5-31-2013

Liquidity, Governance and Adverse Selection in Asset Pricing

Sascha Strobl
Florida International University, sstro004@fiu.edu

DOI: 10.25148/etd.FI13080528

FLORIDA INTERNATIONAL UNIVERSITY

Miami, Florida

LIQUIDITY, GOVERNANCE AND ADVERSE SELECTION IN ASSET PRICING

A dissertation submitted in partial fulfillment of

the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

BUSINESS ADMINISTRATION

by

Sascha Strobl

2013

To: Dean David R. Klock
College of Business Administration

This dissertation, written by Sascha Strobl, and entitled Liquidity, Governance and Adverse Selection in Asset Pricing, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

Kannan Raghunandan

Brice Dupoyet

Arun J Prakash, Co-Major Professor

Suchismita Mishra, Co-Major Professor

Date of Defense: May 31, 2013

The dissertation of Sascha Strobl is approved.

Dean David R. Klock
College of Business Administration

Dean Lakshmi N. Reddi
University Graduate School

Florida International University, 2013

ABSTRACT OF THE DISSERTATION

LIQUIDITY, GOVERNANCE AND ADVERSE SELECTION IN ASSET PRICING

by

Sascha Strobl

Florida International University, 2013

Miami, Florida

Professor Suchismita Mishra, Co-Major Professor

Professor Arun J Prakash, Co-Major Professor

A plethora of recent literature on asset pricing provides plenty of empirical evidence on the importance of liquidity, governance and adverse selection of equity on pricing of assets together with more traditional factors such as market beta and the Fama-French factors. However, literature has usually stressed that these factors are priced individually. In this dissertation we argue that these factors may be related to each other, hence not only individual but also joint tests of their significance is called for.

In the three related essays, we examine the liquidity premium in the context of the finer three-digit SIC industry classification, joint importance of liquidity and governance factors as well as governance and adverse selection. Recent studies by Core, Guay and Rusticus (2006) and Ben-Rephael, Kadan and Wohl (2010) find that governance and liquidity premiums are dwindling in the last few years. One reason could be that liquidity is very unevenly distributed across industries. This could affect the interpretation of prior liquidity studies. Thus, in the first chapter we analyze the relation of industry clustering and liquidity risk following a finer industry classification suggested by Johnson,

Moorman and Sorescu (2009). In the second chapter, we examine the dwindling influence of the governance factor if taken simultaneously with liquidity. We argue that this happens since governance characteristics are potentially a proxy for information asymmetry that may be better captured by market liquidity of a company's shares. Hence, we jointly examine both the factors, namely, governance and liquidity – in a series of standard asset pricing tests. Our results reconfirm the importance of governance and liquidity in explaining stock returns thus independently corroborating the findings of Amihud (2002) and Gompers, Ishii and Metrick (2003). Moreover, governance is not subsumed by liquidity. Lastly, we analyze the relation of governance and adverse selection, and again corroborate previous findings of a priced governance factor. Furthermore, we ascertain the importance of microstructure measures in asset pricing by employing Huang and Stoll's (1997) method to extract an adverse selection variable and finding evidence for its explanatory power in four-factor regressions.

TABLE OF CONTENTS

LIST OF TABLES

PREFACE TO THE DISSERTATION

This dissertation consists of three interlinked essays on liquidity, governance and adverse selection in asset pricing. Even though all the essays are interlinked but they have been presented in such a way that they are quite independent as well. Therefore, the introduction etc. related to any particular essay has been provided in the concerned essay itself. Hence, there is no introduction chapter as such but to familiarize the reader, we provide a synopsis of each of the essays below.

In these closely related essays, we examine the liquidity premium in the context of the finer three-digit SIC industry classification, the joint importance of liquidity and governance factors as well as the joint effect of governance and adverse selection.

In first essay entitled “Liquidity Premium and Industry Clustering Effect”, we analyze the influence of industry-specific differences on market liquidity and its subsequent impact on stock returns in the asset-pricing paradigm. To the best of our knowledge, so far this has not been done. We follow an approach similar to Johnson, Moorman and Sorescu (2009) and use the three-digit SIC codes to study industry clustering. We look into the industry composition of liquidity sorted portfolios as well as portfolios mimicking the best and worst liquidity portfolios. Our results show that industry effects significantly affect liquidity in some tests although neither dominates the other and, thus, both have to be considered in a comprehensive asset-pricing model.

In the second essay, “Governance and Liquidity in Asset Pricing,” we analyze the dwindling influence of the governance factor if taken simultaneously with liquidity. In recent times considerable attention from academics and practitioners has been paid on corporate governance in the last decades since investors are more mature in their demands of good management of their investments. This weariness and activism on part of the investors have increased following corporate scandals such as Enron, WorldCom and later the financial crisis.

In the last essay, “Governance and Adverse Selection in Asset Pricing,” we investigate the link between governance and adverse selection, since the latter measure is supposed to capture information asymmetry contained in liquidity. Information is the most valuable product made anywhere in the world as it is the key to interact sensibly and successfully with our environment. To make smart choices we need to know as much about the consequences of our actions as possible. The more information we have the better we are able to compete for scarce resources and outperform our competitors.. At the same time the lack of information not only will make markets inefficient but then investors will require a higher premium for this disadvantage. Thus in this essay we present our results after analyzing all the attendant advantages (disadvantages) due to availability (unavailability) of information.

CHAPTER 1: LIQUIDITY PREMIUM AND INDUSTRY CLUSTERING EFFECT

1.1 Introduction

Barriers to enter a product market define among other things the intensity of competition between companies.[1] The ability to generate profits is dependent on this intensity of competition; in other words, the industry in which a company is engaged is a crucial factor in determining that company's profitability. It has been established that standard asset pricing models are imprecise in capturing differences between industries; for example, Fama and French (1997) found that standard errors are above 3% in estimations of industry cost of capital.[2] Not only returns differ widely across industries, the liquidity is very different as well. The maximum time-average of Amihud's (2002) Illiquidity is 6.10, whereas the minimum is nearly zero. Furthermore, the standard deviation is nearly three times the mean illiquidity of 0.18. Hence, we expect that liquidity is not only clustered in certain industries but that this clustering is responsible for the liquidity premia found in previous studies. Since the pioneering research of Amihud and Mendelson (1986) and others[3] was published, liquidity has become an essential part of modern asset-pricing models. Therefore, we contribute to the existing literature by formally examining the industry clustering of liquidity. This has not yet been conducted in previous studies. We ask in this study whether or not liquidity and industry characteristics are linked together. Fast-growing industries might attract more investors, and therefore have higher market liquidity. On the other hand, investors might shy away

---

[1] See Bain (1968).

[2] See also Moskowitz and Grinblatt (1999) and Hou and Robinson (2006).

[3] See also Amihud (2002), Acharya and Pedersen (2005) and others.

due to information asymmetries, since faster growth often implies fast changing and new business environments where insiders have superior knowledge. Thus, liquidity characteristics could be closely associated with an industry group and hence one factor could significantly affect the other. Since Johnson, Moorman and Sorescu (2009) investigated the results found by Gompers, Ishii and Metrick (2003), and attributed them to industry clustering, a study of liquidity and industry clustering is warranted. Johnson et al. concluded that the Fama and French (1997) 48 industry classification is not fine enough to capture important aspects of cross-sectional differences; therefore, they used the more detailed three-digit SIC codes. After they adjusted the long-term returns sorted by governance, the abnormal returns found by Gompers, Ishii and Metrick (2003) were zero. We follow a similar approach, using the three-digit SIC codes to study industry clustering. We ask if industry-effects are caused by differences in liquidity cross-sectionally. Or, alternatively, is liquidity affected by differences between industries? To find this answer, we look into the industry composition of liquidity-sorted portfolios as well as portfolios mimicking the best and worst liquidity portfolios. Our results show that industry effects significantly affect liquidity in some tests, although neither dominates the other and, thus, both have to be considered in a comprehensive asset-pricing model. Therefore, industry clustering is not driving the liquidity premium. Furthermore, we run multi-factor regressions using the Fama-French three-factor model which includes momentum (as proposed by Carhart, 1997) and liquidity for each industry. This shows that liquidity indeed is a significant explanatory variable, although it does not fully explain variations between industries. The results confirm the importance of incorporating industry effects in models and so we continue our study with further analyses. We then mimic the most liquid and least liquid portfolios and use them in specification regressions. Again, the results confirm the importance of both factors. We find evidence that supports our alternative hypothesis which states that industry and liquidity characteristics are both needed to meaningfully explain differences in returns among stocks. Our proxies for liquidity in this study are Amihud's Illiquidity as well as Pastor-Stambaugh's liquidity factor.

Section 1.2 provides a brief overview of the relevant literature; Section 1.3 explains the data and methodology used in this study, while Section 1.4 presents the results and Section 1.5 concludes this chapter.

1.2 Literature Review and Development of Hypotheses

"Liquidity" means the ease to turn a financial asset into cash with little or no discount. Thus, stocks with low liquidity should have returns, including a premium for liquidity risks. Amihud and Mendelson (1986), who pioneered in this field, proposed a negative return-liquidity relationship. Plenty of studies have followed their early work, again using the bid-ask spread, or other, better measures for liquidity. Among those measures are the turnover ratio (Chan and Faff, 2005; Datar, Naik, & Radcliffe, 1998), the illiquidity ratio (Amihud, 2002) and trading volume (Brennan, Chordia, & Subrahmanyam, 1998). Researchers looked into the way liquidity affects asset pricing and whether or not traditional asset pricing models are able to capture liquidity risk. Pastor and Stambaugh (2003) found that high liquidity is related to higher stock returns and that liquidity risk and momentum risk are connected. Amihud (2002) concluded that the market risk premium also compensates investors for illiquidity risk. He found that this risk is more pronounced in small firm stocks, and that it develops a new measure for liquidity—the illiquidity ratio. This measure is also known as Amihud's Illiquidity and is widely used in liquidity studies, such as ours. Next, Acharya and Pedersen (2005) enhanced the traditional CAPM by including liquidity risk and showed that the explanatory power of this model is superior. Nguyen, Mishra, Prakash and Ghosh (2007) investigated the ability of the Fama-French three-factor model and the higher moment models to capture liquidity risk. Liquidity is now well established as an important risk factor that captures more than idiosyncratic risks—it captures market-wide systematic risk components.

Further studies examined the microstructure of liquidity issues. Baker and Stein (2004) constructed a model which links liquidity to stock returns with the help of irrational investors boosting the levels of liquidity since they cannot discern the information content of the order flow. Chordia et al. (2002) showed that order imbalances have a negative effect on liquidity and market returns. Furthermore, changes in liquidity can be predicted by market returns. Chordia et al. (2001) found that liquidity is acting asymmetrically and falls more in weak market conditions than it rises in good market conditions. Moreover, interest rate changes allow liquidity measures to fluctuate. Before that, Chordia et al. (2000) investigated the determinants of liquidity, concentrating on commonality. They showed that inventory risk and information asymmetry affects liquidity.

The second important aspect besides liquidity in our study concerns industry clustering. Fama and French (1997) analyzed the capabilities of the three-factor model and the CAPM in explaining industry returns and discovered that standard errors are above 3% in estimations of industry cost of capital. Hou and Robinson (2006) investigated the influences of the composition of an industry on the stock returns of firms and discovered that firms in more competitive industries are commanding premia, thus compensating for that risk. MacKay and Phillips (2005) examined the influence of industry structure on a company's decision-making abilities. They concluded that competitive industries lead to a more diverse decision making set. Chan et al. (2007) analyzed different industry classification systems and found that portfolios of stocks based on industries exhibit more return co-movement than other clustering techniques.

Most studies rely on a very broad industry classification system. This simple approach may not be sufficient to detect the information contained in narrower definitions. Johnson et al. (2009) concluded that the previous studies concerned with governance, such as Gompers, Ishii and Metrick (2003), used models that are not well specified. They found that the long-term excess returns are due to industry clustering. Johnson et al. examined the results using the finer three-digit SIC codes, whereas Gompers et al. based their findings on the Fama-French 48 industry portfolios. This leads to the goal of our study, which is to analyze the effect that industry clustering (using three-digit SIC codes) has on liquidity in an asset-pricing framework. We will achieve this by testing our null hypothesis, which states that industry clustering has no effect on liquidity characteristics in asset pricing.

1.3 Data and Methodology

The sample data consists of all NYSE-AMEX companies included in the CRSP database, available at WRDS, from 1980 to 2009. Utility companies and financial companies were excluded due to their highly regulated legal environment. Firm-months were kept as if the stock price was above \$5, and if there were more than \$3 million shares outstanding and more than 10,000 shares traded. We winsorize our return and illiquidity data to remove the influence of outliers at extreme probability levels of 1% and 99%. We use the monthly version of Amihud's Illiquidity measure as a proxy for illiquidity as follows

$$ILLIQ_{im} = 1/D_{im} \sum_{t=1}^{D_{im}} |R_{im}|/VOLD_{imd} \tag{1}$$

where D_{im} is the number of daily observations for stock i in month m. R_{im} is the daily return of stock i in month m and $VOLD_{imd}$ is the daily volume of stock i in month m. Then we standardize the measure by dividing it by the market-wide illiquidity of each month m. We use the three-digit standard industrial classification (SIC) codes to define our industry classifications following Johnson et al. (2009) (see Table 1.1). The CRSP database contains 526 industries available for these years. After applying our restrictions, 333 industries are left.

We begin the study by examining high and low liquidity portfolios to determine if they are clustered in certain industries in each year or in all years combined. We then investigate the difference between extreme liquidity portfolios and portfolios emulating the relative market equity across industry groups of these extreme liquidity portfolios. This step is to analyze whether they offer the same industry profile or not. Moreover, we employ standard asset pricing tests to see if liquidity is able to explain performance differences of industries. The asset-pricing model used in this study is the four-factor model as proposed by Fama-French (1993), plus a momentum factor as suggested by Carhart (1997). The Fama-French factors are taken from WRDS as well. Essentially we use the following enhanced version of the Fama-French model

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \gamma_i SMB_t + \delta_i HML_t + \theta_i UMD_t + \varepsilon_{i,t} \quad (2)$$

where R_i is the return of asset i, R_m is the market return and SMB_t, $HML_t$and $UMD_t$are the size book-to-market and momentum[4] factors, respectively. Additionally, we add a fifth factor as a proxy for liquidity. For that, we either use Pastor-Stambaugh's liquidity factor or we construct a zero-investment liquidity factor in the style of the Fama-French factors based on Amihud's Illiquidity. We take the difference of returns on portfolios with the highest 30% and lowest 30% illiquidity ($ILIQ_t$). These models are

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \gamma_i SMB_t + \delta_i HML_t + \theta_i UMD_t + \eta_i PSLIQ_t + \varepsilon_{i,t} \quad (3)$$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \gamma_i SMB_t + \delta_i HML_t + \theta_i UMD_t + \eta_i ILIQ_t + \varepsilon_{i,t} \quad (4)$$

where $PSLIQ_t$ and $ILIQ_t$ are the Pastor-Stambaugh liquidity factor and our zero-investment illiquidity factor, respectively. In time-series regressions, a well-specified asset-pricing model that is not overly affected by multicollinearity or endogeneity creates intercepts that are not different from zero, according to Merton (1973) and Fama and French (1993).

We then create mimicking portfolios similar to Johnson et al. (2009) and use these portfolios in specification regressions. For the purpose of mimicking industry clustering in the very liquid portfolio, only firms that are not in the very liquid portfolio are selected. Likewise, only "non-least liquid" portfolios are selected for mimicking industry clustering of the least liquid portfolio. Firms in the random trials are chosen in such a way that the total market capitalization of each industry in the trial portfolio is

[4] The momentum factor used here is the one created by Kenneth French and available on WRDS.

proportional to the market capitalization of that industry in the respective hedge, most liquid, or least liquid portfolio. Then we run 250 random trials to test the hypothesis of zero mean monthly abnormal returns at theoretical significance levels of 10%, 5%, and 1%, respectively. Long-run abnormal returns are measured by the regression intercept using the four-factor model to see if the four-factor model is well specified in industry-clustered portfolios. The random sampling of this Monte Carlo style simulation ensures that misspecification issues of our method are reduced.

Finally, a hedge portfolio long in most liquid stocks and short in least liquid stocks is used as a dependent variable, where the stocks are weighted in regards to the impact their industry has on the total market. This makes the portfolio basically industry-neutral. We then perform the converse of the above experiment; a mimicking hedge portfolio is formed, which is long in stocks mimicking most liquid stocks, and short in stocks mimicking least-liquid stocks (i.e. liquidity neutral firms/ stocks)). This is used as a dependent variable, where the stocks are re-weighted to have the same industry weights as their most and least liquid counterparts. This makes the mimicking hedge portfolio essentially liquidity-neutral, but it mimics the industry clustering of the most and least liquid firms. These procedures allow us to detect any clustering of liquidity in sorted portfolios and to conclude whether market liquidity or industry clustering dominates each other.

1.4 Results

Table 1.1 lists all the SIC codes and the respective industries predominantly used in our study. Summary statistics of the average return across SIC codes and average illiquidity, as well as standard deviation, skewness, maximum and minimum returns and illiquidity of three-digit industries, is reported in Table 1.2. The huge difference of illiquidity across industries—ranging from (almost) zero to 6.1 with a standard deviation of 0.5 and a skewness of over 7—is striking. Already this result shows the importance of examining industry clustering in illiquidity. The average return is 1.0% per annum, ranging from -2.87% to 4.03%. Amihud's Illiquidity dropped from 2.09 in 1980 to 0.07 in 2009 (see Figure 1.1 and Table 1.2). This highlights the overall improvement in liquidity in the U.S. equity market. Pastor-Stambaugh's (2003) liquidity factor (PS_INNOV) in our sample and in their (Pastor-Stambaugh) paper is much noisier and fluctuates from positive to negative values and back. Since the liquidity factor is a scaled measure to reflect the overall growth of the stock market, it does not incorporate improved market liquidity in the time series. The factor (PS_INNOV) is a quasi-fitted residual of the second-order auto-regression of the liquidity level series.[5]

We start our analysis of the relation between liquidity and industry by looking into the industries with the highest and lowest average return during our sample period. If liquidity effects in prior asset pricing studies were merely capturing industry clustering, we would expect to find high liquidity stocks to be overly represented in low performing industries and low liquidity stocks overly represented in industries that had very high returns. Table 1.3 reports the five best and five worst three-digit SIC industries in terms of cumulative stock returns, according to CRSP files between 1980 and 2009. The first column displays the SIC codes of these industries, the second column the average returns, and the third the cumulative market equity in millions of dollars. The column %ME

[5] See Pastor-Stambaugh (2003) for further details on their liquidity factor.

displays the percentage market equity of the respective industries to the overall market. Worst LIQ (Best LIQ) reports the percentage weight of the respective industry in the worst (best) liquidity group. The best industry had an average return of 23.6% and market equity of $437 million. The relative market equity of this industry is 0.003%; the best liquidity portfolios have no share in that industry, whereas the worst liquidity portfolio has a share of 0.10% or slightly above average. The next four best returning industries are again more concentrated in the worst liquidity portfolio than in the best liquidity portfolio, indicating a bias. But, the worst liquidity portfolio is also overly represented in all of the five worst performing industries, whereas the best liquidity portfolio is not overly represented at all, except for SIC 872. Together, this implies that the worst liquidity portfolio is overly concentrated in the extreme portfolios and the best liquidity portfolio is more present in the middle of the return distribution of industries. This could mean that highly active trading in the market in this time period drives big movements in returns. A systematic bias toward illiquid stocks, on the other hand, cannot be found.

Table 1.4 reports the annual difference in percent (%) between the market equity of liquidity groups and average market equity across industries. We take the market equity of the low liquidity group (portfolio) for each SIC code and subtract the average market equity of this SIC code. We then average these differences across industries in each year. Afterward, we repeat this procedure for the high liquidity group and finally take the difference between the high and low liquidity groups across industries in each year (last column). The difference between low and high liquidity is fairly stable throughout our sample time, with a little dip in the nineties. The difference between low liquidity and the mean is, contrarily, continuously declining throughout the sample period to 0.07% from 0.49%. The difference between high liquidity and the mean is again declining to 0.48% from 0.78%. In both the latter cases, most of the decline occurs in the first year of the 30-year sample. Each year of our sample differences between industries in terms of liquidity are significant. All p-values for differences in means are less than 0.001, indicating that liquidity in the form of Amihud's Illiquidity is dominated, since liquidity is more concentrated in some industries as compared to the average company. Therefore, we can say that differences in the performance of industries will affect measures of liquidity. As there is no other result in our study, this repudiates the importance of liquidity in explaining stock returns but does not mean that actual cross-sectional regression results are purely industry-driven. This would be the case only if all (or most) industries where liquidity is high either have high or low returns and vice versa. Table 1.3 already discourages such interpretations.

Table 1.5 reports the results of four-factor time-series regressions (FF3 plus momentum) for the 12 selected three-digit SIC industries. The first four have the highest market equity, the next four average market equity, and the last four have the lowest market equity of our 333 industries.[6] We estimate

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i\left(r_{m,t} - r_{f,t}\right) + \gamma_i SMB_t + \delta_i HML_t + \theta\beta_i UMD_t + \varepsilon_{i,t} \tag{2}$$

where for each month t between January 1980 and December 2009 the three-month T-bill is deducted from return stock i. SMB_t, HML_t and UMD_t are the size, book-to-market and momentum factors. The results show that the four-factor model is not able to explain the

[6] The bottom two SICs would be 832 and 965 instead of 961 and 316, but the former two have too few observations so that a useful regression result was not feasible and, hence, are replaced by the next larger industries.

returns of industry-sorted portfolios with intercepts significantly different from zero in several regressions. All four factors contribute significantly to the explanation of the portfolio returns, with the market return the most significant in all cases. The significance found here are similar to the results of Fama-French (1997). At least for the average industries there seems to be no explanatory disadvantage by using a narrower industry definition.

Next, we investigate the potential improvement by adding liquidity as an independent variable. Table 1.6 reports the results of five-factor time-series regressions (FF3 plus momentum and Pastor-Stambaugh's liquidity factor) for 12 selected three-digit SIC industries. The first four have the highest market equity, the next four have an averagely market equity, and the last four have the lowest market equity of our 333 industries using the following expression

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i\left(r_{m,t} - r_{f,t}\right) + \gamma_i SMB_t + \delta_i HML_t + \theta_i UMD_t + \eta_i PSLIQ_t + \varepsilon_{i,t} \qquad (3)$$

where PSLIQ is the Pastor-Stambaugh's (PS) liquidity factor. The results show that the significance of the intercepts is only marginally improved, although the liquidity factor is four times significant at the 1% level. The adjusted R-square increases to 48.9% from 45.5% in Table 1.5. This highlights the benefit of including this fifth factor in the regression. Overall, we conclude that PS liquidity is providing additional explanatory power to the regressions in explaining industry portfolio without fully explaining the variation in returns over time.

In Table 1.7, we substitute a liquidity factor based on Amihud's Illiquidity for Pastor-Stambaugh's liquidity factor. We create this by sorting all stocks according

Amihud's Illiquidity and then subtract the 30th percentile of the most liquid stocks from the 30th percentile of the least liquid stocks using the following expression

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i\left(r_{m,t} - r_{f,t}\right) + \gamma_i SMB_t + \delta_i HML_t + \theta_i UMD_t + \eta_i ILIQ_t + \varepsilon_{i,t} \qquad (4)$$

where $ILIQ_t$ is the illiquidity zero-investment factor. This liquidity factor appears less effective in explaining liquidity compared to the PS factor. ILIQ is only once signifcant at the 1% level and three more times at the 5% or 10% level. The intercepts are slightly more signifcant than in Table 1.6. In total, we summarize that our five-factor regressions show that liquidity is an important explanatory variable in explaining time-series regressions of industry-sorted portfolios. Nonetheless, liquidity proxies cannot fully explain the variation of returns between industries. These proxies are at least partly driven by industry effects, leading to the conclusion that both industry effects and liquidity factors are important ingredients in a comprehensive asset-pricing model.

Table 1.8 reports the average illiquidity values of very liquid and very illiquid portfolios across industries, as well as portfolios across the same industries mimicking these portfolios. For the purpose of mimicking industry clustering in the very liquid portfolio, only firms that are not in the very liquid portfolio are selected. Likewise, only "non-least liquid" portfolios are selected for mimicking industry clustering in the least liquid portfolio. Firms in 100 random trials are chosen in such a way that the total market capitalization of each industry in the trial portfolio is proportional to the market capitalization of that industry in the respective hedge, most liquid, or least liquid portfolio. We use 10% and 90% as cutoff points for least and most liquidity. The most illiquid portfolio has an average of 2.23, the emulation 0.08. The least illiquid portfolio has a value of only 0.001 and the mimicking portfolio has an average of 0.42. This highlights the wide range of illiquidity values between industries over time. The clear decline in illiquidity over time leaves most values in the tails of the distribution. The difference in differences test between extreme portfolios and mimicking portfolios is significant at the 1% level and shows the validity of the procedure.

In Table 1.9, we use these mimicking portfolios to run specification regressions. First, we employ a hedge portfolio that is long in mimicking least liquid stocks and short in mimicking most liquid stocks. Then we employ a portfolio of stocks mimicking least liquid stocks, followed by a portfolio of stocks mimicking most liquid stocks. The results show that the hedge portfolio is overly rejected on the left and right tail, whereas the other two portfolios are only significantly rejected on the right tail. This indicates that both industry clustering and liquidity characteristics are important in explaining stock returns, thus acting as evidence to support the alternative hypothesis. If liquidity were dominating industry clustering, we would expect no significant results at all. On the contrary, if industry clustering were responsible for liquidity premium, the results would be only significant on the left tail for the most liquid portfolio, on the right tail for the least liquid portfolio, and also for the hedge portfolio.

In Table 1.10, we report the results of two final regressions to conclude our study. First, we reweigh companies of the most and least liquid portfolio with the relative weights of the industries that these companies are operating in to the overall market. We form a hedge portfolio that is long in most liquid and short in least liquid firms that are effectively industry-neutral, and use that portfolio return as our dependent variable. Lastly, we create mimicking portfolios by taking the “non-most liquid” and “non-least liquid" stocks once more. Then, we weigh the companies in the portfolios according to the relative weights that the industries have among one another in the most liquid and least liquid portfolio, respectively. Therefore, the mimicking hedge portfolio is basically liquidity-neutral. These procedures together allow us to distinguish the effect of industry clustering and liquidity characteristics. A major difference compared to the procedures in Table 1.9 is that in Table 1.10 the procedure uses all companies in the respective portfolios and just reweighs them. In Table 1.9, we use a form of Monte Carlo simulation. We also use industry weights in Table 1.10, which are not used in Table 1.9.

We can see that the hedge portfolio has a significant alpha of minus 1 basis point (t = -2.53) and the mimicking hedge portfolio has an insignificant alpha of almost 0 basis points (t = -0.17). This test clearly shows—as no other analysis does in this study—the importance of liquidity and repudiates the influence of industry clustering in asset pricing.

Overall, the results provide ample evidence in support of our alternative hypotheses and show that both factors are important. The last test highlights the importance of liquidity, whereas, especially, Table 1.4 highlights the influence of industry clustering. The other results provide more mixed outcomes leading to our conclusion that liquidity and industry clustering provide important information in explaining stock returns.

1.5 Conclusion

We investigated liquidity risk and industry clustering and found that both are important in explaining stock returns. Our sample consisted of 30 years of data and we used Amihud's Illiquidity as well as Pastor-Stambaugh's liquidity factor as proxies for liquidity. We employed among other tests time-series regressions of industries, as well as specification regressions using mimicking portfolios. The results supported our alternative hypothesis and showed that industry clustering and liquidity characteristics enhance the quality of information contained in standard asset-pricing models. This corroborates the results of Fama and French (1997) and other researchers, stressing the importance of industry effects, as well as the results found by previous researchers such as Amihud (2002) and Acharya and Pedersen (2005), emphasizing the importance of liquidity. More detailed industry classifications should be incorporated in future studies about asset pricing. A comprehensive asset-pricing model should include industry effects and liquidity to provide meaningful conclusions.

Figure 1.1: Time Series of Key Variables

This graph shows the annual averages of return, Amihud's illiquidity (multiplied by 10) and Pastor-Stambaugh's liquidity factor (multiplied by 100) between 1980 and 2009.

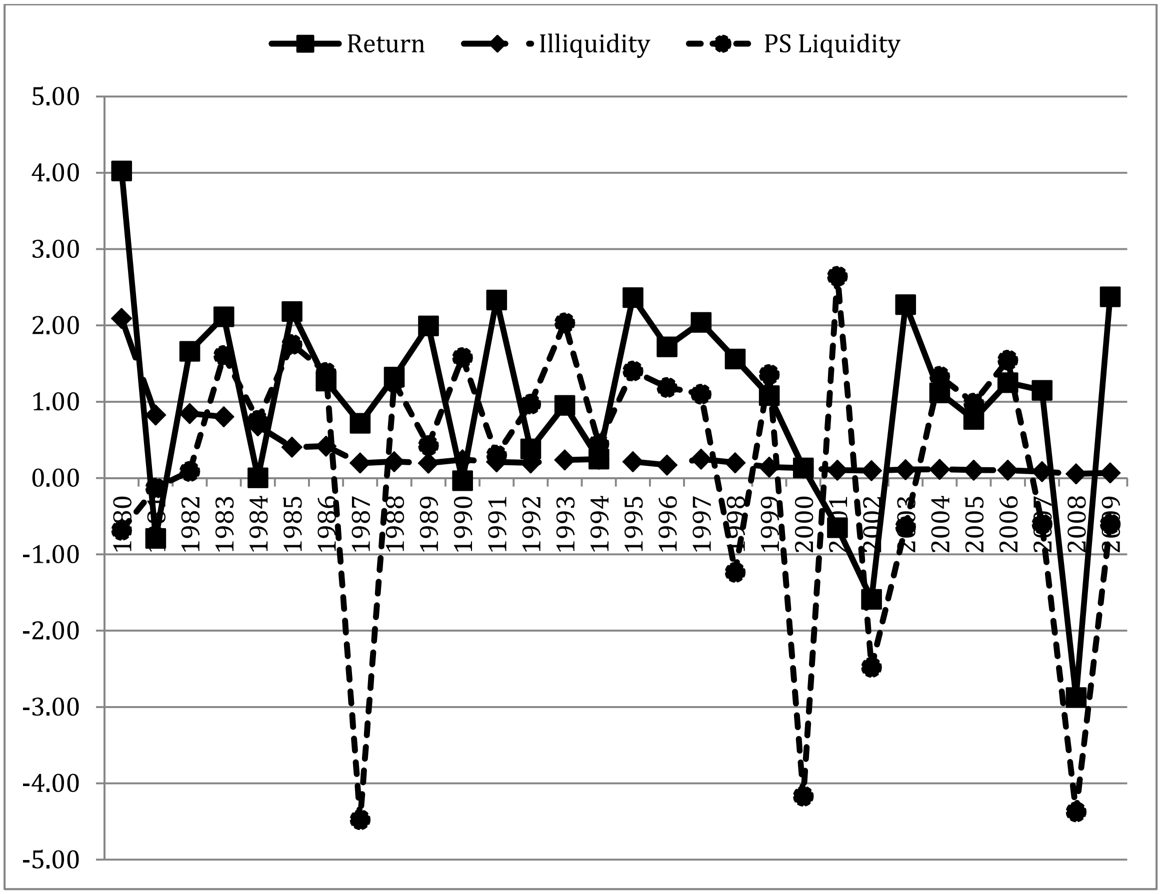


Table 1.1: SIC Code List

The table presents the SIC codes and corresponding industry names for the most used industries in this paper. Overall, we use 333 of the 526 available SIC codes during our sample time in our study. This list shows the SICs directly mentioned in the paper.

SIC	Industry
109	Miscellaneous Metal Ores
131	Crude Petroleum and Natural Gas
148	Nonmetallic Minerals Services
283	Drugs
291	Petroleum Refining
316	Luggage
319	Leather Goods
325	Structural Clay Products
357	Computer and Office Equipment
391	Jewelry, Silverware and Plated Ware
423	Trucking Terminal Facilities
500	Wholesale Trade, Durable Goods
526	Retail Nurseries and Garden Stores
549	Food Stores
557	Motorcycle Dealers
599	Retail Stores, Other
703	Camps and Recreational Vehicle Parks
791	Dance Facilities
800	Health Services
861	Business Associations
872	Accounting, Auditing and Bookkeeping Services
879	Engineering, Accounting, Research, Management and Related Services, Other
961	Administration of General Economic Programs

Table 1.2: Summary Statistics

This table reports the basic statistics such as the average return (Amihud's illiquidity) across SICs during the sample period as well as the standard deviation, skewness, maximum and minimum values. Furthermore, the annual averages of return, Amihud's illiquidity (x10) and Pastor-Stambaugh's liquidity factor (x100) are reported between 1980 and 2009.

	SIC	Return	SIC	Illiquidity
Average across SICs		1.0%		0.18
Std. Deviation		2.3%		0.52
Skewness		5.30		7.07
Maximum of a SIC	879	23.6%	148	6.10
Minimum of a SIC	557	-6.6%	800	0.00

Year	Return	Illiquidity	PS Liquidity
1980	4.03	2.09	-0.68
1981	-0.79	0.83	-0.13
1982	1.66	0.85	0.09
1983	2.12	0.80	1.61
1984	0.01	0.68	0.76
1985	2.18	0.40	1.75
1986	1.27	0.42	1.39
1987	0.72	0.20	-4.47
1988	1.33	0.21	1.25
1989	2.00	0.20	0.43
1990	-0.03	0.24	1.58
1991	2.33	0.21	0.30
1992	0.38	0.20	0.97
1993	0.95	0.24	2.03
1994	0.25	0.25	0.45
1995	2.37	0.21	1.40
1996	1.72	0.17	1.19
1997	2.04	0.25	1.10
1998	1.56	0.20	-1.23
1999	1.08	0.14	1.36
2000	0.14	0.13	-4.17
2001	-0.65	0.10	2.64
2002	-1.59	0.10	-2.48
2003	2.27	0.11	-0.64
2004	1.12	0.11	1.33
2005	0.77	0.10	0.98
2006	1.25	0.10	1.55
2007	1.15	0.08	-0.60
2008	-2.87	0.06	-4.37
2009	2.38	0.07	-0.60

Table 1.3: Industry Clustering

This table reports the five best and worst three-digit SIC industries in terms of average stock return according to CRSP files between 1980 and 2009. The first column displays the SIC codes of these industries, the second column the average returns, the third the cumulative market equity in millions of dollars. %ME shows the percentage market equity of the respective industries to the overall market. Worst LIQ (Best LIQ) reports the percentage weight of the respective industry in the worst (best) liquidity group.

	SIC	Return	ME in Millions	%ME	%Best LIQ	%Worst LIQ
Best	879	23.6%	$437.46	0.00%	0.00%	0.10%
2	703	17.4%	$1,306.12	0.01%	0.00%	0.38%
3	423	16.9%	$1,371.27	0.01%	0.00%	0.39%
4	791	11.9%	$5,901.97	0.04%	0.00%	1.74%
5	549	7.0%	$26,723.44	0.17%	0.00%	5.12%
5	319	-3.4%	$2,726.91	0.02%	0.00%	0.36%
4	526	-3.4%	$1,796.92	0.01%	0.00%	0.53%
3	325	-4.9%	$143,400.39	0.89%	0.03%	17.55%
2	872	-5.2%	$46,617.46	0.29%	0.31%	0.42%
Worst	557	-6.6%	$13,371.04	0.08%	0.00%	1.27%

Table 1.4: Annual Industry Clustering

This table reports the annual difference in percent between the market equity of liquidity groups and average market equity across industries. The percentage of the category's total market capitalization contained in each industry is calculated for low liquidity, high liquidity and the entire sample. The absolute difference in an industry's percentage of total market capitalization is reported for each category, averaged over all industries each year. All p-values for the differences are below 0.001.

Year	Avg. Market Equity - Low Liquidity Group Market Equity	Avg. Market Equity - High Liquidity Group Market Equity	High Liquidity Group - Low Liquidity Group Market Equity
1980	0.49%	0.78%	0.71%
1981	0.15%	0.53%	0.68%
1982	0.12%	0.52%	0.67%
1983	0.13%	0.50%	0.65%
1984	0.13%	0.52%	0.62%
1985	0.11%	0.49%	0.62%
1986	0.10%	0.48%	0.60%
1987	0.09%	0.47%	0.66%
1988	0.09%	0.47%	0.68%
1989	0.08%	0.45%	0.64%
1990	0.08%	0.46%	0.64%
1991	0.07%	0.46%	0.60%
1992	0.08%	0.45%	0.58%
1993	0.07%	0.43%	0.52%
1994	0.07%	0.44%	0.55%
1995	0.06%	0.42%	0.55%
1996	0.06%	0.42%	0.54%
1997	0.05%	0.40%	0.53%
1998	0.04%	0.41%	0.54%
1999	0.04%	0.45%	0.60%
2000	0.04%	0.45%	0.66%
2001	0.06%	0.44%	0.60%
2002	0.08%	0.48%	0.66%
2003	0.06%	0.48%	0.74%
2004	0.07%	0.47%	0.65%
2005	0.07%	0.47%	0.62%
2006	0.07%	0.44%	0.58%
2007	0.07%	0.48%	0.59%
2008	0.10%	0.49%	0.64%
2009	0.07%	0.48%	0.65%

Table 1.5 – Time Series Regressions by Industry

This table reports the results of four factor time-series regressions (FF3 plus momentum) for the 12 three-digit SIC industries. The first four have the highest market equity, the next four an averagely market equity, the last four have the lowest market equity of our 333 industries.

$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \gamma_i SMB_t + \delta_i HML_t + \theta_i UMD_t + \varepsilon_{i,t}$, where for each month t between January 1980 and December 2009 the riskfree rate is being deducted from the value-weighted return i. SMB, HML and UMD are the well known size, book to market and momentum factors. First, the coefficient for each factor is reported, then the t statistics below in italics. The average R^2 of the ten regressions is 45.5%. *, **, ***, significant at the 10%, 5%, and 1% levels, respectively.

SIC		Intercept	MKTRF	SMB	HML	UMD
Big Industries						
283	Coefficient	0.50	0.75	-0.55	-0.11	0.07
	t stat	*2.60***	*17.00****	*-8.96****	*-1.71**	*1.71**
291	Coefficient	0.20	0.80	-0.34	0.25	0.14
	t stat	*0.86*	*14.95****	*-4.65****	*3.09****	*2.88****
131	Coefficient	0.00	0.99	-0.08	0.45	0.09
	t stat	*0.01*	*14.93****	*-0.84*	*4.50****	*1.44*
357	Coefficient	0.40	0.90	0.04	-0.54	-0.29
	t stat	*1.74**	*16.65****	*0.54*	*-6.66****	*-5.93****
Medium Industries						
391	Coefficient	0.08	1.07	0.44	0.51	-0.11
	t stat	*0.15*	*9.42****	*2.75****	*2.95****	*-1.12*
599	Coefficient	0.74	0.96	0.95	0.40	-0.28
	t stat	*1.25*	*6.83****	*4.59****	*1.52*	*-1.89**
500	Coefficient	-3.47	1.08	1.98	3.16	-0.68
	t stat	*-1.49*	*1.37*	*2.73****	*2.54***	*-0.91*
109	Coefficient	-0.05	1.36	0.36	0.51	0.04
	t stat	*-0.09*	*9.58****	*1.97***	*2.43***	*0.29*
Small Industries						
861	Coefficient	0.23	0.92	0.70	0.95	0.29
	t stat	*0.10*	*1.54*	*0.73*	*0.85*	*0.34*
879	Coefficient	6.30	1.02	2.87	4.89	-6.76
	t stat	*0.53*	*0.28*	*0.39*	*0.67*	*-0.74*
961	Coefficient	-8.65	2.51	0.58	1.43	-0.36
	t stat	*-2.99****	*2.87****	*0.69*	*0.89*	*-0.26*
316	Coefficient	9.38	1.57	-4.26	-3.59	5.46
	t stat	*2.13***	*0.53*	*-1.59*	*-1.17*	*2.02***

Table 1.6 – Time Series Regressions by Industry with PS Liquidity

This table reports the results of five factor time-series regressions (FF3 plus momentum and Pastor-Stambaugh liquidity factor) for the 12 three-digit SIC industries. The first four have the highest market equity, the next four an averagely market equity, the last four have the lowest market equity of our 333 industries. For each month we estimate the equation

$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \gamma_i SMB_t + \delta_i HML_t + \theta_i UMD_t + \eta_i PSLIQ_t + \varepsilon_{i,t}$, where for each month t between January 1980 and December 2009 the riskfree rate is being deducted from the value-weighted return i. SMB, HML and UMD are the well known size, book to market and momentum factors and PSLIQ is the Pastor Stambaugh liquidity factor. First, the coefficient for each factor is reported, then the t statistics below in italics. The average R^2 of the ten regressions is 48.9%. *, **, ***, significant at the 10%, 5%, and 1% level, respectively.

SIC		Intercept	MKTRF	SMB	HML	UMD	PSLIQ
Big Industries							
283	Coefficient	0.48	0.81	-0.55	-0.09	0.07	-0.13
	t stat	*2.56***	*17.75****	*-9.02****	*-1.41*	*1.83**	*-3.98****
291	Coefficient	0.21	0.75	-0.35	0.23	0.14	0.10
	t stat	*0.92*	*13.57****	*-4.76****	*2.89****	*2.85****	*2.67****
131	Coefficient	0.01	0.95	-0.08	0.43	0.08	0.08
	t stat	*0.04*	*13.76****	*-0.89*	*4.35****	*1.41*	*1.68**
357	Coefficient	0.40	0.92	0.04	-0.53	-0.29	-0.05
	t stat	*1.71**	*16.29****	*0.58*	*-6.53****	*-5.91****	*-1.34*
Medium Industries							
391	Coefficient	0.13	0.95	0.42	0.46	-0.12	0.27
	t stat	*0.27*	*8.05****	*2.71****	*2.71****	*-1.22*	*3.33****
599	Coefficient	0.77	1.09	0.98	0.43	-0.23	-0.30
	t stat	*1.32*	*7.41****	*4.77****	*1.68**	*-1.60*	*-2.69****
500	Coefficient	-3.77	1.11	1.80	3.07	-0.48	0.29
	t stat	*-1.57*	*1.39*	*2.32***	*2.43***	*-0.59*	*0.68*
109	Coefficient	-0.06	1.37	0.36	0.51	0.03	-0.03
	t stat	*-0.10*	*9.08****	*1.98***	*2.45***	*0.27*	*-0.30*
Small Industries							
861	Coefficient	0.14	0.92	0.73	0.92	0.31	0.13
	t stat	*0.05*	*1.51*	*0.75*	*0.79*	*0.36*	*0.19*
879	Coefficient	8.11	0.16	1.60	4.04	-8.74	2.03
	t stat	*0.63*	*0.04*	*0.20*	*0.51*	*-0.86*	*0.66*
961	Coefficient	-8.20	1.96	0.63	0.92	0.00	0.59
	t stat	*-2.96****	*2.11***	*0.80*	*0.59*	*0.00*	*1.35*
316	Coefficient	6.29	-2.34	-1.49	-0.27	4.25	-1.38
	t stat	*1.20*	*-0.50*	*-0.40*	*-0.06*	*1.46*	*-1.07*

Table 1.7 – Time Series Regressions by Industry with Amihud's Illiquidity

This table reports the results of five factor time-series regressions (FF3 plus momentum and Pastor-Stambaugh liquidity factor) for the 12 three-digit SIC industries. The first four have the highest market equity, the next four an averagely market equity, the last four have the lowest market equity of our 333 industries. The estimated model is

$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \gamma_i SMB_t + \delta_i HML_t + \theta_i UMD_t + \eta_i ILIQ_t + \varepsilon_{i,t}$, where for each month t between January 1980 and December 2009 the riskfree rate is being deducted from the value-weighted return i. SMB, HML and UMD are the well known size, book to market and momentum factors and ILIQ is the Amihud's Illiquidity factor. First, the coefficient for each factor is reported, then the t statistics below in italics. The average R^2 of the ten regressions is 50.7%. *, **, ***, significant at the 10%, 5%, and 1% level, respectively.

SIC		Intercept	MKTRF	SMB	HML	UMD	ILIQ
Big Industries							
283	Coefficient	0.51	0.76	-0.60	-0.13	0.08	-0.07
	t stat	*2.65****	*16.14****	*-6.09****	*-1.81**	*1.81**	*-0.60*
291	Coefficient	0.25	0.84	-0.53	0.20	0.17	-0.29
	t stat	*1.09*	*14.79****	*-4.51****	*2.36***	*3.40****	*-2.03***
131	Coefficient	0.01	1.00	-0.11	0.44	0.09	-0.05
	t stat	*0.04*	*14.07****	*-0.73*	*4.21****	*1.44*	*-0.26*
357	Coefficient	0.36	0.87	0.19	-0.50	-0.31	0.24
	t stat	*1.54*	*15.09****	*1.60*	*-5.88****	*-6.14****	*1.61*
Medium Industries							
391	Coefficient	0.14	1.10	0.29	0.47	-0.09	-0.23
	t stat	*0.27*	*9.06****	*1.15*	*2.60****	*-0.82*	*-0.73*
599	Coefficient	0.76	0.98	0.87	0.37	-0.26	-0.12
	t stat	*1.28*	*6.59****	*2.75****	*1.34*	*-1.69**	*-0.31*
500	Coefficient	-4.88	2.01	-0.18	2.34	-0.74	-3.72
	t stat	*-2.09***	*2.24***	*-0.13*	*1.87**	*-1.05*	*-1.88**
109	Coefficient	0.00	1.39	0.17	0.45	0.07	-0.29
	t stat	*0.01*	*9.40****	*0.60*	*2.05***	*0.52*	*-0.82*
Small Industries							
861	Coefficient	1.21	2.19	-3.50	-0.15	0.21	-5.33
	t stat	*0.56*	*3.30****	*-2.22***	*-0.14*	*0.28*	*-3.13****
879	Coefficient	4.36	1.01	7.43	8.42	-4.42	4.53
	t stat	*0.30*	*0.25*	*0.43*	*0.59*	*-0.35*	*0.30*
961	Coefficient	-10.46	2.47	4.39	3.99	-0.66	5.82
	t stat	*-4.02****	*3.34****	*2.20***	*2.16***	*-0.56*	*2.04***
316	Coefficient	5.55	0.95	-5.39	-3.36	5.60	-3.15
	t stat	*0.73*	*0.29*	*-1.62*	*-1.04*	*1.97***	*-0.63*

Table 1.8 – Mimicking Portfolios

This table reports the average illiquidity values of very liquid and very illiquid portfolios across industries as well as portfolios across the same industries mimicking these portfolios. For the purpose of mimicking industry clustering in the very liquid portfolio, only firms that are not in the very liquid portfolio are selected. Likewise, only "non-least liquid" portfolios are selected for mimicking industry clustering in the least liquid portfolio. Firms in the random trials are chosen such that the total market capitalization of each industry in the trial portfolio is proportional to the market capitalization of that industry in the respective hedge, most liquid, or least liquid portfolio.

	Illiquidity
Least Liquid Stocks	2.23
Mimic least liquid stocks	0.08
Most liquid stocks	0.001
Mimic most liquid stocks	0.42

p-value for difference test between mimicking portfolios is less than 0.0001 for illiquidity. The difference in differences test between extreme and mimicking portfolios has a p-value of less than 0.0001.

Table 1.9 – Specification Regressions on Mimicking Portfolios

The numbers in each row represent the percentage of the 250 random trials that reject the null hypothesis of zero mean monthly abnormal return at theoretical significance levels of 10%, 5%, and 1%, in favor of the alternative hypothesis of the intercept being significantly negative on the left tail, or significantly positive on the right tail. Long-run abnormal returns are measured by the regression intercept using the four-factor model. Excess returns are regressed on RMRF, SMB, HML, and UMD. First, portfolio returns which are long in mimicking least liquid stocks and short in mimicking most liquid stocks are used, then mimicking least (most) liquid stocks are employed. *, **, ***, significantly different from the theoretical rejection rate at the 10%, 5%, and 1% statistical levels, respectively.

	Theoretical Rejection Rates					
	10%		5%		1%	
	Left Tail	Right Tail	Left Tail	Right Tail	Left Tail	Right Tail
	5%	95%	2.50%	97.50%	0.50%	99.50%
Hedge portfolio	21.2%***	38.8%***	17.2%***	36.8%***	13.6%***	28%***
Mimic most liquid	0.00%	100%***	0.00%	100%***	0.00%	100%***
Mimic least liquid	0.00%	100%***	0.00%	99.6%***	0.00%	98.8%***

Table 1.10 – Alternative Regressions

This table reports the results of four factor time-series regressions (FF3 plus momentum). $r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \gamma_i SMB_t + \gamma_i HML_t + \theta_i UMD_t + \varepsilon_{i,t}$, where for each month t between January 1980 and December 2009 the riskfree rate is being deducted from the value-weighted return i. SMB, HML and UMD are the well known size, book to market and momentum factors. First, the coefficient for each factor is reported, then the t statistics below in italics. In Panel A, a hedge portfolio long in most liquid stocks and short in least liquid stocks is used as a dependent variable, where the stocks are weighted according to their relative weight in their industry in the total market. In Panel B, a hedge portfolio long in stocks mimicking most liquid stocks and short in stocks mimicking least liquid stocks is used as a dependent variable, where the stocks are weighted according to the weights of the most and least liquid stocks, respectively. *, **, ***, significant at the 10%, 5%, and 1% level, respectively.

Panel A:

	Intercept	MKTRF	SMB	HML	UMD
Coefficient	-0.01	-0.12	0.85	0.08	-0.18
t stat	*-2.53****	*-2.61****	*12.79****	*1.15*	*-4.17****

Panel B:

	Intercept	MKTRF	SMB	HML	UMD
Coefficient	0.00	0.00	-0.08	0.04	0.05
t stat	*-0.17*	*0.51*	*-7.59****	*3.56****	*7.40****

CHAPTER 2: GOVERNANCE AND LIQUIDITY IN ASSET PRICING

2.1 Introduction

Corporate governance has attracted a lot of attention from academics and practitioners in recent decades, since investors are more mature in their demands of good management of their investments. Investor activism has increased following corporate scandals from companies such as Enron, WorldCom, and later the financial crisis. A good deal of research has been made to determine the impact of governance on firm performance (See Gompers, Ishii & Metrick, 2003).[7] Recently, researchers looked more intensely at the relation of governance and liquidity. Subrahmanyam (2007), for example, found evidence that liquidity is inversely related to governance; i.e., more liquid stocks are poorly governed. He argued that short-term speculators are not interested in the long-term prospects of a company and therefore disregard corporate governance issues. On the other hand, Norli, Ostergaard and Schindele (2010) showed that liquidity enhances the incentive to monitor management. The more liquid a stock is, the more likely it is that shareholder activism is taking place. We jointly examine liquidity and governance to see: (1) if both factors command a premium, and (2) if one factor dominates the other. Our contribution to the literature is to reestablish the importance of each factor in asset pricing in the light of recent studies that have indicated dwindling governance and liquidity premia. Furthermore, we show the interconnection of both factors in the asset-pricing paradigm.

---

[7] See also Bebchuk, Cohen and Ferrell (2009), La Porta et al. (2000) and Daines (2001), as well as others

In our first step, we examine the abnormal returns of portfolios sorted on Amihud's Illiquidity, the G or E index as proxies for liquidity and governance, respectively. Our benchmark model is the four-factor model—the Fama-French (1993) three-factor model as enhanced by Carhart's (1997) momentum factor. Thereby, we corroborate the importance of liquidity and governance, despite the recent results by Core, Guay and Rusticus (2006), and Ben-Rephael, Kadan and Wohl (2010). Extant literature shows liquidity of a stock is priced (See Amihud and Mendelson (1986), and Amihud (2002))[8] and we find evidence to support a priced liquidity risk as well. Then we double-sort our portfolios on liquidity and governance independently and dependently[9] to establish whether or not one factor is dominating the other—liquidity, especially, may dominate governance. Corporate governance characteristics are potentially a proxy for information asymmetry that may be better captured by the market liquidity of a company's shares. Our main results show, however, that governance characteristics are important in their own right or could be capturing some still unknown kind of risk. Afterwards, we look into the clustering of liquidity in the 10 G or 6 E index portfolios. Additionally, we examine governance clustering of liquidity annually. The results confirm clustering, but the clustering is unsystematic. Finally, we adopt a methodology by Johnson, Moorman and Sorescu (2009) and create mimicking portfolios that emulate the clustering of liquidity in the best and worst governance portfolios, as well as portfolios that mimic the clustering of governance in the best and worst liquidity portfolios (but do not consist of these extreme portfolios). Then we take these mimicking

[8] See also Chan and Faff (2005), and Datar, Naik and Radcliffe (1998)

[9] First we sort the portfolios into five liquidity groups and afterwards each liquidity group into five governance groups.

portfolios and run 250 specification regressions to see whether the factors themselves are priced or only their clustering in certain portfolios. The results confirm the earlier results in two ways. First, they show that clustering is present, but that, second, neither factor dominates the other—all of which supports our alternative hypothesis. Hence, we conclude that the results found in previous studies by Gompers, Ishii and Metrick (2003), as well as by Amihud (2002), are still valid today.

Section 2.2 provides a brief overview of the literature, Section 2.3 follows with the data and methodology used in this study, Section 2.4 continues with the results and Section 2.5 concludes our study.

2.2 Literature Review and Development of Hypothesis

We focus on three strands of literature for our study, namely: (1) governance premium, (2) liquidity premium, and (3) joint role of liquidity and governance in asset pricing paradigms. Corporate governance shapes the rules between investors and managers. Before the 1980s these rules were stable, but since then many companies have adopted new rules that vary significantly across firms.

The literature cited below establishes the crucial nature of anti-takeover measures that can be implemented either by state laws or by the company itself in a company's governance practices—corporate by-laws. Borokhovich, Brunarski and Parrino (1997) found that remuneration rises for CEOs of firms that implement takeover defenses. Bertrand and Mullainathan (1999a, 1999b, and 2000) showed similar results for firms being covered by state takeover laws. Several studies have shown that there is a relation between corporate governance laws and the firm's value. La Porta et al. (2000) found that the rights of minority shareholders are positively correlated with the firm's value. Daines (2001) showed that Delaware firms had higher stock values than other U.S. firms.

Later, Gompers, Ishii and Metrick (2003) constructed a Governance index (G) comprised of 28 corporate governance provisions, condensed into 24 distinctive measures in 5 categories, including: state laws, tactics for delaying hostile bidders, manager protection, voting rights, and other takeover defenses. This index from Investor Responsibility Research Center (IRRC) publications should proxy the differences in the relationships between investors and their agents to analyze corporate performance during the 1990s. They found a strong correlation of G values with stock returns where a high G value corresponds to bad governance and low G value to good governance. An investment strategy of buying shares in the firms with strong shareholder rights, and selling shares in firms with weak shareholder rights, earns excess returns of 8.5% annually. On the other hand, Johnson, Moorman and Sorescu (2009) attributed the findings of Gompers et al. to industry clustering. The excess returns found by Gompers et al. are due to some industries outperforming others. Core, Guay and Rusticus (2006) showed that the governance premium is time-sensitive; after 2000, the premium vanishes.

The entrenchment index compiled by Bebchuk, Cohen and Ferrell (2009) used only six provisions out of the 24 as listed above—four constitutional and two takeover-readiness provisions. According to their research, the above factors are enough to drive the results found for the G index. Their results showed that higher levels of their index (entrenchment index or E index) are related to significant reductions in Tobin's Q as a proxy for company valuation. Cremers and Nair (2005) found a range of mechanisms on the firm level connected to governance. These mechanisms can be divided into two categories: external and internal governance mechanisms. “External” governance means primarily the presence of anti-takeover provisions, whereas “internal” governance refers to block holders. Shareholders with a significant amount of shares have an incentive to monitor firm management more closely and facilitate takeovers (Shleifer and Vishny, 1986). On the contrary, Jensen (1993) stated that many internal control mechanisms failed during the 1970s and 1980s.

So far the literature has found overwhelming evidence for liquidity to be a price factor. Liquidity means the ease to turn a financial asset into cash with little or no discount. Thus, stocks with low liquidity should have returns, including a premium for their liquidity risks. Amihud and Mendelson (1986) used the bid-ask spread to study the impact of liquidity in asset pricing. They discovered that there is a negative relationship between expected returns of stocks and liquidity. In later years the bid-ask spread was found to be an imperfect measure for liquidity. Therefore, researchers began to use different kinds of measures, such as turnover ratio (Chan and Faff, 2005; Datar, Naik, & Radcliffe, 1998), the illiquidity ratio (Amihud, 2002), and trading volume (Brennan, Chordia, & Subrahmanyam, 1998) to investigate liquidity issues. Amihud (2002) found evidence that illiquidity risk is priced in the market over time. This leads to the conclusion that market risk premium also includes illiquidity risk. Furthermore, he found that illiquidity has a greater effect on small firm stocks, thus potentially capturing the adverse selection associated with such firms that leads to higher stock returns for small firms. Pastor and Stambaugh (2003) found that high liquidity is related to higher stock returns and that liquidity risk and momentum risk are connected. More recently, Liu (2006) developed a new asset-pricing model based on market risk and liquidity risk that outperforms the Fama-French three-factor model. Similarly, Nguyen, Mishra, Prakash and Ghosh (2007) found that the Fama-French three-factor model is not able to capture liquidity effects. Their analysis showed that stock characteristics are not good proxies for liquidity either.

Recent studies have looked into the linkage between governance and liquidity but have come to different conclusions. Norli, Ostergaard and Schindele (2010) mentioned that liquidity enhances the incentive to monitor management. The more liquid a stock is, the more likely it is that shareholder activism is taking place. Furthermore, Chen et al. (2007) argued that firms that are disclosing less information would suffer higher information asymmetry; in fact, an analysis of the effective spread corroborates that. Similarly, Chung et al. (2010) investigated governance, bid-ask spreads, as well as the market quality index and probability of information-based trading. They too found that well-governed firms are more likely to have liquid stock.

In view of the extant literature cited above on governance and liquidity, the goal of our study is to shed light on the linkage of these variables in a rigorous set of asset pricing tests. Our first null hypothesis states that liquidity is not priced, while our second null hypothesis states that governance is not a priced factor anymore. Lastly, we hypothesize that liquidity dominates governance. Alternatively, both factors—adverse selection and governance—are still priced and neither factor dominates the other.

Our study contributes to the literature by presenting evidence in support of the alternative hypotheses. These findings especially support Amihud (2002), and Gompers, Ishii and Metrick (2003).

2.3. Data and Methodology

The sample data consists of all NYSE companies included in the CRSP database from 1990 to 2006. Utility companies and financial companies were excluded due to their highly regulated legal environment. Firm-months were kept as though they had a positive trading volume, share price and shares outstanding. The governance index was obtained from Metrick's homepage and merged with the CRSP dataset. We also used the entrenchment index compiled by Bebchuk, Cohen and Ferrell (2009) obtained from Bebchuk's homepage for robustness. The governance dataset is constrained by the availability of the governance index, which is only available for years after 1990, when the IRRC first released the data that later was compiled to obtain the governance index. It consists of the ticker symbol and index value from 1990 to 2006. Following common practice, we retained the value of the index until a new index value was available. We used the monthly version of Amihud's Illiquidity as a proxy for liquidity:

$$ILLIQ_{im} = 1/D_{im} \sum_{t=1}^{D_{im}} |R_{im}|/VOLD_{imd} \qquad (1)$$

where D_{im} is the number of daily observations for stock i in month m; R_{im} is the daily return of stock i in month m; and $VOLD_{imd}$ is the daily volume of stock i in month m. We then standardized the measure by dividing it by the market-wide illiquidity of each month

m. Our dataset contains 1,427 companies, ranging from 590 companies in 1990 to 733 in 2006, with a maximum of 837 in 1998.[10]

First, we analyzed all of the variables of interest separately to determine if it was sensible to conduct multivariate tests. Hence, we examined how well the Fama-French three-factors and Carhart's (1997) momentum factor are able to explain returns of stock portfolios sorted on either of our variables: illiquidity, G index, and E index. This analysis enabled us to detect any additional information that these variables might add to the known risk factors. We adopted the GRS test statistic suggested by Gibbons, Ross and Shanken (1989) to determine whether or not the intercepts jointly equal zero for the four-factor model. Additionally, we provided the Sharpe ratio alpha as suggested by Lewellen, Nagel and Shanken (2010). We then sorted the sample companies into five (three) groups or portfolios based on their illiquidity, or G (E) index separately. The number of portfolios depended on the range of the variable. Then the excess returns of the companies were regressed on the four factors as follows:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i\left(r_{m,t} - r_{f,t}\right) + \gamma_i SMB_t + \delta_i HML_t + \theta_i PR1YR_t + \varepsilon_{i,t} \qquad (2)$$

where $\mathrm{r_{i,t}} - \mathrm{r_{f,t}}$ is the excess return of portfolio i in year t, and $\left(r_{m,t} - r_{f,t}\right), SMB_t$, $HML_t$are the Fama and French (1993) factors related to market premium, firm size, and the book-to-market ratio in year t. $PR1YR_t$ is Carhart's momentum factor. In time-series regressions, a well-specified asset-pricing model that is not overly affected by

[10] The dataset is constrained by the few companies available in the G and E indices, and the results of merging these datasets together with our illiquidity data and applying conventional restrictions, such as excluding utilities, financial companies, penny stocks and winsorizing.

multicollinearity or endogeneity creates intercepts that are not different from zero, according to Merton (1973) and Fama and French (1993).

After we established that the single characteristics are of importance in the asset-pricing paradigm, we investigated the joint importance of these characteristics. Therefore, we double sorted the data into several portfolios according to governance and liquidity characteristics, and ran several time series analyses of stock return portfolios, controlling for the four factors described above.

We conducted the above double sorting in two ways: with independent and dependent sorts. First, we sorted each characteristic independently from one another. For the dependent sort, we first sorted it according to liquidity, and then sorted each liquidity portfolio into several governance portfolios.

The next step consisted of investigating the concentration of liquidity in the 10 G index portfolios[11]. The portfolios are sorted according to the annual average excess return. We examined the percentage of high and low liquidity groups in the 10 G index portfolios as well as the average percentage market equity, the average illiquidity, and the average Pastor-Stambaugh liquidity in each G index portfolio. We conducted the same procedure using the 6 E index portfolios (combing the last two E index values).

Afterwards, we analyzed the annual G index clustering. We calculated the annual percentage difference between the market equity of liquidity groups and the average market equity of G index groups. The percentage of the category's total market

[11] We combined all companies with an index value of less than or equal to 5 in one portfolio. We did the same for all companies with index values higher or equal to 14 into one portfolio. This is similar to Johnson et al. (2009).

capitalization contained in each G index value was calculated for low illiquidity, high illiquidity and the entire sample. The absolute difference in a G index's percentage of total market capitalization is reported for each category, averaged over all G index values each year. Then we conducted the same procedure using the 6 E index portfolios.

Finally, we created mimicking portfolios similar to Johnson et al. (2009) and used these portfolios in specification regressions. For the purpose of mimicking G index clustering in the very liquid portfolio, only firms that are not in the very liquid portfolio were selected. Likewise, only "non-least liquid" firms were selected for mimicking G index clustering in the least liquid portfolio. Firms in the random trials were chosen in such a way that the total market capitalization of each G index value in the trial portfolio was proportional to the market capitalization of that G in the respective hedge, least liquid, or most liquid portfolio. Moreover, we reversed the procedure and selected only non-democratic and non-dictatorial companies to mimic democratic and dictatorial companies, respectively. The companies were chosen in such a way that the liquidity clustering of the democratic or dictatorial portfolio was preserved. We then ran 250 random trials to test the hypothesis of zero mean monthly abnormal returns at theoretical significance levels of 10%, 5%, and 1%, respectively. Long-run abnormal returns were measured by the regression intercept using the four-factor model. Once this was completed, we then conducted the same procedure using the E index instead of the G index. These procedures allowed us to detect any clustering of liquidity or governance in sorted portfolios and to conclude whether market liquidity or corporate governance dominates the other. In other words, we were able to see whether the model was well specified or not.

2.4. Results

In Table 2.1, we present the summary statistics of the data used in this study, and in Table 2.2 the simple coefficients of correlation between the key variables. Our dataset contains 1,427 companies and the median value for the governance index is 10. The entrenchment index is 3 and for illiquidity it is 0.009. The means are higher, with 9.79, 2.55 and 0.04, respectively, indicating positive skewness (see Table 2.1, Panel A). Panel B of Table 2.1 shows the development of these measures and excess returns, and Pastor-Stambaugh's liquidity factor (that we used in later analyses) over time. The G and E indices are stable over time with a dip towards democracy in later years. Amihud's Illiquidity decreases starkly to 0.18 from 0.71, highlighting the increasing liquidity in the U.S. stock market in the last several decades. Pastor-Stambaugh's liquidity factor displays no significant trend, although it is much more volatile in the second half of our sample time (see also Figure 2.1).

Table 2.2 displays the correlation among our three key variables. Besides the expected high correlation (0.74) between the two proxies for governance, all correlations are significantly different from each other with all p-values being less than 0.0001. The correlation between illiquidity and governance is negative, as expected. The correlation between the G index and illiquidity is -0.06 and the value for the E index and illiquidity is -0.02.

Table 2.3 reports the value of the intercepts obtained in four-factor model regressions for five portfolios of NYSE stocks sorted either by illiquidity or the G index, respectively. For the entrenchment index, only three portfolios were used due to the small range of this variable (0-6). Portfolios were formed annually from 1990 to 2006. Table 2.3 presents intercepts from the time series regression of the three-factor model as expressed in the following equation:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \gamma_i SMB_t + \delta_i HML_t + \theta_i PR1YR_t + \varepsilon_{i,t} \quad (2)$$

Panel A presents the results for illiquidity-sorted portfolios. The portfolio with the lowest illiquidity has an abnormal return of 0.11 and a t statistic of 1.47. The abnormal returns show that the least liquid portfolio commands a positive premium. The portfolio with the lowest liquidity has an abnormal return of 0.36 and a t statistic of 2.47. This corroborates the results of researchers like Amihud (2002) in showing that standard asset-pricing models cannot account for liquidity effects and that non-liquid stocks command a premium. The portfolios are sorted according to the G and E index in Panels B and C, respectively. In both cases, the most democratic portfolio has the highest alpha. The less democratic the portfolio, the more likely it is negative (although insignificantly so). Additionally, we conduct the GRS test to determine if the intercepts are jointly zero. We can reject that in all three cases at the 1% level (The F value is 16.53, 4.86 and 4.94, respectively). This indicates that all three factors add value to the regressions. They convey information beyond the three well-known Fama-French and momentum risk factors. The barely significant governance results also corroborate results of Core et al.

(2006), which showed that the G index was more successful in the 1990s and loses explanatory power when later years are added.

The first pass results are encouraging and provide the basis for conducting the joint test of importance for governance and liquidity characteristics. Table 2.4 reports the value of the intercepts obtained from the four-factor model regressions for 25 portfolios of NYSE stocks sorted by illiquidity and the governance index. The illiquidity increases across groups. The first panel shows the results when we sorted both groups independently. Panel B is sorted dependently, first based on illiquidity, then on the G index. Both panels show that the least liquid portfolio commands a positive premium. The same is true for the democratic portfolio. The GRS-tests confirms the overall significance of the intercepts with an F-value of 8.43 in Panel A, and 9.84 in Panel B (both significant at the 1% level). The results indicate that both governance and liquidity play an important role in asset pricing and that neither factor dominates the other. Table 2.5 presents the results of the intercepts obtained by 15 portfolios sorted based on illiquidity and the E index in the same manner as Table 2.4. The results again show positive abnormal returns for the democratic portfolio and the least liquid group. The GRS-tests confirm the overall significance of the intercepts with an F-value of 9.92 in Panel A, and 10.21 in Panel B (both significant at the 1% level). The findings show the importance of both factors, although it is still unclear how these factors interact with one another. Therefore, we examine with more intensity whether or not liquidity is clustered in governance portfolios.

Hence, we investigated the possible clustering of liquidity in each G index value. We sorted each G value from high to low average annual excess return. Then we calculated the relative market equity of the companies within each G portfolio and the relative market equity of the 30% stocks with the highest and lowest liquidity. Additionally, we presented the average illiquidity and Pastor-Stambaugh liquidity factor for each G portfolio. The excess returns ranged from 0.93% to 0.39% with no clear pattern of either increasing or decreasing democracy (see Table 2.6). The range was from 0.71% to 0.37% for the E index. Again, no clear pattern of either increasing or decreasing democracy was detectable. G index 9 had the highest market share, with 13.4% of overall market equity, while 14 only had 4%. G index 6 with 0.93% return had 8.3% market equity of the companies with the lowest liquidity, less than the 12.5% it had in the portfolio with the most liquid companies. Overall, though, no bias was visible. The average illiquidity and PS liquidity is not biased towards the high, nor low, G index. For the E index, both the low liquidity for the most dictatorial portfolio and the high liquidity for the most democratic portfolio are of special interest, as well as the low market share of the most dictatorial portfolio.

But Table 2.7 reveals that the annual difference in percentage between the market equity of low or high liquidity groups, and the average market equity of G index groups is highly significant along with the difference between liquidity groups. All p-values for the difference in the means test are less than 1%. This clearly indicates clustering in governance portfolios. For the high liquidity portfolio, the difference is fairly constant at above 1%, but in the late 90s it takes a slight dip. The low liquidity portfolio difference is much higher over time at just below 10% with lows in 1991 and 1995 but similarly stable. Therefore, the difference between low and high liquidity is usually around 8%, with slightly lower values in the first few years. Overall, this table shows that liquidity is not evenly distributed across governance portfolios over time. We conduct further analyses to determine whether or not this bias is systematic.

Therefore, we conducted specification regressions using mimicking portfolios. For the purpose of mimicking G index clustering in the least liquid portfolio, only firms that were not in the least liquid portfolio were selected. Likewise, only firms that were not in the “most liquid” portfolios were selected for mimicking G index clustering in the most liquid portfolio. Least liquid stocks have an average illiquidity of 0.28—much higher than the nearly zero for the most liquid (see Table 2.8). The mimicking portfolios have an average of 0.02 and 0.04, respectively, representing a much less significant difference than the original portfolios, according to the difference in the differences test. We then conducted the reverse procedure with the governance index, in which the democratic stocks had an average G value of 4.6. The mimicking stocks had an average G value of 10.1, whereas the dictatorial stocks and the stocks emulating the liquidity profile of dictatorial stocks had an average of 14.5 and 9.2, respectively. The results for the E index were almost unchanged for illiquidity. The most democratic portfolio was zero by construction, whereas the dictatorial stocks had an average E index value of 5.1. The mimicking portfolios were 2.74 and 2.41, respectively. Again the difference of mimicking portfolios is significantly less than the difference of the original portfolios, thus indicating the fact that the mimicking portfolios are neutral with respect to governance and liquidity, respectively. In the next step, we used the mimicking portfolios to conduct specification regressions to determine whether or not the four-factor model could explain the returns of these portfolios. In Panel A of Table 2.9, we find that the portfolio returns, which are long in mimicking most liquid stocks and short in mimicking least liquid stocks, are overly distributed on both tails. The most liquid and least liquid portfolio is overly rejected on the right tail. For the G index the hedge portfolio is again overly rejected on both tails, whereas the democratic and dictatorial stocks emulating portfolios are rejected overly on the right tails only. The results for the E index in Panels C and D are very similar to the G index results. In sum, this leads to the conclusion that both factors are contributing significantly to asset-pricing models and neither dominates the other, although they are influenced by each other. Overall, the tests present clear evidence in support of the alternative hypotheses that liquidity and governance still matter.

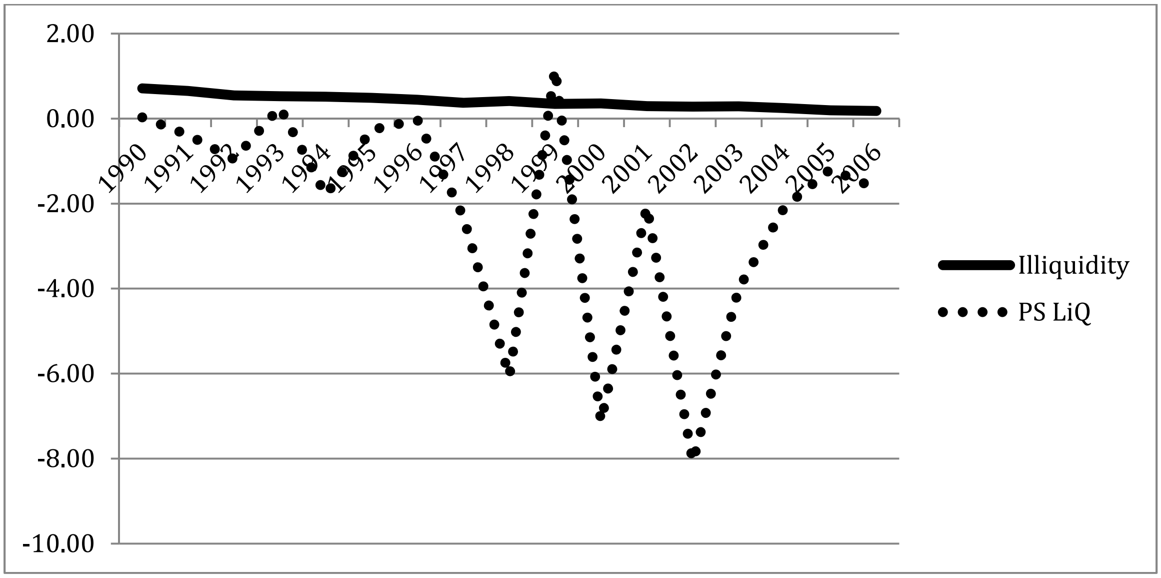
2.5. Conclusion

Studies by Core, Guay and Rusticus (2006) and Ben-Rephael, Kadan and Wohl (2010) found that governance and liquidity premia have been dwindling in the last few years. Governance characteristics are potentially a proxy for information asymmetry that may be better captured by the market liquidity of a company’s shares. We performed several standard asset-pricing tests to show the joint effect of governance and liquidity on the asset-pricing paradigm. We confirmed in several time-series analyses of portfolios (which are sorted according to liquidity and governance) that they are priced factors. This corroborates the results of Amihud (2002) and Gompers, Ishii and Metrick (2003).

Further analysis revealed that liquidity is clustered in the governance-sorted portfolio, but specification regressions of portfolios mimicking liquidity or governance clustering in the extreme portfolios show that this clustering is unsystematic.

Figure 2.1: Time Series of Key Variables

Figure 2.1a shows the annual mean of governance index and entrenchment index. Figure 2.1b shows the annual mean of Amihud's illiquidity (times100) and Pastor-Stambaugh's liquidity factor.



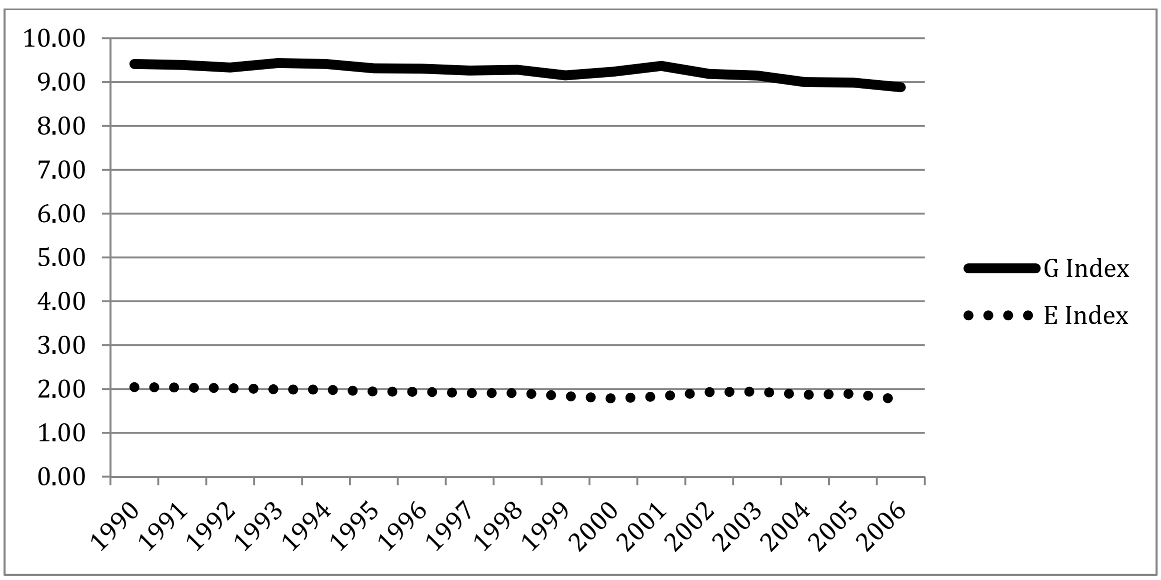


Table 2.1: Summary Statistics

This table reports the summary statistics. Mean, median and standard deviation of the variables used in the later sections are shown in panel A. Illiquidity is defined as the daily average absolute return over trading volume for each month. The governance index is taken from Metrick's website and the entrenchment index from Bebchuk's website. Panel B shows the annual averages of the five key variables (Illiquidity: times 100).

Panel A:

	G Index	E Index	Illiquidity
25% quartile	8	2	0.003
Median value	10	3	0.009
75% quartile	12	4	0.032
Mean value	9.79	2.55	0.04
St. Dev.	2.66	1.30	0.10

Panel B:

Year	Excess Return	G Index	E Index	Illiquidity	PS LiQ
1990	-0.05%	9.41	2.04	0.71	0.03
1991	1.81%	9.39	2.03	0.65	-0.38
1992	0.25%	9.33	2.02	0.55	-0.96
1993	0.47%	9.43	1.99	0.53	0.27
1994	0.00%	9.41	1.99	0.52	-1.80
1995	2.07%	9.31	1.95	0.49	-0.26
1996	1.19%	9.31	1.94	0.45	-0.03
1997	1.88%	9.27	1.91	0.37	-2.31
1998	1.65%	9.28	1.91	0.42	-6.07
1999	0.56%	9.15	1.84	0.35	1.17
2000	-0.41%	9.24	1.79	0.36	-7.13
2001	-0.87%	9.37	1.83	0.29	-2.07
2002	-1.70%	9.19	1.93	0.28	-8.08
2003	1.88%	9.15	1.94	0.29	-4.00
2004	0.94%	9.00	1.87	0.25	-2.08
2005	0.41%	8.99	1.89	0.20	-1.19
2006	0.84%	8.88	1.75	0.18	-1.64

Table 2.2: Simple Correlations

This table reports time series averages of annual cross-sectional correlation of variables in asset pricing tests for all NYSE stocks over the period 1990-2006. Illiquidity is defined as the daily average absolute return over trading volume for each year. The governance index is taken from Metrick's website and the entrenchment index from Bebchuk's website. All correlations have p values that are less than 0.0001.

	G Index	E Index	Illiquidity
G Index	1.00	0.72	-0.06
E Index	0.72	1.00	-0.02
Illiquidity	-0.06	-0.02	1.00

Table 2.3: Single Sorted Time Series Regressions

This table reports the value of the intercepts obtained in three-factor model for five portfolios of NYSE stocks sorted by Amihud's illiquidity. For the entrenchment index only three portfolios were used, for the governance index five. Illiquidity is defined as the daily average absolute return over trading volume for each year. Portfolios are formed yearly for the period 1990-2005. Panel A presents intercepts from the time series regression of three-factor model as in the following equation $r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \gamma_i HML_t + \delta_i SMB_t + \tau_i UMD_t + \varepsilon_{i,t}$, where $r_{i,t} - r_{f,t}$ is the excess return on portfolio i in year t, and $(r_{m,t} - r_{f,t}), HML_t,\ SMB_t$, are the Fama and French (1993) factors related to market premium, the book-to-market ratio and the firm size in year t and $UMD_t$is Carhart's momentum factor. The portfolios are sorted from lowest to highest levels of illiquidity. In Panel B they are sorted from most democratic to dictatorial according to the G index. Panel C presents the intercepts from sorting from most democratic to dictatorial according to the E index. The bottom of each panel presents the Gibbons, Ross, Shanken (1989) test of the hypothesis that the intercepts jointly equal zero for the four-factor model. Intercepts are reported in absolute terms (t-statistics are in italics).

Panel A: Sorted by Amihud's illiquidity

1	2	3	4	5
0.11	0.06	0.02	0.20	0.36
1.47	*0.47*	*0.11*	*1.25*	*2.46*

F-value for Gibbons, Ross, Shanken, test that the intercepts jointly equal to zero is 3.75*** (significant at 1 percent level) SR(α): 0.33

Panel B: Sorted by governance index

1	2	3	4	5
0.30	0.25	0.01	-0.03	0.02
2.15	*2.16*	*0.05*	*-0.27*	*0.12*

F-value for Gibbons, Ross, Shanken, test that the intercepts jointly equal to zero is 6.23*** (significant at 1 percent level) SR(α): 0.42

Panel C: Sorted by entrenchment index

1	2	3
0.12	0.12	-0.05
1.37	*1.39*	*-0.40*

F-value for Gibbons, Ross, Shanken, test that the intercepts jointly equal to zero is 13.37*** (significant at 1 percent level) SR(α): 0.48

Table 2.4: Double Sorted Time Series Regressions – G Index

This table reports the value of the intercepts obtained in three-factor model for 25 portfolios of NYSE stocks sorted by illiquidity and governance index. Illiquidity is defined as the daily average absolute return over trading volume for each year. Portfolios are formed yearly for the period 1990-2006. Panel A presents intercepts from the time series regression of three-factor model as in the following equation $r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \gamma_i HML_t + \delta_i SMB_t + \varepsilon_{i,t}$, where $r_{i,t} - r_{f,t}$ is the excess return on portfolio i in year t, and $(r_{m,t} - r_{f,t}), HML_t,\ SMB_t$, are the Fama and French (1993) factors related to market premium, the book-to-market ratio and the firm size in year t. In Panel A, the portfolios are sorted independently. Portfolio 1,1 has the least illiquidity and is democratic. Panel B presents the portfolios sorted dependently. The bottom of each panel presents the Gibbons, Ross, Shanken (1989) test of the hypothesis that the intercepts jointly equal zero for the four-factor model. Intercepts are reported in absolute terms (t-statistics are in italics).

Panel A: Sorted independently

		Illiquidity groups				
		1	2	3	4	5
G index	1	0.34	0.07	0.18	0.12	0.27
		2.17	*0.28*	*0.68*	*0.53*	*1.21*
groups	2	0.27	0.19	0.16	0.31	0.80
		1.93	*0.91*	*0.79*	*1.49*	*3.80*
	3	0.02	0.00	-0.01	0.26	0.18
		0.15	*-0.02*	*-0.06*	*1.36*	*1.04*
	4	-0.05	0.03	0.06	0.14	0.48
		-0.34	*0.20*	*0.32*	*0.75*	*2.19*
	5	0.07	-0.10	-0.26	0.00	0.05
		0.37	*-0.58*	*-1.26*	*-0.02*	*0.24*

F-value for Gibbons, Ross, Shanken (1989) test that the intercepts jointly equal to zero is 8.43*** (significant at 1 percent level) SR(α): 1.16

Panel B: Sorted dependently

		Illiquidity groups				
		1	2	3	4	5
G index	1	0.32	0.16	0.17	0.16	0.36
		2.99	*0.83*	*0.79*	*0.78*	*1.65*
groups	2	0.00	-0.12	0.22	0.39	0.63
		-0.02	*-0.63*	*1.17*	*1.93*	*2.88*
	3	0.08	-0.05	-0.20	0.24	0.43
		0.47	*-0.27*	*-1.03*	*1.12*	*2.14*
	4	0.09	0.22	0.00	0.19	0.29
		0.51	*1.27*	*0.00*	*0.97*	*1.27*
	5	-0.04	-0.10	-0.23	-0.02	0.24
		-0.27	*-0.58*	*-1.11*	*-0.09*	*1.20*

F-value for Gibbons, Ross, Shanken (1989) test that the intercepts jointly equal to zero is 9.84*** (significant at 1 percent level) SR(α): 1.26

Table 2.5: Double Sorted Time Series Regressions – E Index

This table reports the value of the intercepts obtained in three-factor model for 15 portfolios of NYSE stocks sorted by illiquidity and entrenchment index. Portfolios are formed yearly for the period 1990-2006. Panel A presents intercepts from the time series regression of three-factor model as in the following equation $r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \gamma_i HML_t + \delta_i SMB_t + \varepsilon_{i,t}$, where $r_{i,t} - r_{f,t}$ is the excess return on portfolio i in year t, a and $(r_{m,t} - r_{f,t}), HML_t,\ SMB_t$, are the Fama and French (1993) factors related to market premium, the book-to-market ratio and the firm size in year t. The portfolios are sorted independently and portfolio 1,1 has the lowest illiquidity and is the most democratic. Panel B presents the portfolios sorted dependently. The bottom of each panel presents the Gibbons, Ross, Shanken (1989) test of the hypothesis that the intercepts jointly equal zero for the four-factor model. Intercepts are reported in absolute terms (t-statistics are in italics).

Panel A: Sorted independently

		Illiquidity groups				
		1	2	3	4	5
E Index	1	0.14	0.06	0.24	0.32	0.22
		1.44	*0.33*	*1.21*	*1.55*	*1.13*
groups	2	0.15	0.04	-0.04	0.24	0.52
		1.54	*0.28*	*-0.25*	*1.35*	*3.36*
	3	-0.12	-0.04	0.00	0.00	0.17
		-0.68	*-0.23*	*0.00*	*0.02*	*0.88*

F-value for Gibbons, Ross, Shanken (1989) test that the intercepts jointly equal to zero is 9.92*** (significant at 1 percent level) SR(α): 0.96

Panel B: Sorted dependently

		Illiquidity groups				
		1	2	3	4	5
E Index	1	0.14	0.05	0.05	0.37	0.23
		1.44	*0.35*	*0.28*	*1.98*	*1.21*
groups	2	0.19	0.04	0.01	0.17	0.53
		1.81	*0.25*	*0.05*	*0.97*	*3.12*
	3	0.04	-0.04	0.00	0.00	0.27
		0.29	*-0.23*	*0.00*	*0.02*	*1.45*

F-value for Gibbons, Ross, Shanken (1989) test that the intercepts jointly equal to zero is 10.21*** (significant at 1 percent level) SR(α): 0.97

Table 2.6 – G and E Index Clustering

This table reports the average excess return of each G and E index value sorted from high to low from 1990 to 2006. %ME shows the percentage market equity of the respective G or E index value to the overall market equity. Low LIQ (High LIQ) reports the percentage weight (in terms of market equity) of the respective G or E index value in the worst (best) liquidity group. Finally, the average illiquidity and the average of Pastor-Stambaugh's liquidity factor are reported.

G Index	Excess Return	PercentME	Low LIQ	High LIQ	Illiquidity	PS Liq
6	0.93%	11.6%	8.3%	12.5%	0.23	-2.50
10	0.67%	10.5%	13.1%	10.2%	0.43	-2.58
8	0.61%	10.8%	11.9%	10.7%	0.34	-2.64
7	0.59%	11.4%	10.0%	11.9%	0.29	-2.63
14	0.56%	4.0%	5.7%	3.3%	0.61	-2.28
13	0.55%	9.0%	7.2%	9.1%	0.32	-2.78
5	0.52%	7.7%	9.7%	8.0%	0.44	-2.46
11	0.49%	12.4%	12.0%	12.0%	0.34	-2.55
9	0.44%	13.4%	13.6%	13.4%	0.34	-2.73
12	0.39%	9.2%	8.5%	8.9%	0.34	-2.50

E Index	Excess Return	PercentME	LowLIQ	HighLIQ	Illiquidity	PS Liq
2	0.71%	25.6%	23.6%	26.1%	0.32	-2.58
5	0.68%	2.1%	4.7%	1.6%	0.73	-2.17
4	0.65%	11.6%	19.7%	9.8%	0.54	-2.58
0	0.63%	22.1%	8.3%	24.7%	0.17	-2.58
3	0.49%	21.0%	27.1%	19.6%	0.44	-2.60
1	0.37%	17.6%	16.8%	18.2%	0.33	-2.65

Table 2.7 – Annual G and E Index Clustering

This table reports the annual difference in percent between the market equity of liquidity groups and average market equity of G index groups. The percentage of the category's total market capitalization contained in each G index value is calculated for low illiquidity, high illiquidity and the entire sample. The absolute difference in a G's percentage of total market capitalization is reported for each category, averaged over all G index values each year. Panel B shows the same for the E index. All p-values for Panel A are less than 0.01. In Panel B, all p-values are less than 0.01 except the ones with an asterisk, which are less than 0.05.

Panel A: G Index

Year	High Liquidity	Low Liquidity	Low - High Liquidity
1990	1.79%	9.65%	7.86%
1991	1.48%	9.50%	8.02%
1992	1.70%	9.68%	7.98%
1993	1.78%	9.64%	7.85%
1994	1.89%	9.69%	7.80%
1995	1.51%	9.48%	7.97%
1996	1.52%	9.60%	8.09%
1997	1.36%	9.55%	8.19%
1998	1.16%	9.58%	8.42%
1999	0.94%	9.72%	8.77%
2000	1.06%	9.82%	8.76%
2001	1.29%	9.88%	8.59%
2002	1.45%	9.96%	8.51%
2003	1.18%	9.60%	8.41%
2004	1.34%	9.63%	8.29%
2005	1.47%	9.65%	8.19%
2006	1.47%	9.60%	8.13%

Panel B: E Index

Year	High Liquidity	Low Liquidity	Low - High Liquidity
1990	2.98%	16.08%	13.10%*
1991	2.47%	15.84%	13.37%
1992	2.84%	16.14%	13.29%
1993	2.97%	16.06%	13.09%
1994	3.15%	16.14%	12.99%
1995	2.52%	15.80%	13.29%
1996	2.53%	16.01%	13.48%
1997	2.27%	15.91%	13.6%*
1998	1.94%	15.97%	14.03%
1999	1.57%*	16.20%	14.62%*
2000	1.77%	16.37%	14.59%*
2001	2.14%	16.47%	14.32%
2002	2.42%*	16.61%	14.19%
2003	1.97%*	15.99%	14.02%
2004	2.24%*	16.06%	13.82%
2005	2.44%*	16.09%	13.65%
2006	2.45%*	16.00%	13.55%*

Table 2.8 – Mimicking Portfolios

This table reports in panel A the annual average illiquidity values of very liquid and very illiquid portfolios across G index values as well as portfolios across the same G index values mimicking these portfolios. For the purpose of mimicking G index clustering in the least liquid portfolio, only firms that are not in the least liquid portfolio are selected. Likewise, only "non-most liquid" portfolios are selected for mimicking G index clustering in the most liquid portfolio. Firms in the random trials are chosen such that the total market capitalization of each G index values in the trial portfolio is proportional to the market capitalization of that G in the respective hedge, least liquid, or most liquid portfolio. Panel B reports the annual average G index values of democratic and dictatorial portfolios across liquidity values as well as portfolios mimicking these portfolios. Panels C and D repeat the above two procedures for the E index. p-values for the difference test between mimicking portfolios and the difference in differences test between extreme and mimicking portfolios are less than 0.0001 for all four panels.

Panel A:	Average Illiquidity
Least liquid stocks	0.28
Mimi least liquid stocks	0.02
Most liquid stocks	0.00
Mimi most liquid stocks	0.04
Panel B:	Average G Index
Democratic stocks	4.6
Mimic democratic stocks	10.1
Dictatorial stocks	14.5
Mimic dictatorial stocks	9.2
Panel C:	Average Illiquidity
Least liquid stocks	0.28
Mimi least liquid stocks	0.02
Most liquid stocks	0.00
Mimi most liquid stocks	0.05
Panel D:	Average E Index
Democratic stocks	0.00
Mimic democratic stocks	2.74
Dictatorial stocks	5.10
Mimic dictatorial stocks	2.41

Table 2.9 – Specification Regressions on Mimicking Portfolios

The numbers in each row represent the percentage of the 250 random trials that reject the null hypothesis of zero mean monthly abnormal return at theoretical significance levels of 10%, 5%, and 1%, in favor of the alternative hypothesis of the intercept being significantly negative on the left tail, or significantly positive on the right tail. Long-run abnormal returns are measured by the regression intercept using the four-factor model. Excess returns are regressed on RMRF, SMB, HML, and UMD. In Panel A, portfolio returns which are long in mimicking most liquid stocks and short in mimicking least liquid stocks are used, then mimicking most (least) liquid stocks are employed. In Panel B, portfolio returns which are long in mimicking "democratic" stocks and short in mimicking "dictatorial" stocks are used, then mimicking "democratic" ("dictatorial") stocks are employed. Panels C and D repeat the above two procedures for the E index. *, **, ***, significantly different from the theoretical rejection rate at the 10%, 5%, and 1% statistical levels, respectively.

Panel A:

	Theoretical Rejection Rates					
	10%		5%		1%	
	Left Tail	Right Tail	Left Tail	Right Tail	Left Tail	Right Tail
	5%	95%	2.50%	97.50%	0.50%	99.50%
Hedge portfolio	30.8%***	28.4%***	26.8%***	26.8%***	23.2%***	21.6%***
Mimic least liquid stocks	1.60%	14%***	0.40%	7.6%***	0.40%	2%***
Mimic most liquid stocks	0.00%	49.6%***	0.00%	36.8%***	0.00%	16.4%***

Panel B:

	Theoretical Rejection Rates					
	10%		5%		1%	
	Left Tail	Right Tail	Left Tail	Right Tail	Left Tail	Right Tail
	5%	95%	2.50%	97.50%	0.50%	99.50%
Hedge portfolio	60.4%***	32.4%***	60%***	31.2%***	56.8%***	30.4%***
Mimic democratic stocks	0.00%	100%***	0.00%	100%***	0.00%	100%***
Mimic dictatorial stocks	0.00%	16%***	0.00%	10.8%***	0.00%	4%***

Panel C:

	Theoretical Rejection Rates					
	10%		5%		1%	
	Left Tail	Right Tail	Left Tail	Right Tail	Left Tail	Right Tail
	5%	95%	2.50%	97.50%	0.50%	99.50%
Hedge portfolio	38%***	26%***	33.2%***	23.2%***	28.4%***	20.4%***
Mimic least liquid stocks	2.40%	11.2%***	0.80%	6.4%***	0.00%	2%***
Mimic most liquid stocks	0.00%	37.2%***	0.00%	25.6%***	0.00%	11.6%***

Panel D:

	Theoretical Rejection Rates					
	10%		5%		1%	
	Left Tail	Right Tail	Left Tail	Right Tail	Left Tail	Right Tail
	5%	95%	2.50%	97.50%	0.50%	99.50%
Hedge portfolio	60%***	33.6%***	58.4%***	33.6%***	56.4%***	31.6%***
Mimic democratic stocks	0.00%	100%***	0.00%	100%***	0.00%	100%***
Mimic dictatorial stocks	0.00%	21.2%***	0.00%	12.8%***	0.00%	3.2%***

CHAPTER 3: GOVERNANCE AND ADVERSE SELECTION IN ASSET PRICING

3.1. Introduction

Information is the most valuable product made anywhere in the world. It is the key to interact sensibly and successfully with our environment. To make smart choices, we need to know as much about the consequences of our actions as possible. The more information we have, the better we are able to compete for scarce resources and outperform our competitors. Investors face the same challenges in the financial markets. The better a company is able to predict future pay-offs, the better her investment choices will be and the higher her returns for a given level of risk. But investors are aware that they do not have all necessary information available at any given point in time. In fact, lack of information poses a risk for investors (see Barry and Brown (1986)). Hence, investors demand a premium for that disadvantage. Easley et al. (2002) developed a theoretical model in which private information affects the price evolution and subsequently the risk of holding a stock. Moreover, Gompers, Ishii and Metrick (2003) constructed a governance index and found significant abnormal returns holding a portfolio long in well-governed stocks, and short in poorly governed stocks. Both are linked to the disclosure policies of companies. Healy and Palepu (2001) provided a framework for these policies: good governance is related to better disclosure policies and less information asymmetry. Sufi (2007) found that financial disclosure could help reduce information asymmetry. We contribute to the literature by looking at the interaction of these two factors: corporate governance and asymmetric information between investors. As a proxy of the former, we used the governance index (G index) by Gompers, Ishii and

Metrick (2003), and the entrenchment index (E index) created by Bebchuk, Cohen and Ferrell (2009). We also adopted the methodology of Huang and Stoll (1997) to obtain our adverse selection variable, which we used as a proxy for asymmetric information between investors. Our results confirm the importance of each factor separately and hence corroborate the importance of governance in asset pricing despite recent studies like Core, Guay and Rusticus (2006), who found a dwindling governance premium. Furthermore, we ascertained the importance of microstructure measures in asset pricing by employing Huang and Stoll's (1997) method to extract an adverse selection variable and finding evidence for its explanatory power in four-factor regressions.

We first ran the Fama-French (1993) three-factors, plus the Carhart (1997) momentum factor on sorted portfolios to establish the importance of each variable separately. Next, we used portfolios that were double-sorted on governance and adverse selection in four-factor regressions to jointly analyze these two variables. Our results showed that both factors are significant and do not dominate one another. Then we examined the clustering of adverse selection in governance portfolios and performed this analysis for each year. The results indicated that clustering is present but not systematic. To confirm this, we created mimicking portfolios in the spirit of Johnson, Moorman and Sorescu (2009) in the following way: We took only companies that were not in the "most adverse selection" group or in the "least adverse selection" group, but we ensured that the relative weights of these companies in the various governance groups were preserved. Hence, our mimicking portfolios were adverse-selection-neutral. Additionally, we conversed the experiment for governance portfolios and chose only "non-democratic" and "non-dictatorial" companies with the same adverse selection profile so the portfolios were governance-neutral. Both sets of mimicking portfolios were then used in 250 specification regressions to determine the influence of either adverse selection or governance clustering. The results confirmed our previous findings that clustering is present but unsystematic. Therefore, we can say that neither factor dominates the other and that our empirical analysis finds ample evidence in support of our alternative hypotheses. Governance and adverse selection are important factors in asset pricing; they are measuring two different dimensions of information risk that are essential to investors' choices.

Section 3.2 gives a brief overview of the relevant literature; Section 3.3 explains the data and methodology used in this study. Section 3.4 presents the results and Section 3.5 concludes this paper.

3.2. Literature Review and Development of Hypothesis

Corporate governance shapes the rules between investors and managers. Before the 1980s, these rules were stable, but the internal control mechanism failed in the 1970s and 1980s, according to Jensen (1993); since then, however, many companies have adopted new rules that vary significantly across firms to address these problems. Firms adopted anti-takeover amendments, although for different reasons. Some firms try to deter potential bidders because they believe standing alone provides a higher return for investors in the long run, while others just want to wield more bargaining power in the takeover process. Managers are, on the other hand, willing to use this issue to pursue their own goals. By and large the market seems not to be deterred by those laws. Comment and Schwert (1994) found evidence that poison pills and anti-takeover laws did not systematically cause a decline in takeovers, but buyers had to pay a premium if such measures were in place. Cremers and Nair (2005) found a range of mechanisms on the firm level connected to governance. These mechanisms can be divided into two categories: external and internal governance mechanisms. "External" governance means primarily the presence of anti-takeover provisions, whereas "internal" refers to block holders. Shareholders with a significant amount of shares have an incentive to monitor the management more closely and facilitate takeovers, according to Shleifer and Vishny (1986). Gompers, Ishii and Metrick (2003) constructed an index from Investor Responsibility Research Center (IRRC) publications and called it the "Governance index" (G index). They chose 28 corporate governance provisions, 24 of which were distinctive measures that characterized the interaction of management and investors. These measures were grouped into 5 categories: manager protections, tactics for delaying hostile bidders, state laws, voting rights, and other takeover defenses. A hedge portfolio investing in stocks with low G index values (i.e. good governance) and shortening stocks with high G index values (i.e. bad governance) earns an 8.5% annual rate of return. Thereafter, Bebchuk, Cohen and Ferrell (2009) suggested that only six provisions out of the 24 above—four constitutional and two takeover-readiness provisions—are driving the results of Gompers et al. They called their index "Entrenchment index" (E index) and found that higher index values are significantly correlated with reduced company values, as measured by Tobin's q.

Our second string of interesting literature stems from research on adverse selection. The first strategic trading model was developed by Kyle (1985). In his model, insiders who have superior information about an underlying asset use their information advantage strategically. Glosten and Milgrom (1985) modeled the bid-ask spread assuming that transaction costs and profits by the specialist are zero. Some traders possess superior information than the specialist. In their model, adverse selection by itself can account for the bid-ask spread, which depends on many parameters, including the exogenous arrival pattern of insiders and outsiders, the elasticity of supply and demand among outsiders, and the quality of insider information. Easley et al. (2002) developed a theoretical model in which private information affects the price evolution and subsequently the risk holding a stock. They used a sequential market microstructure model to come up with a measure of the probability of information-based trading for a single stock. Using Fama and French (1993) style regressions, the significance of the so-called PIN measure is confirmed for NYSE stocks. The authors also looked into the possibility of capturing another variable such as volume, turnover or spread with their PIN measure. Thereafter, Duarte and Young (2009) investigated the PIN measure and its effects on asset prices by separating it into an asymmetric and a liquidity component. First, the authors extended the previous models by allowing for symmetric order flow shocks to account for positive correlations between buy and sell order flow. This way they got new measures, called adjusted PIN (for asymmetric shocks), and the probability of symmetric order flow shocks, or PSOS (for symmetric or liquidity shocks). They then empirically chose the version of their model in which the parameters better fit the data, and showed that PSOS is related to liquidity measures (such as Amihud's). Finally, they showed that in regressions including PIN and liquidity measures, only the latter are significant. Bharath et al. (2009) used a microstructure measure, the information asymmetry index, to establish that adverse selection affects capital structure decisions.

Governance and information asymmetry are linked through the disclosure policies of companies, for which Healy and Palepu (2001) provided a framework. They hypothesized that information asymmetry drives the need for financial reporting and disclosure. Also, Armstrong, Guay and Weber (2010) emphasized in their survey paper the effects of information asymmetry on governance. They viewed the company as consisting and existing in a web of contracts. Some of these contracts are explicit but others are only implicit. These implicit contracts, nevertheless, play an important role in the governance of a company. Empirically, Sufi (2007), for example, found supportive evidence in the syndicated loan market that efficient financial reporting mitigates information asymmetry problems between borrowers and lenders. Otherwise, lenders have to increase their monitoring and form a more concentrated syndicate.

According to Van Ness, Van Ness and Warr (2001), the most appropriate adverse selection measure for our purposes is the one developed by Huang and Stoll (1997)[12], as it shows low correlation with other variables. To construct our measure for adverse selection, we borrowed their methodology. They constructed a model that allows distinguishing the components of the bid-ask spreads. Adverse selection, inventory holding costs and order processing costs are separated from each other in a basic trade indicator model. Then the model is modified to distinguish between small, medium and large trades to show how the composition of the spread changes. The authors estimated their model with adjusting for clustering of trades because large trades typically are split

[12] The other models considered: Madhavan, Richardson, and Roomans (1997); Lin, Sanger, and Booth (1995); George, Kaul, and Nimalendran (1991); Glosten and Harris (1988).

up and make inferences from the covariance difficult. All trades at the same price and in the absence of quote changes are lumped into a single order.

Our first null hypothesis states that liquidity is not priced, while our second null hypothesis states that governance is not a priced factor anymore. Lastly, we hypothesize that liquidity dominates governance. Alternatively, both factors—adverse selection and governance—are still priced and neither factor dominates the other.

3.3 Data and Methodology

Our sample data includes all CRSP companies except for utility and financial companies between 1993 and 2006. We excluded these due to their highly regulated legal environment. Next, we kept firm-months when the trading volume was above 10,000, the share price was above \$5, and shares outstanding exceeded \$5,000,000. Then, we merged these companies with the governance index data obtained from Metrick's homepage and with the entrenchment index data compiled by Bebchuk, Cohen and Ferrell (2009). This was obtained from Bebchuk's homepage. Following common practice, we retained the value of the indices until a new index value became available. Since the indices were constrained by their availability, our dataset ended in 2006. On the other hand, we were only able to calculate a meaningful adverse selection variable from 1993 and thereafter. The final dataset contains 1,961 companies—from 762 companies in 1993 to 989 in 2006, with a low of 751 in 1994 and a high of 1,143 in 2004.

The first step in our analysis was to calculate abnormal returns of portfolios sorted on both the G and E index, as well as adverse selection to see whether the standard four-factor model (Fama-French three-factors and the Carhart (1997) momentum factor) is able to explain these returns or not. Additionally, we calculated the GRS test statistic proposed by Gibbons, Ross and Shanken (1989) to determine if intercepts jointly equal zero for the four-factor model. Therefore, we sorted the sample companies into five (three) groups or portfolios based on their adverse selection, or G (E) index separately. The number of portfolios depended on the range of the variable. Then the excess returns of the companies were regressed on the four factors as follows:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i\left(r_{m,t} - r_{f,t}\right) + \gamma_i SMB_t + \delta_i HML_t + \theta_i PR1YR_t + \varepsilon_{i,t} \quad (1)$$

where $\mathrm{r}_{\mathrm{i,t}} - \mathrm{r}_{\mathrm{f,t}}$ is the excess return of portfolio i in year t, and $\left(r_{m,t} - r_{f,t}\right), SMB_t$, $HML_t$are the Fama and French (1993) factors related to market premium, firm size, and the book-to-market ratio in year t. $PR1YR_t$ is Carhart's momentum factor. In time-series regressions, a well-specified asset-pricing model that is not overly affected by multicollinearity or endogeneity creates intercepts that are not different from zero, according to Merton (1973) and Fama and French (1993).

In our next step, we double sorted the data into several portfolios according to adverse selection and governance characteristics. We either sorted the data independently or on an adverse selection dependent. Then we ran time series analyses of portfolio returns, controlling for the four factors as described above. Afterwards, we examined the concentration of adverse selection in the 10 G index portfolios[13], sorted in descending

[13] We combined all companies with an index value of less than or equal to 5 in one portfolio. We did the same for all companies with index values higher or equal to 14 into one portfolio, similar as Johnson et al. (2009).

order by average excess returns. The purpose was to detect any clustering of adverse selection in the indices (it is possible that adverse selection might be simply driven by governance characteristics). Additionally, we investigated clustering annually by calculating the difference between the market equity of adverse selection groups and the average market equity of G index or E index groups in percent (%) for each year.

Lastly, we adopted a methodology similar to Johnson et al. (2009), calculating mimicking portfolios. We then ran specification regressions with these mimicking portfolios, which are constructed as follows: to mimic the highest adverse selection portfolio, all companies that are not in this portfolio but have the same G index profile were selected. Similarly, only "non-least adverse selection" portfolios were selected for mimicking G index clustering in the least adverse selection portfolio. Companies were then chosen in random trials in such a way that the total market capitalization of each G index value in the "original" portfolio was the same in the respective mimicking portfolio. Additionally, we performed the same procedure with the E index instead of the G index. Then we performed the converse experiment by selecting portfolios to find adverse selection clustering among G index groups. For that, we picked companies so that the total market capitalization of the "original" democratic or dictatorial portfolio across 10 adverse selection portfolios was unchanged in portfolios mimicking the democratic or dictatorial portfolio. Using these portfolios, we ran 250 random trials to test the hypothesis of zero mean monthly abnormal returns at theoretical significance levels of 10%, 5%, and 1%, respectively. Long-run abnormal returns were measured by the regression intercept using the four-factor model. These procedures allowed us to detect any clustering of adverse selection or governance in sorted portfolios and to conclude whether either factor dominates the other. In other words, we were able to see if the model is well specified.

3.4 Results

First, we present the summary statistics in Table 3.1 and the Pearson correlations in Table 3.2. Adverse selection (AS) is high during the 90s and peaks at 0.46 in 2000, then declines quickly (see also Figure 3.1) to 0.13. Both G and E indices decline moderately over time, indicating increasing shareholder rights. The G index falls to 8.75 from 9.41 and the E index to 1.66 from 1.97. Both indices are significantly negatively correlated with adverse selection with -0.03 and -0.08, respectively.

Next, we look into the abnormal returns of portfolios sorted by our three key variables and find that the four-factor model is not able to explain such portfolios. Furthermore, a pattern is discernable in which the high adverse selection ($t = 3.2$) and most democratic portfolios ($t = 2.21$ for G index and $t = 2.96$ for E index) command a significant positive premium. Then the premium vanishes as adverse selection diminishes and the portfolios are less democratic (see Table 3.3). The GRS test for the joint significance of the intercepts is also significant at the 1% level. Then we investigate the joint effect of adverse selection and corporate governance by sorting the data accordingly. First, we sort the data on adverse selection, and then (either independently or dependently) on the adverse selection portfolios based on either the G or E index. The results again show a pattern. Across adverse selection groups, the abnormal returns increase in both tables in Table 3.4. Column 5, with the highest adverse selection values, is significantly positive and the GRS tests are twice as significant at the 1% level. The G index shows a less pronounced pattern. Only the 1-1 portfolios (meaning the most democratic and least adverse selected) in both tables highlight the importance of corporate governance. In Table 3.5, this pattern of increasing abnormal returns across adverse selection portfolios is again visible, with Column 5 showing significantly positive alphas. The E index shows a less salient result for the 1-1 portfolio. Once again, the GRS tests are significant at the 1% level. In general, the results are similar for all four tables (of Tables 3.4 and 3.5) and support the notion that both factors are important in asset pricing despite the somewhat weak results for the G and E index. To further examine the relation of governance and adverse selection, we reexamine their interaction.

We look into the G and E index clustering of adverse selection to see if the results for adverse selection are driven by corporate governance characteristics. Table 3.6 presents the average adverse selection for each G and E index value sorted by descending excess returns. Additionally, the relative market equity and the relative market equity of high and low adverse selection portfolios are shown. Average adverse selection is fairly evenly distributed across G and E index values. As expected, adverse selection is slightly falling along decreasing excess returns to 0.25 from 0.30, and to 0.25 from 0.33 for the G and E index, respectively. In addition, the most democratic E index value falls from dictatorial to democratic with decreasing excess returns, which is unusual given the "democracy premium." Relative market equity is low in G index value 14 (3.38%) and high in 9 (14.81%). The high and low adverse selection portfolios follow a similar pattern and no bias is apparent, as one group is alternately greater or less than the other. In the E index, however, high adverse selection market equity is only greater than low adverse selection market equity in the most democratic portfolio. Here, adverse selection and the E index appear more intertwined.

Moving onto the annual clustering, we calculate the average market equity across G and E index values and subtract it from the market equity of the low adverse selection portfolio, then from the high adverse selection portfolio (see Table 3.7). Finally, we calculate the difference between the market equities of low and high adverse selection portfolios across corporate governance groups. Most of the differences are significant at the 1% level. All but one are significant—the low minus high adverse selection difference, which is generally less significant with the E index. Overall, this indicates that adverse selection is not evenly distributed across governance characteristics and could lead to the conclusion that governance dominates adverse selection. Therefore, we conduct an additional analysis following Johnson, Moorman and Sorescu (2006), to see whether the clustering in governance portfolios is random or influences the premium found for adverse selection earlier in our study.

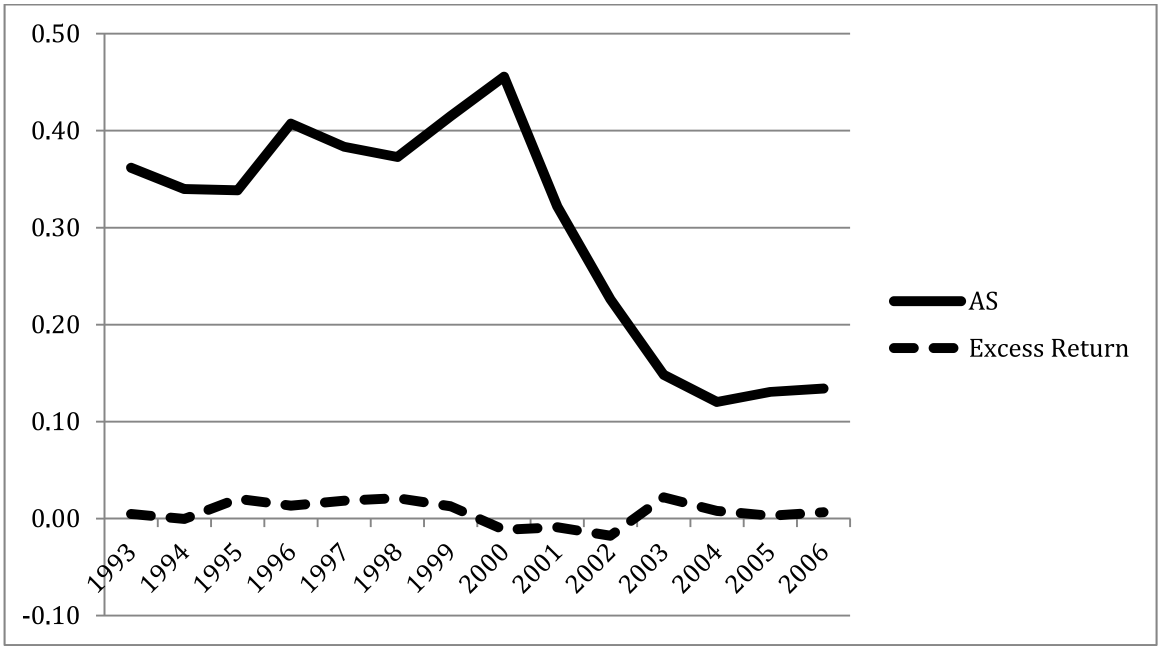
Hence, we intend to separate the adverse selection effect and the governance clustering effect from each other by emulating the governance clustering of adverse selection portfolios. We then form portfolios with stocks that are not in the high or low adverse selection group and run specification regressions on these mimicking portfolios. Additionally, we conduct the reverse experiment by emulating the adverse selection clustering of G and E index portfolios. Table 3.8 presents the means of all portfolios; in Panel A, we see that the average adverse selection of the highest adverse selection portfolio is 0.59 and the least 0.04, whereas the mimicking portfolios have averages of 0.18 and 0.25, respectively. It is a common effect of this method that the mimicking portfolios have lower values for "most" portfolios and vice versa. The difference in differences shows at the 1% level that the mimicking portfolios have a narrower difference than the "original" portfolio. This is true for all four panels and only confirms that our method is working. In Panel C, the values are virtually the same using the E index instead of the G index. Panel B and D show the means of the G and E index, respectively. Most democratic G index stocks have an average of 4.5, while E index stocks have exactly zero. Dictatorial G stocks have an average of 14.5 (E index stocks 5.1). The respective mimicking portfolios have averages of 9.8 and 9.0, and 2.6 and 2.4. Again the values seem reversed and the differences in differences are significant at the 1% level. We then utilize the mimicking portfolios in simulations. The specification regression results are presented in Table 3.9. Overall, the results show that the four-factor model is not able to explain the mimicking portfolio returns well. All right tails are significant, while both tails are significant in hedge portfolios. This indicates that neither governance characteristics nor adverse selection characteristics dominate each other; rather, they are influenced by each other. A possible common source of information asymmetry can be attributed to that. Moreover, both factors are independently of importance, leading to our conclusion that investors price governance and adverse selection separately. This acts as evidence directly supporting our alternative hypothesis.

3.5 Conclusion

Information is the key asset of our time, especially in the business world. The possession of it or the lack thereof decides who gains or loses on a trade. Two different variables measuring two different dimensions of information asymmetry have been employed in this study—governance and adverse selection. Corporate governance shapes the relation between management and investors. But is it priced as a risk factor in face of the dwindling governance premium as expressed in recent studies? This paper reconfirms the findings of studies such as Gompers, Ishii and Metrick (2003), by providing supportive evidence of a significant governance premium. Additionally, we contribute to the literature by confirming the importance of a microstructure in the asset-pricing paradigm. We generate an adverse selection variable based on Huang and Stoll's (1997) methodology and show that is priced. Moreover, we jointly analyze governance and adverse selection and show that neither variable dominates the other. Investors are willing and able to distinguish between these two sources of information asymmetry when making investment decisions. Further research in this area is warranted to determine exactly how these variables influence investors' choices.

Figure 3.1: Time Series of Key Variables

Figure 3.1a shows the annual averages of governance index and entrenchment index. Figure 3.1b shows the annual averages of adverse selection and excess stock returns.



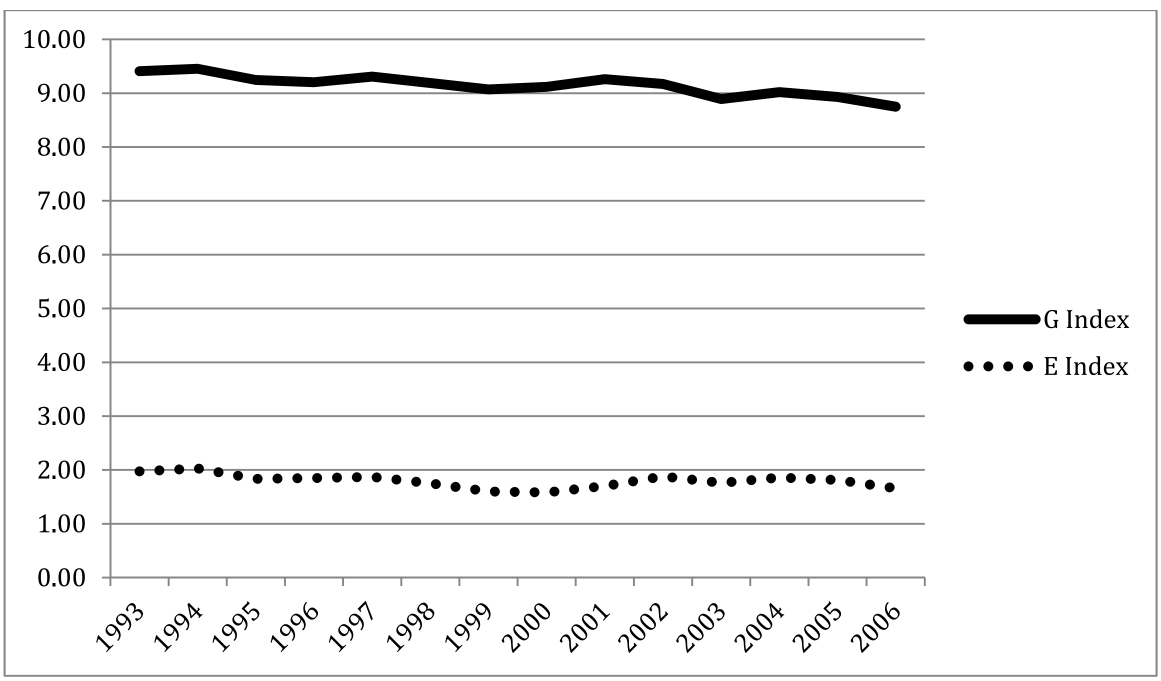


Table 3.1: Summary Statistics

This table presents the mean, median and standard deviation of the key variables. Adverse selection is calculated following Huang and Stoll (1997). The governance index is taken from Metrick's website and the entrenchment index from Bebchuk's website. Panel B shows the annual averages of our key variables and excess returns.

Panel A:

	G Index	E Index	AS
25% quartile	7	2	0.11
Median value	9	2	0.20
75% quartile	11	3	0.29
Mean value	9.40	2.43	0.22
St. Dev.	2.70	1.30	0.16

Panel B:

Year	Excess Return	G Index	E Index	AS
1993	0.47%	9.41	1.97	0.36
1994	-0.03%	9.45	2.03	0.34
1995	2.05%	9.25	1.83	0.34
1996	1.34%	9.20	1.85	0.41
1997	1.84%	9.31	1.87	0.38
1998	2.11%	9.19	1.75	0.37
1999	1.27%	9.07	1.60	0.42
2000	-1.16%	9.12	1.58	0.46
2001	-0.89%	9.26	1.70	0.32
2002	-1.77%	9.17	1.88	0.23
2003	2.19%	8.89	1.76	0.15
2004	0.79%	9.02	1.86	0.12
2005	0.29%	8.93	1.81	0.13
2006	0.66%	8.75	1.66	0.13

Table 3.2: Simple Correlations

This table reports time series averages of annual cross-sectional correlation of variables in asset pricing tests for all stocks over the period 1993-2006. Adverse selection is calculated following Huang and Stoll (1997). The governance index is taken from Metrick's website and the entrenchment index from Bebchuk's website. All correlations have p values that are less than 0.0001.

	G Index	E Index	AS
G Index	1.00	0.74	-0.03
E Index	0.74	1.00	-0.08
AS	-0.03	-0.08	1.00

Table 3.3: Single Sorted Time Series Regressions

This table reports the value of the intercepts obtained in three-factor model for five portfolios of stocks sorted by adverse selection and G index. For the entrenchment index only three portfolios were used due to the small range of the variable. Adverse selection is calculated following Huang and Stoll (1997). Portfolios are formed yearly for the period 1993-2006. Panel A presents intercepts from the time series regression of three-factor model as in the following equation $r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \gamma_i HML_t + \delta_i SMB_t + \tau_i UMD_t + \varepsilon_{i,t}$, where $r_{i,t} - r_{f,t}$ is the excess return on portfolio i in year t, and $(r_{m,t} - r_{f,t}), HML_t,\ SMB_t$, are the Fama and French (1993) factors related to market premium, the book-to-market ratio and the firm size in year t and $UMD_t$is Carhart's momentum factor. The portfolios are sorted from lowest to highest levels of adverse selection. In Panel B they are sorted from most democratic to dictatorial according to the G index. Panel C presents the intercepts from sorting from most democratic to dictatorial according to the E index. The bottom of each panel presents the Gibbons, Ross, Shanken (1989) test of the hypothesis that the intercepts jointly equal zero for the four-factor model. Intercepts are reported in absolute terms (t-statistics are in italics).

Panel A: Sorted by Adverse Selection

1	2	3	4	5
0.08	-0.08	-0.20	0.10	0.44
0.46	*-0.45*	*-1.13*	*0.74*	*3.20*

F-value for Gibbons, Ross, Shanken (1989) test that the intercepts jointly equal to zero is 4.38*** (significant at 1 percent level) SR(α):0.40

Panel B: Sorted by governance index

1	2	3	4	5
0.33	0.26	0.09	0.22	0.02
2.21	*2.05*	*0.71*	*1.45*	*0.11*

F-value for Gibbons, Ross, Shanken (1989) test that the intercepts jointly equal to zero is 9.11*** (significant at 1 percent level) SR(α): 0.59

Panel C: Sorted by entrenchment index

1	2	3
0.35	0.11	-0.13
2.96	*1.15*	*-0.91*

F-value for Gibbons, Ross, Shanken (1989) test that the intercepts jointly equal to zero is 13.82*** (significant at 1 percent level) SR(α): 0.54

Table 3.4: Double Sorted Time Series Regressions – G Index

This table reports the value of the intercepts obtained in three-factor model for 25 portfolios of stocks sorted by adverse selection and governance index. Adverse selection is calculated following Huang and Stoll (1997). Portfolios are formed yearly for the period 1993-2006. Panel A presents intercepts from the time series regression of three-factor model as in the following equation $r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \gamma_i HML_t + \delta_i SMB_t + \varepsilon_{i,t}$, where $r_{i,t} - r_{f,t}$ is the excess return on portfolio i in year t, and $(r_{m,t} - r_{f,t}), HML_t, SMB_t$, are the Fama and French (1993) factors related to market premium, the book-to-market ratio and the firm size in year t. The portfolios are sorted independently and portfolio 1,1 has the least adverse selection and is highly democratic. Panel B presents the portfolios sorted dependently. The bottom of each panel presents the Gibbons, Ross, Shanken (1989) test of the hypothesis that the intercepts jointly equal zero for the four-factor model. Intercepts are reported in absolute terms (t-statistics are in italics).

Panel A: Sorted independently

		Adverse Selection Groups				
		1	2	3	4	5
G index	1	0.65	-0.03	0.39	0.27	0.52
		1.87	*-0.10*	*1.01*	*0.89*	*1.92*
groups	2	-0.19	0.25	0.11	0.13	0.57
		-0.56	*0.74*	*0.37*	*0.56*	*2.61*
	3	0.13	-0.45	-0.22	-0.16	0.60
		0.52	*-2.22*	*-0.80*	*-0.65*	*2.97*
	4	0.01	0.27	-0.44	0.20	0.43
		0.03	*1.02*	*-1.72*	*0.89*	*1.60*
	5	-0.27	-0.49	-0.51	-0.05	0.65
		-1.10	*-1.76*	*-1.56*	*-0.20*	*2.15*

F-value for Gibbons, Ross, Shanken (1989) test that the intercepts jointly equal to zero is 10.53*** (significant at 1 percent level) SR(α): 1.46

Panel B: Sorted dependently

		Adverse Selection Groups				
		1	2	3	4	5
G index	1	0.50	-0.07	0.27	0.23	0.50
		1.51	*-0.30*	*0.85*	*0.82*	*1.92*
groups	2	-0.14	0.20	-0.17	-0.14	1.03
		-0.44	*0.59*	*-0.54*	*-0.54*	*4.04*
	3	0.14	-0.56	0.06	-0.02	0.44
		0.49	*-2.17*	*0.23*	*-0.07*	*1.92*
	4	-0.06	0.37	-0.47	0.24	0.40
		-0.23	*1.32*	*-1.69*	*0.86*	*1.41*
	5	-0.25	-0.34	-0.39	-0.13	0.57
		-1.06	*-1.45*	*-1.51*	*-0.66*	*2.55*

F-value for Gibbons, Ross, Shanken (1989) test that the intercepts jointly equal to zero is 8.32*** (significant at 1 percent level) SR(α): 1.32

Table 3.5: Double Sorted Time Series Regressions – E Index

This table reports the value of the intercepts obtained in three-factor model for 15 portfolios of stocks sorted by adverse selection and entrenchment index. Adverse selection is calculated following Huang and Stoll (1997). Portfolios are formed yearly for the period 1993-2006. Panel A presents intercepts from the time series regression of three-factor model as in the following equation $r_{i,t-r_{f,t}} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \gamma_i HML_t + \delta_i SMB_t + \varepsilon_{i,t}$, where $r_{i,t} - r_{f,t}$ is the excess return on portfolio i in year t, and $(r_{m,t} - r_{f,t}), HML_t,\ SMB_t$, are the Fama and French (1993) factors related to market premium, the book-to-market ratio and the firm size in year t. The portfolios are sorted independently and portfolio 1,1 has the lowest adverse selection and it is the most democratic. Panel B presents the portfolios sorted dependently. The bottom of each panel presents the Gibbons, Ross, Shanken (1989) test of the hypothesis that the intercepts jointly equal zero for the four-factor model. Intercepts are reported in absolute terms (t-statistics are in italics).

Panel A: Sorted independently

		Adverse Selection Groups				
		1	2	3	4	5
E Index	1	0.33	0.65	0.05	0.20	0.52
		1.10	*2.28*	*0.18*	*0.93*	*2.58*
groups	2	-0.03	-0.33	-0.20	0.07	0.47
		-0.15	*-1.88*	*-0.95*	*0.43*	*2.57*
	3	-0.27	-0.30	-0.26	-0.11	0.10
		-1.26	*-1.42*	*-1.28*	*-0.46*	*0.37*

F-value for Gibbons, Ross, Shanken (1989) test that the intercepts jointly equal to zero is 8.15*** (significant at 1 percent level) SR(α): 0.96

Panel B: Sorted dependently

		Adverse Selection Groups				
		1	2	3	4	5
E Index	1	0.36	0.71	0.18	0.20	0.57
		1.28	*2.55*	*0.71*	*0.93*	*2.95*
groups	2	0.03	-0.45	-0.26	0.11	0.48
		0.15	*-2.50*	*-1.21*	*0.64*	*2.68*
	3	-0.26	-0.32	-0.26	-0.03	0.29
		-1.25	*-1.48*	*-1.28*	*-0.16*	*1.25*

F-value for Gibbons, Ross, Shanken (1989) test that the intercepts jointly equal to zero is 9.08*** (significant at 1 percent level) SR(α): 1.02

Table 3.6 – G and E Index Clustering

This table reports the average excess return of each G and E index value sorted from high to low from 1993 to 2006. %ME shows the percentage market equity of the respective G or E index value to the overall market equity. HighAS (LowAS) reports the percentage weight (in terms of market equity) of the respective G or E index value in the high (low) adverse selection group. Finally, the average adverse selection value is reported.

G Index	Excess Return	PercentME	HighAS	LowAS	AS
6	0.90%	10.42%	13.00%	8.37%	0.30
7	0.76%	10.53%	10.94%	11.04%	0.30
10	0.70%	10.54%	10.12%	10.49%	0.29
14	0.60%	3.38%	3.22%	4.21%	0.27
5	0.55%	9.19%	10.67%	7.10%	0.30
13	0.48%	7.41%	6.84%	8.98%	0.26
11	0.47%	14.70%	15.07%	13.82%	0.31
9	0.39%	14.81%	12.40%	18.94%	0.24
8	0.33%	11.02%	10.35%	9.84%	0.23
12	0.29%	8.00%	7.39%	7.22%	0.25

E Index	Excess Return	PercentME	HighAS	LowAS	AS
0	0.82%	25.09%	31.93%	20.71%	0.33
5	0.76%	1.76%	1.23%	2.45%	0.21
2	0.56%	24.38%	23.98%	24.38%	0.28
4	0.55%	10.45%	9.80%	11.45%	0.25
3	0.49%	19.20%	16.75%	21.58%	0.25
1	0.18%	19.12%	16.31%	19.44%	0.25

Table 3.7 – Annual G and E Index Clustering

This table reports the annual difference in percent between the market equity of adverse selection groups and average market equity of G and E index groups. The percentage of the category's total market capitalization contained in each G index value is calculated for low adverse selection, high adverse selection and the entire sample. The absolute difference in a G's percentage of total market capitalization is reported for each category, averaged over all G index values each year. In Panel B, the same variables are shown for the E index. *, **, *** indicate that the numder is significantly different from zero at the 10%, 5%, and 1% levels, respectively.

Panel A: G Index

Year	Low AS	High AS	Low - High
1993	7.5%***	4.9%***	2.9%***
1994	7.8%***	5.2%***	3.2%***
1995	6.5%***	5.2%***	2.8%***
1996	7.4%***	4.6%***	2.8%***
1997	8.3%***	3.4%***	4.9%***
1998	8.3%***	3.6%***	4.7%***
1999	8.7%***	3.3%***	5.4%***
2000	9.5%***	3.1%***	6.3%***
2001	8.8%***	5.1%***	4.2%***
2002	8.5%***	5.4%***	3.2%***
2003	7.0%***	6.1%***	2.2%**
2004	7.4%***	6.2%***	1.8%***
2005	6.8%***	6.7%***	2.2%***
2006	7.6%***	6.6%***	1.80%**

Panel B: E Index

Year	Low AS	High AS	Low - High
1993	12.6%***	8.2%***	4.7%
1994	13.0%***	8.6%***	4.4%*
1995	10.8%***	8.6%***	2.2%*
1996	12.4%***	7.7%***	4.7%**
1997	13.9%***	5.7%***	8.3%**
1998	13.9%***	6.1%***	7.9%**
1999	14.5%**	5.5%***	9.1%*
2000	15.8%**	5.2%**	10.6%**
2001	14.7%**	8.5%**	6.2%**
2002	14.2%***	9.0%***	5.3%**
2003	11.7%***	10.1%***	1.6%**
2004	12.3%***	10.3%***	2.0%*
2005	11.3%***	11.1%***	1.3%**
2006	12.7%***	11.1%**	1.9%**

Table 3.8 – Mimicking Portfolios

This table reports in panel A the annual average adverse selection (AS) values of least AS and most AS portfolios across G index values as well as portfolios across the same G index values mimicking these portfolios. For the purpose of mimicking G index clustering in the most AS portfolio, only firms that are not in the most AS portfolio are selected. Likewise, only "non-least AS" portfolios are selected for mimicking G index clustering in the least AS portfolio. Firms in the random trials are chosen such that the total market capitalization of each G index values in the trial portfolio is proportional to the market capitalization of that G in the respective hedge, most AS, or least AS portfolio. Panel B reports the annual average G index values of democratic and dictatorial portfolios across adverse selection values as well as portfolios mimicking these portfolios. Panels C and D repeat the above two procedures for the E index. p-values for the difference test between mimicking portfolios and the difference in differences test between extreme and mimicking portfolios are less than 0.0001 for all four panels.

Panel A:	Average AS
Most AS stocks	0.59
Mimi most AS stocks	0.18
Least AS stocks	0.04
Mimi least AS stocks	0.25

Panel B:	Average G Index
Democratic stocks	4.5
Mimic democratic stocks	9.8
Dictatorial stocks	14.5
Mimic dictatorial stocks	9.0

Panel C:	Average AS
Most AS stocks	0.59
Mimi most AS stocks	0.19
Least AS stocks	0.04
Mimi least AS stocks	0.25

Panel D:	Average E Index
Democratic stocks	0.0
Mimic democratic stocks	2.6
Dictatorial stocks	5.1
Mimic dictatorial stocks	2.4

Table 3.9 – Specification Regressions on Mimicking Portfolios

The numbers in each row represent the percentage of the 250 random trials that reject the null hypothesis of zero mean monthly abnormal return at theoretical significance levels of 10%, 5%, and 1%, in favor of the alternative hypothesis of the intercept being significantly negative on the left tail, or significantly positive on the right tail. Long-run abnormal returns are measured by the regression intercept using the four-factor model. Excess returns are regressed on RMRF, SMB, HML, and UMD. In Panel A, portfolio returns which are long in mimicking least AS stocks and short in mimicking most AS stocks are used, then mimicking least (most) AS stocks are employed. In Panel B, portfolio returns which are long in mimicking "democratic" stocks and short in mimicking "dictatorial" stocks are used, then mimicking "democratic" ("dictatorial") stocks are employed. . Panels C and D repeat the above two procedures for the E index. *, **, ***, significantly different from the theoretical rejection rate at the 10%, 5%, and 1% statistical levels, respectively.

Panel A:

	Theoretical Rejection Rates					
	10%		5%		1%	
	Left Tail	Right Tail	Left Tail	Right Tail	Left Tail	Right Tail
	5%	95%	2.50%	97.50%	0.50%	99.50%
Hedge portfolio	11.2%***	46.4%***	8.4%***	38.8%***	5.2%***	26.4%***
Mimic least AS stocks	0%	97.2%***	0%	93.6%***	0%	73.2%***
Mimic most AS stocks	0%	47.6%***	0%	35.6%***	0%	18%***

Panel B:

	Theoretical Rejection Rates					
	10%		5%		1%	
	Left Tail	Right Tail	Left Tail	Right Tail	Left Tail	Right Tail
	5%	95%	2.50%	97.50%	0.50%	99.50%
Hedge portfolio	18.4%***	69.6%***	16.4%***	68.4%***	14.8%***	66.4%***
Mimic democratic stocks	0%	100%***	0%	100%***	0%	100%***
Mimic dictatorial stocks	0.40%	21.2%***	0%	12.8%***	0%	2.8%***

Panel C:

	Theoretical Rejection Rates					
	10%		5%		1%	
	Left Tail	Right Tail	Left Tail	Right Tail	Left Tail	Right Tail
	5%	95%	2.50%	97.50%	0.50%	99.50%
Hedge portfolio	10%***	43.6%***	7.6%***	39.2%***	3.6%***	31.2%***
Mimic least AS stocks	0%	92.8%***	0%	87.6%***	0%	66.0%***
Mimic most AS stocks	0%	40.8%***	0%	30.0%***	0%	14.0%***

Panel D:

	Theoretical Rejection Rates					
	10%		5%		1%	
	Left Tail	Right Tail	Left Tail	Right Tail	Left Tail	Right Tail
	5%	95%	2.50%	97.50%	0.50%	99.50%
Hedge portfolio	32.0%***	49.2%***	30.8%***	47.6%***	28.4%***	44.8%***
Mimic democratic stocks	0%	99.2%***	0%	96.8%***	0%	89.2%***
Mimic dictatorial stocks	0%	12.4%***	0%	7.6%***	0%	2.0%***

CHAPTER 4: CONCLUSION

This dissertation focuses on crucial risk factors in asset pricing, such as liquidity, governance and adverse selection risks. These factors provide unique insights into different liquidity aspects. For example, governance and adverse selection are potential proxies for information asymmetry that could be better captured by the market liquidity of a company's shares. Hence, a thorough examination of variables related to liquidity is warranted. The methodology in this dissertation includes, among other analyses, specification regressions using mimicking portfolios—a technique adopted by Johnson, Moorman and Sorescu (2009). The mimicking portfolios used in this research are formed using all but the extreme portfolios of the variables of interest. The relative weights that the extreme portfolios have in the second variable of interest are then preserved. That way, the model is neutral in one variable, and the influence of the other can be examined in detail. Next, these mimicking portfolios are employed in specification regressions, which are a type of Monte Carlo simulation. This allows for valuable insight into the interaction of this study's key variables. Liquidity risk and industry clustering are investigated in the first chapter, and it was determined that both are important in explaining stock returns. The study uses two proxies for liquidity–Amihud's Illiquidity as well as Pastor-Stambaugh's liquidity factor. The results corroborate the findings of Fama and French (1997) and other researchers, who emphasize the importance of an industry's effects on its firms. It also emphasizes the results of previous liquidity studies by Amihud (2002) and Acharya and Pedersen (2005), highlighting the importance of liquidity. We conclude that a comprehensive asset-pricing model should include industry effects and liquidity.

The study also concentrated on the interaction of governance and liquidity. Information asymmetry acts as an intermediary between the two factors. Despite recent research showing diminishing premia for governance and liquidity, we can reconfirm their importance in explaining stock returns. Therefore, we performed several standard asset-pricing tests of the joint effect of governance and liquidity on the asset-pricing paradigm. Our results corroborate the findings of Amihud (2002) and Gompers, Ishii and Metrick (2003). But detailed analysis revealed that liquidity is clustered in governance-sorted portfolios. So we further ran specification regressions of portfolios mimicking liquidity or governance clustering in the extreme portfolios to show that this clustering is unsystematic. Hence, we conclude that governance and liquidity contribute significantly to asset-pricing models independently from one another.

The dissertation concludes by examining the interaction of governance and adverse selection, and the results reconfirm once more the importance of governance in asset pricing. We generated an adverse selection variable based on Huang and Stoll's (1997) methodology and found that it is in fact priced. Governance and adverse selection can be both interpreted as measuring information asymmetry. Hence, a joint study of both is interesting and insightful. The main findings suggest that the two factors are priced individually but that they are both influencing one another. Further research in this area is warranted and essential in understanding the impact of information on the prices of financial assets. All three studies together provide an important new view into interaction of factors beyond the four-factor model. These factors–governance, liquidity and adverse selection–will shape our future understanding of asset pricing.

References

Acharya, V.V. and L.H. Pedersen (2005). Asset pricing with liquidity risk. Journal of Financial Economics, 375–410.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets, 31–56.

Amihud, Y. and H. Mendelson (1986). Asset pricing and the bid-ask spread. Journal of Financial Economics, 223–249.

Armstrong, C.S., Guay, W.R., and J.P. Weber (2010). The role of information and financial reporting in corporate governance and debt contracting. Journal of Accounting and Economics, 179–234.

Bain, J.S., 1968 "Industrial organization," John Wiley & Sons.

Baker, M. and J.C. Stein (2004). Market liquidity as a sentiment indicator. Journal of Financial Markets, 271–299.

Barry, C.B. and S.J. Brown (1986). Limited Information as a source of risk. Journal of Portfolio Management, 66–72.

Ben-Rephael, A., Kadan, O. and A. Wohl (2010). The diminishing liquidity premium. Working paper, Tel Aviv University.

Bebchuk, L., Cohen, A. and A. Ferrell (2009). What Matters in Corporate Governance? Review of Financial Studies, 783–827.

Bertrand, M. and S. Mullainathan (2003). Enjoying the Quiet Life? Corporate Governance and Managerial Preferences. Journal of Political Economy, 1043–1075.

Bharath, S.T., Pasquariello, P. and G. Wu (2009). Does asymmetric information drive capital structure decisions? Review of Financial Studies, 3211–3243.

Borokhovich, K. A., Brunarski, K. R. and R. Parrino (1997). CEO Contracting and Antitakeover Amendments. Journal of Finance, 1495–1517.

Brennan, M. J., Chordia, T. and A. Subrahmanyam (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. Journal of Financial Economics, 345–373.

Carhart, M.M. (1997). On persistence in mutual fund performance. Journal of Finance, 57–82.

Chan, H. W. and R. W. Faff (2005). Asset pricing and the illiquidity premium. Financial Review, 429–458.

Chan, L.K.C., Lakonishok, J. and B. Swaminathan (2007). Industry classifications and return comovement. Financial Analysts Journal, 56–70.

Chen, W.-P., Chung, H., Lee, C. and W.-L. Liao (2007). Corporate Governance and Equity Liquidity: analysis of S&P transparency and disclosure rankings. Corporate Governance: An International Review, 644–660.

Chordia, T., Roll, R. and A. Subrahmanyam (2000). Commonality in liquidity. Journal of Financial Economics, 3–28.

Chordia, T., Roll, R. and A. Subrahmanyam, A. (2001). Market liquidity and trading activity. Journal of Finance, 501–530.

Chordia, T., Roll, R. and A. Subrahmanyam (2002). Order imbalance, liquidity, and market returns. Journal of Financial Economics, 111–130.

Chung, K. H., Elder, J. and J.-C. Kim (2010). Corporate Governance and Liquidity. Journal of Financial and Quantitative Analysis, 265–291.

Core, J. E., W. R. Guay, and T. O. Rusticus (2006). Does Weak Governance Cause Weak Stock Returns: An Examination of Firm Operating Performance and Investors' Expectations. Journal of Finance, 655–687.

Cremers, K.J.M., and V.B. Nair (2005). Governance Mechanisms and Equity Prices. Journal of Finance, 2859–2894.

Daines, R. (2001). Does Delaware law improve firm value? Journal of Financial Economics, 525–558.

Datar, V. T., Naik, N. Y. and R. Radcliffe (1998). Liquidity and asset returns: an alternative test. Journal of Financial Markets, 203–219.

Duarte, J. and L. Young (2009). Why is PIN priced? Journal of Financial Economics, 119–138.

Easley, D., Hvidkjaer, S. and M. O'Hara (2002). Is information risk a determinant of asset returns? Journal of Finance, 2185–2221.

Fama, E.F. and J.D. MacBeth (1973). Risk, Return and Equilibrium: Empirical Tests. Journal of Political Economy, 607–636.

Fama, E.F. and K.R. French (1993). Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 3–56.

Fama, E.F. and K.R. French (1997). Industry costs of equity. Journal of Financial Economics, 153–193.

George, T.J., Kaul, G. and M. Nimalendran (1991). Estimation of the bid-ask spread and its components: a new approach. Review of Financial Studies, 623–656.

Gibbons, M. R., Ross, S. A. and J. Shanken (1989). A test of the efficiency of a given portfolio. Econometrica, 1121–1152.

Glosten, L.R. and L.E. Harris (1988). Estimating the components of the bid/ask spread. Journal of Financial Economics, 123–42.

Glosten, L.R. and P.R. Milgrom (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. Journal of Financial Economics, 71–100.

Gompers, P.A., Ishii, J.L. and A. Metrick (2003). Corporate governance and equity prices. Quarterly Journal of Economics, 107–155.

Healy, P.M. and K.G. Palepu (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. Journal of Accounting and Economics, 405–440.

Hou, K. and D.T. Robinson (2006). Industry concentration and average stock returns. Journal of Finance, 1927–1956.

Huang, R. D. and H. R. Stoll (1997). The components of the bid-ask spread: A General Approach. Review of Financial Studies, 995–1034.

Jensen, M. (1986). Agency costs of free cash flow, corporate finance, and takeovers. American Economic Review, 323–329.

Johnson, S. A., Moorman, T. and S. Sorescu (2009). A reexamination of corporate governance and equity prices. Review of Financial Studies, 4753–4786.

Kyle, A. (1985). Continuous auctions and insider trading. Econometrica, 1315–1335.

LaPorta, R., Lopez-de-Silanes, F., Shleifer, A. and R. W. Vishny (2000). Investor protection and corporate governance. Journal of Financial Economics, 3–27.

Lewellen, J., Nagel, S. and J. Shanken (2010). A Skeptical Appraisal of Asset Pricing Tests. Journal of Financial Economics, 175–194.

Lin, J., Sanger, G. and G.G. Booth (1995). Trade size and components of the bid-ask spread. Review of Financial Studies, 1153–1183.

Liu, W. (2006). A liquidity-augmented capital asset pricing model. Journal of Financial Economics, 631–671.

MacKay, P. and G.M. Phillips (2005). How does industry affect firm financial structure? Review of Financial Studies, 1433–1466.

Madhavan A. and S. Smidt (1991). A Bayesian Model of Intraday Specialist Pricing. Journal of Financial Economics, 99–134.

Merton, R.C (1973). An intertemporal capital asset pricing model. Econometrica, 867–887.

Moskowitz, T.J. and M. Grinblatt (1999). Do industries explain momentum? Journal of Finance, 287–329.

Nguyen, D., Mishra, S., Prakash, A.J. and D.K. Ghosh (2007). Liquidity and asset pricing under the three-moment CAPM paradigm. Journal of Financial Research, 379–398.

Norli, O., Ostergaard, C. and I. Schindele (2010). Liquidity and Shareholder Activism. Working paper, Norwegian School of Management.

Pastor, L. and R.F. Stambaugh (2003). Liquidity risk and expected stock returns. Journal of Political Economy, 642–685.

Paternoster, R., Brame, R., Mazerolle, P. and A. Piquero (1998). Using the correct statistical test for the equality of regression coefficients. Journal of Criminology, 859–866.

Shleifer, A. and R. W. Vishny (1986). Large Shareholders and Corporate Control. Journal of Political Economy, 461–488.

Sufi, A. (2007). Information asymmetry and financing arrangements: evidence from syndicated loans. Journal of Finance, 629–668.

Van Ness, B. F., Van Ness, R. A. and R. S. Warr (2001). How well do adverse selection components measure adverse selection? Financial Management, 77–98.

VITA

SASCHA STROBL

	Born, Linz, Austria
2004	Diploma, Business University of Passau Passau, Germany
2006	MBA St. Joseph's University Philadelphia, Pennsylvania
2009-2013	Teaching Assistant Florida International University Miami, Florida

PRESENTATIONS

Governance and Liquidity in Asset Pricing, with S. Mishra, and A. J. Prakash. MFA Annual Meeting, New Orleans, Louisiana, March 2012

Governance and Liquidity in Asset Pricing, with S. Mishra, and A. J. Prakash. EFA Annual Meeting, Boston, Massachusetts, April 2012

Liquidity premium and industry clustering effect examined, with S. Mishra, and A. J. Prakash. EFA Annual Meeting, St. Pete's Beach, Florida, April 2013

The Anatomy of a Crash: ETF Options During the Flash Crash, with A. S. Oztekin, and R. T. Daigler. EFA Annual Meeting, St. Pete's Beach, Florida, April 2013