns are regressed each month on univariate factor betas. Newey-West (1987) t-statistics are reported in parentheses. The financial factors are described in Table 1. Panels A, B and C present results for return horizons of one, three and six months, respectively.

Panel A: 1-month returns										
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{Illiq}	$\beta^{IlliqRKW}$	$\beta^{IlliqMA}$	β^{KLV}	$\beta^{Illiqzero}$	β^{Gamma}
0.0380	0.0061									
(4.07)	(1.20)									
0.0427		0.0008								
(4.36)		(0.32)								
0.0415			0.0026							
(4.24)			(1.54)							
0.0422				-0.0007						
(4.14)				(-0.42)						
0.0444					0.0542					
(4.35)					(1.73)					
0.0445						0.0007				
(4.35)						(2.00)				
0.0444							0.0011			
(4.29)							(2.25)			
0.0444								0.0543		
(4.35)								(1.73)		
0.0445									0.0123	
(4.31)									(0.65)	
0.0431										-0.0057
(4.25)										(-0.35)

Panel B: 3-month returns										
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{Illiq}	$\beta^{IlliqRKW}$	$\beta^{IlliqMA}$	β^{KLV}	$\beta^{Illiqzero}$	β^{Gamma}
0.1267	0.0204									
(4.39)	(1.34)									
0.1348		0.0044								
(4.22)		(0.62)								
0.1323			0.0095							
(4.26)			(1.44)							
0.1413				0.0003						
(4.30)				(0.05)						
0.1485					0.2039					
(4.48)					(2.02)					
0.1483						0.0024				
(4.46)						(2.18)				
0.1478							0.0034			
(4.44)							(2.50)			
0.1485								0.2032		
(4.47)								(2.02)		
0.1500									0.0758	
(4.38)									(1.13)	
0.1487										0.0546
(4.44)										(1.03)

Panel C: 6-month returns										
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{Illiq}	$\beta^{IlliqRKW}$	$\beta^{IlliqMA}$	β^{KLV}	$\beta^{Illiqzero}$	β^{Gamma}
0.2664	0.0516									
(4.55)	(1.53)									
0.2852		0.0068								
(4.25)		(0.53)								
0.2878			0.0153							
(4.48)			(1.00)							
0.3116				0.0063						
(4.54)				(0.55)						
0.3222					0.4113					
(4.61)					(2.06)					
0.3221						0.0048				
(4.59)						(2.22)				
0.3221							0.0076			
(4.56)							(2.58)			
0.2911								0.3325		
(4.27)								(2.09)		
0.3275									0.1810	
(4.54)									(1.25)	
0.3230										0.2223
(4.57)										(1.49)

Table 4. Multivariate Regressions of Expected Stock Returns on Carhart's (1997) Four Factors and Illiquidity Betas

This table reports the time-series averages of the intercepts and slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of future individual stock returns on multivariate factor betas for the sample period 1992-2015. In the first stage, monthly factor betas are estimated for each stock from multivariate time-series regressions of stock returns on the selected factors. In the second stage, the cross-section of one-month as well as three- and six-month-ahead stocks' excess returns are regressed each month on the factor betas. Newey-West (1987) t-statistics are reported in parentheses. The factor betas are defined in Table 1. Panels A, B, C and D present results for β^{Illiq}, $\beta^{IlliqRKW}$, $\beta^{IlliqMA}$, β^{KLV}, respectively.

Panel A:

1-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{Illiq}
0.0412	0.0030	-0.0010	0.0026	0.0004	-0.0014
(4.46)	(0.86)	(-0.47)	(1.88)	(0.25)	(-0.20)
3-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{Illiq}
0.1369	-0.0034	0.0043	0.0063	-0.0008	0.0123
(4.68)	(-0.29)	(0.59)	(1.09)	(-0.17)	(0.54)
6-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{Illiq}
0.2849	0.0012	0.0068	0.0132	-0.0046	0.1102
(4.76)	(0.06)	(0.51)	(0.89)	(-0.51)	(1.47)

Panel B:

1-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	$\beta^{IlliqRKW}$
0.0463	0.0028	-0.0010	0.0027	0.0005	0.0001
(4.48)	(0.76)	(-0.47)	(1.98)	(0.38)	(0.34)

3-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	$\beta^{IlliqRKW}$
0.1363	-0.0023	0.0031	0.0093	-0.0013	0.0008
(4.57)	(-0.20)	(0.45)	(1.68)	(-0.29)	(1.67)

6-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	$\beta^{IlliqRKW}$
0.2875	-0.0010	0.0050	0.0210	-0.0048	0.0029
(4.64)	(-0.04)	(0.38)	(1.47)	(-0.53)	(2.28)

Panel C:

1-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	$\beta^{IlliqMA}$
0.0415	0.0041	-0.0022	0.0026	0.0005	0.0029
(4.29)	(0.97)	(-1.04)	(2.02)	(0.30)	(2.57)

3-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	$\beta^{IlliqMA}$
0.1299	0.0113	-0.0041	0.0074	-0.0017	0.0070
(4.54)	(0.92)	(-0.62)	(1.49)	(-0.35)	(3.28)

6-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	$\beta^{IlliqMA}$
0.2755	0.0249	-0.0080	0.0176	-0.0043	0.0104
(4.77)	(1.07)	(-0.67)	(1.31)	(-0.47)	(2.59)

Panel D:

1-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{KLV}
0.0412	0.0031	-0.0010	0.0026	0.0003	-0.0018
(4.46)	(0.84)	(-0.47)	(1.89)	(0.22)	(-0.25)

3-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{KLV}
0.1369	-0.0033	0.0042	0.0065	-0.0008	0.0105
(4.68)	(-0.29)	(0.58)	(1.12)	(-0.18)	(0.45)

6-month returns					
Intercept	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	β^{KLV}
0.2849	0.0012	0.0067	0.0133	-0.0047	0.1107
(4.77)	(0.06)	(0.50)	(0.90)	(-0.52)	(1.48)

Table 5. Univariate Portfolios of Stock Returns sorted by $\beta^{IlliqMA}$

This table presents return comparisons between equity portfolios formed based on *IlliqMA* beta. The portfolios are formed in each month between January 1994 and December 2015. Low $\beta^{IlliqMA}$ portfolio contains stocks with the lowest 30 percent *IlliqMA* betas and high $\beta^{IlliqMA}$ portfolio contains stocks with the highest 30 percent *IlliqMA* betas. The last row shows the differences of monthly returns between the high-beta and low-beta portfolios. Newey-West (1987) adjusted t-statistics are presented in parenthesis.

Portfolios	$\beta^{IlliqMA}$	Next-month average returns
Low $\beta^{IlliqMA}$	-4.1352	0.0344
Medium $\beta^{IlliqMA}$	-0.0848	0.0410
High $\beta^{IlliqMA}$	1.9897	0.0387
High $\beta^{IlliqMA}$ - Low $\beta^{IlliqMA}$		0.0043
		(4.44)

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[1] The average inflation has been high in Turkey between 1993-2002 as compared to period 2003-2015. The average inflation is around 70% for the former period, and around 9% for the latter period. The inflation adjusted illiquidity proxy is therefore needed to correct for this immense variation in inflation rates.

[2] StockGround is designed by Rasyonet Inc. and it is a financial and technical analysis software.

[3] Six lags are used to correct for standard errors using Newey-West methodology. The findings are quantitively similar for different lag selection.

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