ESSAYS ON CROSS-SECTIONAL ASSET PRICING

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A Thesis Submitted for the Degree of Doctor of Philosophy

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JANUARY 2009

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DEDICATION

To my parents, for teaching me the value of knowledge and for their selfless support.

ACKNOWLEDGEMENTS

I am deeply grateful to my supervisor, Soosung Hwang, for his kindness, support, and exceptional guidance. I would also like to express my gratitude to several other members of the faculty — Roy Batchelor, Aneel Keswani, Ian Marsh, Gulnur Muradoglu, Steve Satchell and Dylan Thomas — for their insightful comments, suggestions and encouragement at different stages of my study.

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ABSTRACT

Essays on Cross-Sectional Returns and Asset Pricing

The dissertation aims at the further understanding of several critical issues in the stock markets. It contains four chapters.

Cross-sectional stock returns and asset pricing has been one of the most important areas in financial economics. With the empirical failure of the Capital Asset Pricing Model (CAPM), an increasing number of studies have been conducted in the US stock market, and consequently many alternative asset pricing models and factors, have been proposed. Chapter One investigates the role of liquidity risk in cross-sectional asset pricing in both the USA and the UK. This study finds that a liquidity-augmented CAPM explains asset returns. Liquidity explains a sizeable spectrum of cross-sectional stock returns; and its effect is robust in the presence of other well-known empirical factors and a range of macroeconomic factors. Given the influential work of Fama and French (1992 and 1993), the performance of size and value premiums, (i.e., the excess return of small-capitalization stocks over large-capitalization stocks and the excess return of high book-to-market over low book-to-market stocks) are also compared. It is found that value premium is robust while the size premium disappears in the data for both countries.

Chapter Two investigates the relationship between liquidity and beta, as this relationship has been given little attention in the literature. Using the illiquidity measure of Amihud (2002), Acharya and Pedersen (2005) show that liquidity is priced in the framework of CAPM, and illiquid stocks have higher betas. This

study, however, provides empirical evidence that Amihud's measure is highly correlated with firm's size, and the results of Acharya and Pedersen (2005) could be spurious because of inappropriate choice of liquidity proxy. Using the size-free liquidity measure proposed in this study, it is demonstrated that liquid stocks have higher betas. This is consistent with the model of Holden and Subrahmanyam (1996), in which risk-averse investors resist holding risky (high beta) stocks. As a consequence, they trade risky stocks more often than low beta stocks, thus increasing the liquidity of high beta stocks. The evidence that illiquid stocks have low betas while still commanding higher returns implies that liquidity is priced in a multifactor, rather than CAPM, framework, which is consistent with the work of Brennan and Subrahmanyam (1996) and Pastor and Stambaugh (2003).

In Chapter Three, many different factors proposed in the cross-sectional asset pricing literature are reviewed; and it is argued that the number of factors in the literature seems to be too large, as suggested by the Arbitrage Pricing Theory (APT). It is hypothesized that all the existing factors cannot be mutually exclusive and/or equally important, thus there must be redundant factors. More importantly, many of the successful factors are not well economically or theoretically motivated. For example, there is still no consensus on the underlying risk of the well-known Fama and French factors. Last but not least, many of these successful empirical factors suffer in terms of the data-mining critique of Lo and MacKinlay (1990). In this study, a total of 18 factors are assembled and categorized into three groups: five risk-related, eight firm characteristics and five APT motivated principal component factors. Individual stocks rather than portfolio returns are used in testing factor models to avoid the data-snooping problem. The results suggest a risk-related four-factor model can serve as a replacement for the controversial Fama-French and momentum factors. More importantly, the four factors, i.e., excess market return, co-skewness, downside risk, and liquidity, are economically and theoretically better motivated than the firm-characteristics based factors. It is also found that many of these firm-characteristics sorted factors are not pervasive in explaining individual stock returns. It is, therefore, concluded that most of the factors are redundant and may be the outcome of data-mining.

Chapter Four examines the cross-sectional effect of the nominal share price. This chapter endeavours to understand two interesting puzzles associated with share price. First, the nominal share prices of the US stocks have remained remarkably constant since the Great Depression despite inflation. Second, there is no consensus about the motivations for firms to split their stocks, since financial theory suggests share price is independent of its value. The findings indicate that share price *per se* matters in cross-sectional asset pricing: stock return is inversely related to its nominal price. It is shown that a strategy of buying these penny stocks can generate a significant alpha even after considering the transaction costs. The abnormal returns of these penny stocks are robust in the presence of other firm characteristics such as size, book-to-market equity, earning/price ratio, liquidity and past returns; and are also not explained by the existing factors. These results also cast some light on the stock-split phenomenon. Intuitively, if firm managers know that low price would generate higher future returns, they are more likely to split their stocks on behalf of shareholders.

This thesis makes several major contributions in the area of cross-sectional asset pricing. First, it highlights the importance of liquidity risk in the financial markets. For example, Chapter One and Three suggest the robust significance of liquidity risk in both the UK and US stock markets. Second, this study investigates the interaction between liquidity and other well-known factors in asset pricing. For instance, the well-documented value premium can be explained by liquidity risk (Chapter One), by the close link between liquidity and beta (Chapter Two); and by the close association between liquidity and size, share price and other factors (Chapters One to Four). Third, this study addresses the issue arising in the asset-pricing literature regarding the number of factors used in explaining asset returns. Chapter Three concludes that many of the existing empirical factors are not pervasive and may be the outcome of data-snooping as a result of grouping. Consequently, this chapter indicates that a theoretically better justified four-factor model, comprising excess market return, co-skewness, downside risk and liquidity, is competent to explain stock returns. Last but not least, this thesis also challenges the Efficient Market Hypothesis. Chapter Four demonstrates that investors buying low price stocks (penny stocks) and selling high price stocks can generate significant profits, and rational asset-pricing models cannot explain this abnormal return. Nevertheless the inverse relationship between share price and return does shed some light on stock split motivations.

The results of this thesis, suggest a number of future research projects. For example, most of the academic work on cross-sectional returns and asset pricing are accomplished for the major developed markets such as the UK and US. With the maturation and growing importance of emerging markets, it is feasible to test asset pricing hypotheses in these markets. The extent to which these hypotheses are validated in the emerging markets would significantly impact both academia and practitioners.

1. Cross-Sectional Stock Returns in the UK Market: the Role of Liquidity Risk

1.1. Introduction

Liquidity in the financial markets has been one of the critical issues in both practice and academia. Since the 1980s, a number of episodes of financial market distress have underscored the importance of the smooth functioning of the markets for the stability of the financial system. At the heart of these episodes was a sudden and drastic reduction in market liquidity, characterized by disorderly adjustments in asset prices, a sharp increase in the costs of executing transactions, and so forth. The well-known 1998 episode involving Long-Term Capital Management (LTCM) is a representative example and has prompted investors to pay more attention to their liquidity risk when making portfolio decisions.

In this study, the role of liquidity risk in explaining the cross-sectional stock returns is investigated. In particular, the link between liquidity and the well-documented value premium is examined. Fama and French (1992) point out that liquidity, though important, does not need to be specifically measured and accounted for, as it is subsumed by the combination of size and book-to-market factors. It is generally accepted that illiquid stocks tend to be small and that people would not be surprised to see the high correlation between size and liquidity. However, Brennan and Subrahmanyam (1996) show that there is a statistically significant positive relationship between expected stock returns and illiquidity, even after taking Fama–French risk factors into account. Additionally, Chordia, Subrahmanyam and Anshuman (2001) demonstrate that liquidity does need to be accounted for individually, even after controlling for size, book-to-market and momentum.

Liquidity is a broad and elusive concept, which is not directly observed. Many liquidity proxies have been proposed, such as bid–ask spread, trading volume, or a combination of return and volume.[1] Among these liquidity measures, a few studies use trading volume as the proxy for the aggregate demand of liquidity traders (Campbell, Grossman and Wang, 1993), which suggests there could be some link between liquidity and other factors. Lee and Swaminathan (2000) demonstrate that low (high) volume stocks display many characteristics commonly associated with value (growth) stocks. Therefore, the return spread between value and growth could contain the difference of liquidity risk inherited by them.

Since Fama and French (1992, 1993), many researchers have documented the existence of the value premium, i.e., the excess return of value stocks (high book-to-market) over growth stocks (low book-to-market). Fama and French (1998) even find international evidence of this value anomaly. There are an increasing number of studies that attempt to explain this value anomaly using different theories.[2] None of these, however, can successfully account for this value spread. Although Lee and Swaminathan (2000) document the empirical connection between trading volume and value/growth, they do not investigate the interaction between value/growth and liquidity. The relationship between value anomaly and liquidity risk is formally tested in this study.

[1] See section 1.2 for detailed descriptions.

[2] Zhang (2005) uses rational expectation theory in a neoclassical framework to explain this value anomaly. He finds that value is riskier than growth in poor market conditions when the price of risk is high and high book-to-market signals persistent low profitability. Petkova and Zhang (2005) find time-varying risk goes in the right direction in explaining value premium; however, the beta-premium covariance in their study is still too small to explain the observed magnitude of the value anomaly. Other studies state that value spread is a premium for distress using a behavioural theory. These argue that this value anomaly is real but irrational, which is the result of the investor's overreaction that leads to the under-pricing of value (distress) stocks and over-pricing of growth stocks.

The contribution of this study is twofold: first, it is demonstrated that in the UK market there is a significant liquidity premium which can not be explained by the Capital Asset Pricing Model (CAPM), Fama and French three-factor model, or Fama and French with a momentum factor model;[3] and second, evidence is provided that variations in liquidity explain variations in the value premium. The value anomaly can be explained by a liquidity-augmented CAPM, which offers important implications for the link between value/growth and liquidity. Furthermore, the evidence of liquidity in explaining the value premium is not subsumed by the distress factor proposed by Agarwal and Taffler (2005) and a number of macroeconomic variables. These results are not consistent with those of Fama and French (1995, 1996) and Saretto (2004), who suggest the excess return of value over growth stocks is due to the distress risk inherited by them.

This study proceeds as follows: the next section describes the development of the hypotheses and research designs. Section 3 shows the empirical results. The last section offers concluding remarks and future research directions.

1.2. Hypotheses and Calculating Factors

The first part of this section explains the methods by which liquidity is employed to explain cross-sectional stock returns. The construction of the liquidity measure and factor are then presented in the next subsection. The method used to construct the size and value/growth factors in the UK market is explained, as it is not necessarily the same as the method used in the US market.

[3] Overall, a considerable amount of literature has been written about liquidity and asset pricing, but most research has been performed on the US market, with only a few investigations having been performed on the UK market. As pointed out by Dimson, Marsh and Staunton (2003), "It would be dangerous for investors to extrapolate into the future from the US experience. We need to also look outside of the United States." Thus, the UK data is adopted in this research to address the crucial question in asset pricing of "whether the results obtained for the US stock markets can be generalized to markets in other countries".

1.2.1. Liquidity Effects and Cross-Sectional Stock Returns

Since Fama and French (1992, 1993), many empirical papers have documented that average stock returns are related to firm characteristics, such as size and book-to-market. These return patterns are apparently not explained by the CAPM and are thus called anomalies. Among these, the value premium, i.e., the excess return of value stocks (high book-to-market) over growth stocks (low book-to-market) has been extensively researched. With Fama and French (1998, 2006) providing additional international evidence for the robustness of the value premium, there are an increasing number of studies that attempt to explain this value anomaly using different theories. Ang and Chen (2005) show that the value premium can be explained by a conditional CAPM. Fama and French (2006), however, argue that Ang and Chen's (2005) evidence is specific to the period of 1926–1963. Other studies, such as Zhang (2005) and Petkova and Zhang (2005), use different theories and methods to explain the value premium; however, their results show that the observed value premium is still too large to be wholly explained. Overall, none of the research has successfully accounted for this value anomaly.

In this paper, the robustness of the size and value premium in the UK stock market is investigated. To examine the cross-sectional stock return differences related to size and book-to-market, decile, quintile and $30^{th}/70^{th}$ percentile-breakpoint portfolios with regard to the stocks' characteristics, such as size and book-to-market, are formed. Taking 10 decile portfolios (Pi,t) for example, at the end of June in year *t*, 10 size decile portfolios are formed on the stocks' ranked market value. Similarly, at the end of December year *t* based on the stocks' book-to-market value, 10 value decile portfolios are formed. In regression analysis, similar to Ang and Chen (2005), the dependent variable is a hedge portfolio that takes a long position in a small (high book-to-market) portfolio and a short position in a big (low book-to-market) portfolio ($R_{L,t} - R_{S,t}$), where $R_{L,t}$ stands for the long position of this portfolio, which is either small or high book-to-market stock groups; and $R_{S,t}$ refers to the short position of this portfolio, i.e., either big or low book-to-market portfolios. We test the CAPM upon ($R_{L,t} - R_{S,t}$) via the significance of alphas. If the intercept (alpha) is significant, it suggests that the single market factor CAPM cannot explain the cross-sectional returns.

Size is commonly referred to as one type of liquidity proxy, as investors would not expect the same level of liquidity between large and small stocks; thus, the return difference between small and big could be the result of the variations in liquidity risks associated with each of them. Campbell, Grossman and Wang (1993) argue that trading volume is a proxy for the aggregate demand of liquidity traders. Lee and Swaminathan (2000) and Fama and French (2006) demonstrate that low (high) volume stocks display many characteristics commonly associated with value (growth) stocks. Therefore, the return spread between value and growth could reflect the differences in the liquidity risk inherited by them. In order to test these two hypotheses, we test the liquidity effects over the hedge portfolio, i.e., the following liquidity-augmented CAPM is estimated:

$$R_{L,t} - R_{S,t} = \alpha_i + \beta_{i,1}(Rm_t - R_f) + \beta_{i,2}LIQ_t + \varepsilon_{i,t} \qquad \textbf{(1)}$$

The factor sensitivity for liquidity factor ($\beta_{i,2}$) should be significant in the above cross-sectional regression if liquidity is related to size or book-to-market.

If liquidity is one of the missing factors for the explanation of size or value premium, it should be able to explain return differences to some extent. Following Pastor and Stambaugh (2003) and Ang and Chen (2005), the intercepts (alphas) of different portfolio strategies (such as small minus big, high minus low book-to-market) should not be significantly different from zero if liquidity is included.

1.2.2. Calculating Factors in the UK Market

1.2.2.1. Liquidity Measures and Liquidity Factor

1.2.2.1.A Concept of Liquidity

Like volatility, liquidity is not directly observed and many different liquidity measures have been proposed for different purposes. Liquidity has many dimensions. When market-wide liquidity is low, the probability of a seller completing a large transaction in a timely manner without making a significant price concession is low relative to the times of high market liquidity. Therefore, the key elements in a liquidity risk measure include volume, time, and transaction costs. Kyle (1985) suggests that three aspects of the transaction process need to be considered while measuring market liquidity: *tightness*, the cost of liquidating a position over a short period; *depth*, the ability to sell or buy a large number of shares with little price impact; and *resiliency*, the extent to which prices recover from random shocks with no structural information.

Previous research, such as Amihud and Mendelson (1986), Chordia, Roll and Subrahmanyam (2000) and Hasbrouck and Seppi (2001), has focused on the bid–ask spread as a measure of illiquidity. This type of measure focuses on the aspect of tightness since the cost is the main concern of this measure. However, as highlighted by Brennan and Subrahmanyam (1996), bid–ask spread is a noisy measure of illiquidity because many large trades appear outside the spread and many small trades occur within the spread. When liquidity is measured in terms of depth, there are a number of proxies in the literature. For instance, Brennan and Subrahmanyam (1996) assign stock illiquidity as a proxy for price impact, which is measured as the price response to signed order flow (order size). Amihud (2002) measures a stock's illiquidity as the ratio of its absolute return to dollar volume. Finally, Pastor and Stambaugh (2003) estimate a resiliency-based liquidity risk measure based on the idea that price changes accompanying large volumes tend to be reversed when market-wide liquidity is low.

1.2.2.1.B Liquidity Measure and Liquidity Factor

Among these liquidity proxies, Amihud's (2002) illiquidity measure is widely used in empirical studies because of its superior advantage of simple calculation. In addition, this proxy only needs return and volume data so that liquidity for a relatively long time span can be estimated. Amihud's measure is also consistent with Kyle's (1985) concept of illiquidity, the response of price to the order flow and Silber's (1975) measure of thinness, which is defined as the ratio of the absolute price change to the absolute excess demand for trading. Hasbrouck (2006) reviews different liquidity measures, and find that Amihud's measure is most strongly correlated with other price impact and cost-related liquidity proxies. Amihud's liquidity measure for stock i is defined as:

$$\gamma_{i,m} = -\frac{1}{D_{i,m}} \sum_{t=1}^{D_{i,m}} \frac{\left| r_{i,m,d} \right|}{v_{i,m,d}} \qquad \textbf{(2)}^{4}$$

where: $D_{i,m}$ is the number of days for which data are available for stock i in month *m*,

$r_{i,m,d}$ is the return on stock i on day d of month *m*, and

$v_{i,m,d}$ is the dollar trading volume for stock i on day d of month *m*.

However, this measure has two disadvantages. The first is that Amihud (2002) takes dollar trading volume as the denominator, which may result in a high correlation between the liquidity measure and size since large volume stocks are usually more frequently traded than small volume stocks. That is, it is not expected that the dollar amount of trading for a firm whose market capitalization is 10 million dollars will be the same as that for a firm whose market capitalization is 10 billion dollars. In addition, as share prices increase over time, liquidity appears to increase when it is measured by Amihud's method even if there are no changes in liquidity.

[4] There is no negative sign in the original paper of Amihud (2002). The negative sign is included here, so that large negative values signify low liquidity.

In order to construct a liquidity measure that is robust with respect to size, we scale the denominator by the market capitalization of the stock; in other words, dollar trading volume is replaced by turnover in the denominator. Furthermore, as argued by Lo and Wang (2000), turnover is a canonical measure of trading activity. Therefore, while replacing the dollar trading volume by turnover does not alter the principle of this price reversal nature, it would enable us to construct a relative liquidity proxy that is free from the size effect.

The second disadvantage is that the liquidity measure may have extreme outliers when trading activity is extremely low (i.e., trading volume could be very close to zero); therefore, we use the natural logarithm of these values to minimize the effect of the outliers. The modified relative liquidity measure ($\psi_{i,m}$) for stock i is defined as:

$$\psi_{i,m} = -\frac{1}{D_{i,m}} \sum_{t=1}^{D_{i,m}} \ln \frac{|r_{i,m,d}|}{Turnover_{i,m,d}} \quad \textbf{(3)}$$

where: $D_{i,m}$ is the number of days for which data are available for stock i in month m,

$r_{i,m,d}$ is the return on stock i on day d of month m, and

$Turnover_{i,m,d}$ is the turnover for stock i on day d of month m.

The liquidity measures in equations (2) and (3) are calculated for all the stocks in the market every month, from which the monthly liquidity measures for each stock are obtained. Then, using the liquidity measures, market-wide liquidity factors as in Fama and French (1993) are created. At the end of each year, two portfolios are formed on liquidity using the median liquidity as the breakpoint. The performance of the hedge portfolio that consists of a long position in a liquid portfolio and a short position in an illiquid portfolio in the following 12 months is defined as the liquidity factor (LIQ_t). The portfolios are rebalanced at the end of each year. We calculate each stock's liquidity and market-wide liquidity factor for

Amihud's (2002) illiquidity measure ($\gamma_{i,m}$) and size-adjusted liquidity measure ($\psi_{i,m}$). With this mimicking liquidity factor, the role of liquidity in explaining the cross-sectional return differences is further explored.

1.2.2.2. Size and Value/Growth Factors

UK *SMB* (Small minus Big) and *HML* (high minus low book-to-market) factor returns are calculated in a similar way to those in Fama and French (1993) except for the breakpoints. Fama and French (1993) use the 50th percentile (for size) and 30th and 70th percentiles (for book-to-market) NYSE-based breakpoints. Following Dimson, Nagel and Quigley (2003) [DNQ hereafter], this study uses the 70th percentile of ranked size and 40th and 60th percentiles of book-to-market in the UK market. In the UK, large capitalization stocks are concentrated in the low book-to-market segment, and small capitalization stocks, in contrast, are concentrated in the high book-to-market class.[5] Choosing less extreme book-to-market breakpoints and a wider range for the small-capitalization group ensures acceptable levels of diversification in these corner portfolios throughout the sample period. In addition, the 70% breakpoint for the size results in a distribution of aggregate market value across portfolios that is relatively similar to the distribution in Fama and French (1993), where most NASDAQ stocks, most of which are smaller than the NYSE-based 50% breakpoint, are sorted into the small-capitalization group.

1.3. Empirical Results

1.3.1. Data

In this study, the sample covers all the stocks traded on the London Stock Exchange from January 1987 to December 2004 because the trading volume data

[5] Similar results are found in this study. They are displayed in the empirical section.

which is used for calculating liquidity is available from 1987. All the data on stock returns, market capitalizations, book-to-market ratios and trading volumes is from DataStream. To construct data set, the identities of all UK listed companies are extracted from the 'live' constituents of the FTSE All Share Index held on DataStream, and also, in order to mitigate survivorship bias, from formerly listed companies in the DataStream 'DEADUK' file. This DataStream 'DEADUK' file comprises companies which have been, but no longer, listed in the UK. Book-to-Market ratio is the inverse of price to book value in DataStream. The DataStream data type code for market capitalization, price to book value, and volume are MV, PTBV and VO. In calculating liquidity measures, the daily frequency returns and dollar trading volume data are needed. The book-to-market ratio is the end of the calendar year value, and any negative book-to-market stocks are deleted from the sample following Fama and French (1992); in addition, all the delisted equities are included in the sample so that survivorship bias is controlled for in this study. Initially, the number of stocks in this study is 945 in 1987 and this gradually increases to 2306 in 2004. While calculating the liquidity measures, due to the lack of availability of data regarding trading volume, the sample size is much smaller than the total number of available stocks; for example, less than 200 stocks from 1987 to 1990, 576 stocks in 1991 and 1459 stocks in 2004.[6] For the time-series regression analysis in this study, a sample period from January 1991 to December 2004 was chosen in order to minimize any bias that may arise from the small number of stocks in the early sample period.

1.3.2. Market Liquidity

In a manner that is consistent with Amihud (2002) and Pastor and Stambaugh (2003), market liquidity is defined as the average of an individual stock's liquidity. The first two rows of Table 1.1 display the value and equally weighted Amihud's liquidity measure. The value-weighted Amihud's liquidity measure suggests that

[6] The number of stocks used to calculate liquidity measures and factors are displayed in the last row of Table 1.1.

the most illiquid year is 2001, which corresponds with September 11th; while 1998 is the second lowest liquidity period, which corresponds with the Russian Crisis.[7] The equally weighted Amihud's illiquidity also shows similar patterns; however, it has more weight in small stocks, and thus is more volatile. It is not surprising that the level of liquidity of small stocks changes more than that of large stocks. Figure 1.1 clearly shows that the liquidity measures are associated with market crashes; for instance, the 1997 Asian financial crisis, the 1998 Russian default, September 11th in 2001 etc.

The third row of Table 1.1 is the relative liquidity measure (adjusted by stocks' market values), described in section 1.2. Figure 1.2 plots the relative liquidity measure. While the correlation between this relative measure and the value (equally)-weighted Amihud's measure is significant, i.e., 0.29 (0.25), it is interesting to note that there is a significant difference between Amihud's absolute liquidity measure and the new relative measure. The new relative measure is much smoother and less volatile than Amihud's measure. Extreme outliers in Figure 1.1 are now apparently reduced according to this new liquidity measure. With the new measure, it is clear that the most illiquid year is 1998, when market liquidity is widely perceived to have dried up because of the LTCM collapse and Russian default.[8] The next illiquid period is the Asian financial crisis of 1997 and September 11th in 2001. By contrast, the most liquid period is during the recent bull market. Amihud (2002) shows that liquidity displays persistence; and, indeed, the new measure has first- and second-order autocorrelations of 0.83 and 0.72, which are both significant at the 1% level.

[7] By contrast, the most liquid year is 1989; however, the high liquidity in the early sample period is likely due to a result of the sample selection bias in the early sample period.

[8] Pastor and Stambaugh (2003), who use the US data and their proposed price-reversal liquidity measure, identify that the US stock market experienced the third largest liquidity drop in 1998. Within the same time span, however, this study shows results consistent with theirs.

1.3.3. Different Portfolio Strategies in the UK

Previous work shows that average stock returns are related to firm characteristics like size and book-to-market equity. In this section, the cross-sectional stock returns related to size, book-to-market equity and liquidity in the UK are examined. The results are compared to the US as in Fama and French (1993), and the previous work on the UK market in DNQ (2003).

1.3.3.1. Size-Sorted Portfolios

As described in the previous section, the 10 decile portfolios are formed based on size (market equity). Panel A of Table 1.2 shows the statistical properties of the 10 decile portfolios. Contrary to the findings of Banz (1981) and Fama and French (1993), where evidence is found that small firms outperform big firms, it is interesting to see that big firms perform better than small firms in the UK equity market. (There is a 5.7% annual difference in the portfolio returns between the largest and smallest decile portfolios, i.e. S-B_d.)

The largest 10% of stocks represent, on average, 81% of the total market capitalization (the largest 20% of stocks account for over 90% of the total market capitalization). During the same period in the US market, the largest 20% of stocks account for about 80% of the total market capitalization.[9] This suggests a more skewed distribution of large stocks in the UK stock market.

Next, the mimicking size factor (*SMB*) for the UK stock market was calculated. The statistical properties of the *SMB* are reported in the last column of Table 1.2, Panel A. Over this period, the *SMB* has a negative average monthly return of 0.35% (which is equal to an annual negative average return of 4.08%) with a standard deviation of 2.7%. The results for the UK market are consistent with the findings of DNQ (2003) where, although the data in their research is only up to 2001, the correlation of their monthly *SMB* and this study's is nearly 92%.

[9] The US data over this period is from Professor Kenneth French's website.

By contrast, the *SMB* is positive with an average monthly return of 0.2% in the US over this period. Nevertheless, the trends for the *SMB* in the UK and the US are very similar, as shown by Figure 1.3. Indeed, the annual (monthly) *SMB* between the UK and the US has a correlation of 0.70 (0.33). Panel B of Table 1.2 compares the statistical properties of monthly *SMB* in the UK and the US. The t-tests with regard to a zero mean for the *SMB* suggest that both the UK and the US *SMBs* are not different from zero. Ang and Chen (2005) and Dimson and Marsh (1999) also document the disappearance of the size effect in the US and the UK, respectively.

1.3.3.2. Book-to-Market Sorted Portfolios

Panel A of Table 1.3 reports the summary statistics for the 10 decile book-to-market portfolios. The annual return difference between the high and low book-to-market portfolios (H-L_D) is over 10%.[10] Consistent with Fama and French (1998) and DNQ (2003), there is strong evidence of the existence of the book-to-market premium. The first row of the table also shows that small stocks are usually distributed in the high book-to-market category. For example, half of the highest book-to-market stocks only account for 20% of the total market capitalization. These results are consistent with the finding of Fama and French (1993) and DNQ (2003).

The mimicking value/growth factor (*HML*) is reported in the last column of Table 1.3, Panel A. With a standard deviation of 2.5%, the monthly *HML* has a return of 0.32% (which equals an annual rate of 3.9%). In the US, these numbers are larger. (The annual *HML* is 4.9%, with a standard deviation of 3.4%.) There is again a similar trend in the *HML* during the same period in the US and the UK, which can be seen from Figure 1.4. Panel B of Table 1.3 reports the statistical comparison of the monthly *HML* in the UK and the US. The zero-mean tests suggest that both of them are significantly different from zero.

[10] Fama and French (1998) find that there is a value premium of 4.62%. This is because they use a very small sample for the UK market: on average, only 185 stocks are examined.

1.3.3.3. Liquidity-Sorted Portfolios

Based on the liquidity measure of Amihud (2002), 10 decile liquidity portfolios are formed and summarized in Panel A of Table 1.4. The risk–return relationship suggests that illiquid stocks should earn higher expected returns than liquid stocks, because investors should be compensated for bearing the illiquidity risk. However, Table 1.4 indicates that this is not the case in the UK equity market. On average, the highly illiquid 30% of the stocks display a negative annual return from 1988 to 2004. The most illiquid-decile equity group in the UK even experience a -13.7% annual loss. In contrast, the most liquid-decile stocks show an annual return of nearly 9%, which results in an annual return spread of over 22% between the liquid and illiquid stocks (ILLIQ-LIQ_D).

The three most illiquid portfolios include many small stocks, where the total market value of these portfolios is only 2.59% relative to the whole market. As liquidity increases, so does the size of the firms, where the most liquid 10% of the stocks account for over 72% of the total market capitalization. As expected, Amihud's liquidity measure is affected by the size of firms, where large firms' stocks are more liquid than those of small firms. From Panel A of Table 1.2, it can be seen that that big stocks have an average annual return of 7.05%, which is very similar to the return for the liquid stocks. By contrast, because the illiquid stocks (usually small) show negative returns, it can be inferred that small stocks with low liquidities perform poorly.

While Amihud's liquidity measure is apparently highly correlated with size,[11] the relative liquidity measure from the present research should not be so correlated. Summary statistics of the ten portfolios made upon the relative liquidity measure are presented in Panel B of Table 1.4. The first row reports the percentage of each liquidity-deciles' market capitalization to the total market capitalization. Although this time the most liquid stock group shows a smaller

[11] In Panel A of Table 5, it can be seen that the correlation between the liquidity mimicking factor based on Amihud's measure and the *SMB* is 75%.

weight than other groups, the remaining nine deciles are much more evenly distributed in terms of size. Therefore, small stocks are illiquid in absolute measure: they could be as liquid as, or more liquid than, larger stocks according to our relative measure.

However, the return spread (ILLIQ-LIQ_D) based on this relative liquidity measure is still large (almost 18% annually), although it is smaller than that based on Amihud's measure. The standard deviation of the most liquid portfolio of the relative liquidity measure is larger than that of Amihud's measure. This could arise because liquid stocks based on Amihud's measure are usually large, and their returns less volatile.

The correlation matrix of monthly observations between the *RM* (market return), *SMB*, *HML* and the two liquidity mimicking factors is displayed in Panel A of Table 1.5. The mimicking liquidity factor based on the relative liquidity measure of the present research barely shows any relationship with that based on Amihud's measure, and also a very low correlation with *SMB* and *RM*. Amihud's measure is, however, highly correlated with size. There is almost no relationship between the *SMB* and the *HML* in the UK, a result similar to the US (Fama and French, 1993). Panel B describes the statistical properties of these factors. Because liquid and big stocks display excess returns over illiquid and small stocks in the UK, this causes the mimicking liquidity factor (*LIQ*) and size factor (*SMB*) to display negative values. The last row of Panel B reports the Sharpe Ratios of various factors. *LIQ* and *LIQ_AMIHUD* produce the largest absolute Sharpe Ratios, which implies that investors may be significantly rewarded for perusing liquidity strategies; specifically, buying liquid and selling illiquid stocks. Trading long big and short small also tends to be a good investment strategy in the UK stock market, as it has the third largest Sharpe Ratio.

1.3.4. Liquidity Effects in Explaining Cross-Sectional Returns

From the previous section, it can be seen that average returns are closely related to stock characteristics such as size, book-to-market and liquidity. In this section, the cross-sectional effect of liquidity on stock returns is examined.

The statistical properties of different hedge portfolios are reported in Panel A of Table 1.6. It is evident that the strategy of small minus big displays negative average returns regardless of breakpoints. However, the t-tests suggest that these negative values are not statistically significant. The book-to-market strategy, by contrast, shows a significantly positive average return whatever breakpoint is employed. Liquid stocks have significant excess returns over illiquid stocks as highlighted by the right panel of the table.

Panel B of Table 1.6 reports the results of the CAPM on different hedge portfolios related to size, book-to-market and liquidity. Although the size premium is not different from zero as shown in Panel A, the CAPM can still further reduce the magnitude. For example, the average return for the S-B_D (the return difference between the smallest and biggest decile portfolios) is reduced from -0.3% to -0.1% after being adjusted by the excess market return. By contrast, the significance of value and liquidity premiums remains in the presence of a market portfolio.

Table 1.7 describes the effect of liquidity on the size and book-to-market strategies. Although the CAPM is efficient in explaining the return regularities associated with size, as shown in Table 1.6, it is still of interest to note that factor loadings on liquidity are all significant at the 95% confidence level in the left panel of Table 1.7. This evidence implies that the liquidity risk partly explains the excess return of big over small stocks; and the connection between size and liquidity is robust in the presence of a market factor. The right panel of Table 1.7 shows that all the factor loadings on liquidity are statistically significant at the 99% confidence level, which suggests that liquidity plays a significant role in describing the observed value anomaly. In this liquidity-augmented CAPM, all three book-to-market strategies show insignificant intercepts. Compared with the results in Panel B of Table 1.6, the magnitude of intercepts is dramatically reduced in this liquidity-augmented model, which illustrates the success of the liquidity factor in explaining value anomalies.

Fama and French (1995) argue that the *HML* is a suitable proxy for relative financial distress risk. Saretto (2004) provides empirical evidence that *HML* can be interpreted as a distress factor. Chen and Zhang (1998) also demonstrate that the high returns from value stocks compensate for the high risks induced by characteristics such as financial distress, earnings uncertainty or financial leverage.

A seminal work by Agarwal and Taffler (2005) uses a z-score as a proxy for distress risk, and shows that momentum is largely subsumed by their distress risk factor. This study investigates whether the role of liquidity in explaining the value premium is not subsumed by their distress factor. The distress risk factor is calculated using the same method described by Agarwal and Taffler (2005).[12] The correlation in the present research between the liquidity factor (LIQ_t) and the distress factor is -0.09. The financial distress factor cannot explain the value premium in the UK market. Panel A of Table 1.8 describes a distress-factor-augmented CAPM, where it is clear that the CAPM intercepts remain significant and the factor loadings on the distress factor are all insignificantly different from zero. In Panel B, when the distress factor is included in the liquidity-augmented CAPM, the relation between liquidity and value premium continues to be significant.

The possible explanation for the close relationship between liquidity and value premium can be found in Campbell, Grossman and Wang (1993), where they present a model in which trading volume is a suitable proxy for the aggregate demand of liquidity trading. In addition, the empirical work of Lee and Swaminathan (2000) demonstrates that low (high) volume stocks display many

[12] The generous provision of the UK financial distress factor by Vineet Agarwal is gratefully acknowledged.

characteristics commonly associated with value (growth) stocks. Therefore, the return spread between value and growth could contain the difference in the liquidity risk inherited by them. Thus, liquidity could help to explain this value premium.

1.3.5. Robustness of Liquidity Effects

In this section, it is first demonstrated that variations in liquidity provide an explanation for variations in the value premium in the UK, and are robust with respect to a variety of macroeconomic variables. Second, it is argued that the liquidity factor in the present research is robust in the sense that the cross-sectional return difference related to liquidity is unable to be explained by other well-known factors, such as *SMB*, *HML* and momentum.

Zhang (2005) proposes that the value premium is linked to macroeconomic conditions. He explains that value firms are burdened with more unproductive capital when the economy is bad, and find it more difficult to reduce their capital stock than growth firms do. The dividends and returns of value stocks will hence covary more with economic downturns. We demonstrate that the ability of liquidity in explaining the value premium is robust in the presence of specific macroeconomic variables,[13] such as industrial production, CPI, money supply, term spread (i.e., yield difference between ten-year government bond and one-month T-bill) and corporate spread (i.e., the yield difference between BBB and AAA bonds). Such results are displayed in Table 1.9.

Table 1.10 suggests that the liquidity premium remains pronounced in different models, such as the CAPM, the Fama and French model, the Fama and French model augmented with a distress factor and the Fama and French model augmented with a momentum factor (winners minus losers).[14]

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[13] The data for these macroeconomic variables are from the OECD. Refer to Table 1.9 for details.
[14] The case of decile breakpoints are reported only to simplify the presentation. However, the results are similar regardless of different strategies such as ILLIQ-LIQ_q or ILLIQ-LIQ_p.

In short, the finding that the value premium is related to liquidity is robust in the presence of a number of macroeconomic variables. The premium of liquid over illiquid stocks is robust even after being adjusted by *SMB*, *HML* distress and momentum factors.

1.4. Conclusions

In this study, it is found that the UK small stocks, on average, display a poor performance compared with big stocks in the last two decades. The US data, however, shows a slight positive *SMB* over the same period, but the t-test conducted illustrates that *SMB* is statistically indifferent from zero. Similar results can also be found in Dimson and Marsh (1999) and Ang and Chen (2005). Consistent with the majority of the literature on the value premium, there is a statistically significant value premium in the UK stock market. The return spread between high and low book-to-market decile portfolios (HML_d) is over 10% annually. This *HML* is also pronounced and comparable with the US results.

Amihud's absolute liquidity measure is compared with the relative liquidity measure in this study. According to Amihud's measure, small stocks are illiquid where illiquid stocks, on average, show negative returns over time, and liquid stocks have high positive expected returns. The return difference between liquid and illiquid is over 22% annually; however, as expected, Amihud's measure is highly correlated with stock size. The relative liquidity measure in the present research produces little correlation with stock size and any other pervasive risk factors. Nevertheless, the return spread between liquid and illiquid decile portfolios is still striking: 18% annually.

Cross-sectional analysis shows that there is no size anomaly in the UK from 1991 to 2004. There is, however, a pronounced value anomaly within this period. The CAPM fails to explain this return difference. A liquidity-augmented CAPM can successfully explain the observed value anomaly.

Finally, the ability of liquidity to explain the value premium is robust with respect to the financial distress factor and a number of macroeconomic variables. The liquidity premium of liquid over illiquid stocks is statistically significant even after being adjusted by the *SMB*, *HML*, *distress* and *momentum factors*. Some natural questions arise: what are the underlying risk factors that are responsible for this pronounced liquidity premium? Is liquidity a more important common risk factor? Is there any connection between liquidity and beta? An unreported result shows that the betas of the most liquid and illiquid decile portfolios are 1.36 and 0.90, respectively, and the Wald test rejects the equality of these two betas.

The interaction between liquidity and other stock characteristics remains an unexplored area in empirical finance. In modern finance, some of the observed return irregularities cannot be explained by the rational asset pricing model, for example, the short-term momentum, the cross-sectional difference related to volatility, etc. This could be the result of the flaws in the models themselves. The success of variations in liquidity in explaining the value anomaly in this study gives much momentum to pursue further research in this area.

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2. Do Illiquid Stocks Really Have Higher Betas?

2.1. Introduction

Liquidity in the financial markets has been one of the critical issues in both practice and academia. It is well-documented in the literature that liquidity impacts expected returns. There have been an increasing number of studies on cross-sectional return and liquidity, such as Amihud and Mendelson (1986, 1989), Eleswarapu and Reinganum (1993), Amihud (2002), Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) among others. Although it is generally accepted that illiquid stocks tend to be small and it would not be surprising to see the high correlation of size and liquidity, Brennan and Subrahmanyam (1996) show that there is a statistically significant positive relationship between expected stock returns and illiquidity, even after taking Fama-French risk factors into account. Additionally, Chordia, Subrahmanyam and Anshuman (2001) argue that liquidity does need to be accounted for individually, after controlling for size, book-to-market and momentum.

In the traditional CAPM framework, these empirical findings imply that betas increase as illiquidity increases. Betas increase as liquidity decreases and thus illiquidity stocks have higher expected returns than liquid stocks. However the link between liquidity and return is not straightforward. Suppose, for example, that there are two stocks in the market which are identical except for their liquidity: one is liquid and another is illiquid. When market moves at the arrival of new information, the price of the liquid stock would change correspondingly to its beta. For the illiquid stock, however, the price may not move as predicted by its beta due to its illiquidity. The return of this illiquid stock may move more or less than its beta implies, and thus betas estimated using ex post returns are noisy.

In this study, the impact of liquidity on beta is examined. Despite the existence of many studies on the relationship between asset return and liquidity, little research on the interaction between betas and liquidity has been conducted. A closely related study has been undertaken by Acharya and Pedersen (2005). They explicitly present an equilibrium asset pricing model with liquidity risk. By applying the CAPM for returns net of illiquidity costs, they decompose beta into four components: standard market beta and three betas representing different forms of liquidity risk. However, their empirical evidence is not strong in showing that liquidity risk is important in addition to the market risk.

The present study makes several contributions. Evidence is provided that the illiquidity measure of Amihud (2002) is problematic given its high correlation with size. Considering the strong relationship between size and betas (see, for example, Fama and French, 1992), the effects of liquidity on returns in the literature could be affected by size. In order to overcome the high correlation between size and liquidity, the relative illiquidity measure documented in Chapter One, a modified version of Amihud's illiquidity measure, is used. It is found that liquid stocks have higher betas than illiquid stocks. To test the robustness of these results, a two-dimensional size/liquidity sorting procedure is conducted using both Amihud's measure and the present study's relative liquidity measure, obtaining the same results.

Although illiquidity is expected to affect betas, it is the sign between betas and liquidity that is surprising. Following Holden and Subrahmanyam (1996), it is suggested that investors' trading behaviours are responsible for this phenomenon. Risk-averse investors would trade the high beta stocks more frequently than the low beta stocks, which results in the more liquidity of the risky (high beta) assets. It is this mechanism that produces a positive link between beta and liquidity.

Despite the existence of the negative association between illiquidity and beta, the positive relationship between illiquidity and returns still holds. Contrary to the results of Acharya and Pedersen (2005), who claim that liquidity is priced within the CAPM framework, the results of the present study suggest that illiquidity plays an important role in cross-sectional asset pricing. The effect of liquidity on return is, however, *not* through beta as in the CAPM; instead, it should be treated as an additional factor, as in Brennan and Subrahmanyam (1996), Pastor and Stambaugh (2003) and others.

This paper is organised as follows. In the next section the relationship between beta and liquidity in the CAPM framework is discussed. In section 2.3 the inter-relationship among beta, size and liquidity is investigated, and the implications of the results discussed. The last section concludes.

2.2. Liquidity and Beta in the CAPM Framework

2.2.1. The Relationship between Liquidity and Beta in the CAPM Framework

When the market is not liquid in the conventional CAPM, assets are not appropriately priced by their betas. Following Acharya and Pedersen (2005), this study also assumes a CAPM in net returns in the economy where market is frictionless. Excess return of asset i is generated by:

$$E(r^*_{i,t}) = \beta^*_i E(r^*_{m,t}), \qquad \textbf{(1)}$$

where $r^*_{m,t}$ is the excess market return, β^*_i is the true beta, and *E(.)* denotes time-series expectation (and hereafter). The asterisk denotes that all the variables are in the imagined frictionless (or perfectly liquid) economy. The CAPM in the presence of illiquidity can be express as:

$$E(r_{i,t}) = \beta_i E(r_{m,t}), \qquad \textbf{(2)}$$

where

$$r_{i,t} = r^*_{i,t} + \delta_{i,t}\,, \qquad \textbf{(3)}$$

and $\delta_{i,t}$ represents noise due to the different liquidity levels of asset i.

It is important to understand the properties of $\delta_{i,t}$. The expected value of the noise is zero; $E(\delta_{i,t}) = 0$ or the long run average value of the noise is zero. If not, the price difference between the liquid and illiquid assets increases over time, which is then expected to be arbitraged away once the price difference becomes large enough to compensate for illiquidity risks. Second, an important difference between the proposed model and Acharya and Pedersen (2005) is that market illiquidity is not modelled. This is not because the market is always liquid, but in this study it is assumed that the illiquidity noise $\delta_{i,t}$ is measured relatively to the market. One such example in empirical studies is that a stock market index is used as the market portfolio, and individual stocks or stock portfolios are investigated with respect to the market portfolio. When illiquidity premium (risk) is measured, it is the individual stocks' illiquidity relative to the market that matters, not the illiquidity of the entire stock market. Thus it is assumed that $E_c(\delta_{i,t}) = 0$ at time *t*, where $E_c(.)$ represents cross-sectional expectation.

With the assumptions it can be easily shown that

$$\begin{aligned} \beta_i &= \frac{\operatorname{cov}(r_{i,t}, r_{m,t})}{\operatorname{var}(r_{m,t})} \\ &= \frac{\operatorname{cov}[(r^*_{i,t} + \delta_{i,t}), r_{m,t}]}{\operatorname{var}(r_{m,t})} \\ &= \frac{\operatorname{cov}(r^*_{i,t}, r_{m,t}) + \operatorname{cov}(\delta_{i,t}, r_{m,t})}{\operatorname{var}(r_{m,t})} \qquad \textbf{(4)} \\ &= \beta^*_i + \Delta_i, \end{aligned}$$

where $\Delta_i = \dfrac{\operatorname{cov}(\delta_{i,t}, r_{m,t})}{\operatorname{var}(r_{m,t})}$. Note that when the cross-sectional probability measure is proportional to the market capitalization, the cross-sectional expectation of betas are one, i.e., $E_c(\beta_i) = E_c(\beta_i^*) = 1$. This would further imply that $E_c(\Delta_i) = 0$ which is consistent with an assumption of $E_c(\delta_{i,t}) = 0$.

Now suppose that there are two assets in the market that are identical except for their liquidity: one is liquid and another is illiquid. For the liquid asset, its observed beta would be unbiased because $\delta_{i,t} = 0$. The illiquid asset, on the other hand, would have a biased beta. Since $E_c(\Delta_i) = 0$ as long as the cross-sectional probability measure matches its weight within the market portfolio, the impact of illiquidity would appear differently for different assets; some may be downward biased, others may be upward biased, but the cross-sectional expectation of the biases should be zero. It is interesting to see that an upward bias in beta happens when the illiquidity noise is positively related with the market return while beta is downward biased when the illiquidity noise is negatively related with the market return. When market goes up (or down), individual assets move higher (or lower) than their betas suggest because of illiquidity, and higher betas are observed for these assets. On the other hand when market goes up (or down), individual assets move lower (or higher) than their betas suggest because of illiquidity, and biased (lower) betas are observed for these assets.

This simple analysis suggests that the link between liquidity and returns, i.e., illiquidity increases beta which in turn increases expected return, may not necessarily hold. Therefore, our hypothesis is that observed beta, β_i, could be negatively or positively related to the illiquidity, and thus there is no clear relationship between illiquidity and beta. The present empirical investigation would reveal whether illiquidity is priced through beta, or whether illiquidity is priced as an additional factor.

2.2.2. Illiquidity Measures

To investigate the relationship between beta and liquidity, a suitable liquidity measure needs to be chosen. Following up the discussion in Chapter One, Amihud's illiquidity measure and the relative illiquidity measure proposed in the first chapter are chosen. Amihud's illiquidity measure for stock i is defined as:

$$\gamma_{i,y} = \frac{1}{D_{i,y}} \sum_{d=1}^{D_{i,y}} \frac{|r_{i,y,d}|}{v_{i,y,d}} \tag{5}$$

where: $D_{i,y}$ is the number of days for which data are available for stock i in year *y*, $r_{i,y,d}$ is the return on stock i on day d of year *y*, and $v_{i,y,d}$ is the dollar trading volume for stock i on day d of year *y*.

And the relative illiquidity measure ($\psi_{i,y}$) for stock i is defined as:

$$\psi_{i,y} = \frac{1}{D_{i,y}} \sum_{d=1}^{D_{i,y}} \ln \frac{|r_{i,y,d}|}{Turnover_{i,y,d}} \tag{6}$$

where $Turnover_{i,y,d}$ is the turnover rate for stock i on day d of year *y*.[15]

2.3. Empirical Results

2.3.1. Data and Calculation of Liquidity Measures

The two illiquidity measures are calculated on December of each year. Twenty portfolios are then formed in December of year *t* using the illiquidity measures that are calculated with daily data of year *t*. Stocks are used that are traded on at least 200 days and at values of greater than 5 dollars in a year, as in

[15] The negative sign is not included in the liquidity proxies as in Chapter One because the main focus of this chapter is to examine the relation between illiquidity and beta.

Amihud (2002).[16] As in Fama and French (1992), all non-financial firms in the NYSE and AMEX which have return files in CRSP are used;[17] and NASDAQ stocks are not included because the volume data includes inter-dealer trades (Atkins and Dyl, 1997, Acharya and Pedersen, 2005 and others). The number of stocks each year ranges from 1069 (in 1962) to 2430 (in 2005) over this sample period.

For each of these portfolios equally weighted annual returns are calculated for year *t+1* (henceforth 'post-formation' returns). Using equal-weighted portfolio returns is consistent with Amihud (2002) and Acharya and Pedersen (2005), because it is a way of compensating for the over-representation of large liquid stocks that exist in the sample. The process is repeated from December 1962 to December 2004 and 43 post-formation annual returns from 1963 to 2005 are obtained for each portfolio. Betas are re-estimated by regressing the post-formation returns on CRSP value weighted portfolio returns. Following Kothari, Shanken, and Sloan (1995), annual returns are used rather than monthly returns since betas estimated with higher frequency returns are likely to be biased due to trading frictions and non-synchronous trading, or other phenomena including systematic cross-temporal covariances in short-interval returns.

2.3.2. Returns, Beta and Liquidity

Table 2.1 records the properties of the portfolios ranked on the two illiquidity measures. Panel A displays the results of Amihud's illiquidity measure[18]. The most illiquid portfolio (portfolio 20) has an annual return of over 18 percent in excess of the most liquid portfolio (portfolio 1). The panel also shows that Amihud's illiquidity measure is closely associated with other characteristics;

[16] Amihud (2002) argues that these selection criteria make the liquidity estimation more reliable.
[17] Both Amihud (2002) and Acharya and Pedersen (2005) have the same sample selection as the current study. All firms including financials have also been used, but the results are not different from what is reported in this study.
[18] We take the natural logarithm of Amihud's measure because the measure shows a strong nonlinear relationship with other firm characteristics reported in this study. The nonlinearity could cause complicated econometric problems since most asset pricing models are linear. Nevertheless, the results from using ln(Amihud) and Amihud are not different. In this study, we report the results in logarithms (Amihud).

liquid stocks have high absolute dollar trading volume and price level, but have low turnovers. In particular, as expected, illiquid stocks are much smaller than liquid stocks.

The relative illiquidity measure, described in Panel B, in contrast, does not necessarily have similar properties. First of all, while the relationships between liquidity and dollar trading volume and price still hold, they are much weaker than those in panel A. For example, the average price level for the most liquid (illiquid) stocks is 34.10 (23.93) dollars as opposed to 59.45 (10.99) dollars of Amihud's illiquidity measure. Secondly, as argued in Chapter One, although one of the advantages of the relative illiquidity measure proposed in this study is to measure liquidity free from size, there is still some evidence that illiquid stocks tend to be small. Nevertheless, the relationship between the relative measure and size becomes less pronounced than that in panel A. For instance, the difference in the average logarithm of market capitalization between the most and least liquid stocks is 1.76 from the relative measure, while it is 6.57 from Amihud's measure. Thirdly, the relative measure shows that the most liquid stocks have the highest trading activities as reflected in their turnover.

The most interesting observation is that the relationships between betas and liquidity are not the same between these two illiquidity measures. The relative measure shows a strong negative relationship between betas and liquidity, while Amihud's measure does not. Acharya and Pedersen (2005) modify Amihud's measure and provide empirical evidence that their 'net' market beta is increasing with illiquidity. This study, however, has different results: after the size effect is taken out, there is a significant negative association between beta and illiquidity. This is somewhat surprising, because it suggests that illiquid stocks have lower systematic risk (betas) and therefore, investors holding the illiquid securities would not be compensated with higher expected returns under the CAPM framework.

2.3.2. Does Illiquidity Increase Betas?

The difference between the two illiquidity measures lies in how size is treated. The problem with Amihud's measure is that the measure is highly related to size, which in turn is related to betas (Fama and French, 1992). Therefore, the size effect needs to be separated from illiquidity measures. In this section, the inter-relationship among different stock characteristics is further investigated by forming two-dimensional size/liquidity portfolios. Cross-sectional regression analysis is also used to examine the link between beta and liquidity.

2.3.2.1. Two-dimension Size/Liquidity Portfolios

An alternative method to reduce the effects of size on liquidity is to form two-dimensional portfolios using size and liquidity. At the end of each year, all available non-financial stocks are first ranked into 10 size-decile portfolios, each of which are further divided into 10 decile portfolios using the two illiquidity measures. Portfolios are equally-weighted, and annually rebalanced. One of the benefits of using this two-way sorting method is that it enables the investigation of the inter-relations between liquidity, return and beta free from size effect. Table 2.2 presents the portfolios' post-formation betas and holding periods' time-series averages of annual returns, logarithms of market capitalization and turnover. Panels A and B report the results based on Amihud's measure and relative measure, respectively.

Fama and French (1992, 1993) show that the post-formation returns of small stocks are higher than those of big stocks. Similar results are portrayed in Table 2.2, where the return difference between small and big (*Small-Big*) is reported in the second to the last column. Moreover, *Small-Big* increases with illiquidity: from 7% to 26% in terms of Amihud's measure, and from 10% to 19% in terms of our relative liquidity measure.

The illiquidity premium, i.e., the return difference between the most illiquid and liquid portfolio, *ILLIQ-LIQ*, monotonically decreases with size. For instance, in terms of Amihud's measure, *ILLIQ-LIQ* remains significant from 15% for the smallest portfolio and declines to 6% the middle-size portfolio, and then becomes insignificantly different from zero for large portfolios (Panel A of Table 2.2). The relative liquidity measure also has similar patterns. However, both panels A and B suggest that the illiquidity premium only exists within the small stocks.

The magnitude of *ILLIQ-LIQ* for the smallest portfolio is 15% in terms of Amihud's measure, which is nearly twice as much as that in terms of the relative illiquidity measure. This could be the result of the strong correlation between Amihud's measure and size. For example, panel A of Table 2.2 shows that in the smallest size-decile the logarithmic values of the market capitalization decreases from 10.44 to 9.61 as portfolios become more illiquid. Similar relationships between size and Amihud's measure can be found in other size deciles. Therefore, the relationship between Amihud's liquidity measure and size is too strong to be removed even after the two dimensional portfolio sorting procedure. Although there is no clear association between beta and the illiquidity measure of Amihud in Panel A of Table 2.1, it becomes clearer that liquidity is positively linked to beta in this two-dimensional sorting procedure. As reflected in the upper Panel A of Table 2.2, when the size effect is controlled, it is observed that liquid stocks have higher betas than illiquid stocks in 9 out of 10 size-deciles. More importantly, beta increases almost monotonically with liquidity.

The relative illiquidity measure, presented in Panel B of Table 2.2, displays a similar result to that of Amihud's measure in this two-path sorting procedure. Furthermore, the advantage of this relative liquidity proxy is reflected in the lower part of Panel B, where liquidity is not related to size within in each size-decile. Thus the size effect on liquidity disappears by using the relative illiquidity measure and the two dimensional portfolios; on the other hand, we note that betas increase with liquidity.

In short, after size is controlled, a consistent relation is observed between beta and liquidity in terms of both the illiquidity proxies: liquid stocks have significantly higher betas than illiquid stocks.

2.3.2.2. Cross-sectional Regression Analysis

The results with the two-dimensional portfolios formed on size and liquidity suggest that liquidity, size and beta are highly correlated. Further investigation is undertaken to ascertain if beta is explained by liquidity in the presence of size in the following cross-sectional regression.

$$\beta_p = \Phi_{1t} + \Phi_{2t} ILLIQ_{pt-1} + \Phi_{3t} \ln(Size)_{pt-1} + \varepsilon_{p,t} \quad \textbf{(7)}$$

where β_p is the post-formation beta for portfolio *p*. $ILLIQ_{pt-1}$ and $\ln(Size)_{pt-1}$ are the illiquidity level and natural logarithm of the market capitalization for portfolio *p* at the end of year *t-1*. The test assets are 20 and 100 liquidity portfolios, and 25 and 100 two-dimensional portfolios formed on size and liquidity. If liquidity is not related to systematic risk, then Φ_{2t} should not be statistically significant. Table 2.3 presents the results from using Fama and MacBeth (1973) cross-sectional regression.

In Panel A where Amihud's measure is used, the estimates for different portfolios are inconsistent. The signs from one-dimensional portfolios are not the same as those with two dimensional portfolios, and the signs of Φ_{2t} with 20 liquidity ranked portfolios are opposite to those with 100 liquidity ranked portfolios. The relative measure in Panel B, on the other hand, produces consistent estimations for different portfolios: in particular the coefficients on the illiquidity measure are always significant and negative. Recall that the larger value of $ILLIQ_{pt-1}$ implies the more illiquid this portfolio, and therefore the negative sign suggests that the liquid stock has higher betas than the illiquid stocks.

To sum up, the regression results confirm the findings in the previous section: liquidity is positively linked to beta when the size effect is considered.

2.3.3. Does Illiquidity Increase Returns?

In this section we re-investigate the cross-sectional relationship between illiquidity and return in the presence of the size effect. In the previous section we show that illiquidity (liquidity) has a negative (positive) relationship with betas. This negative association implies that illiquid stocks should display lower returns than liquid stocks in the CAPM framework.

In order to investigate if illiquid stocks do have lower returns, we use the Fama-MacBeth cross-sectional regression;

$$r_{pt} = \Phi_{1t} + \Phi_{2t}\beta_{pt} + \Phi_{3t} ILLIQ_{pt-1} + \Phi_{4t}\ln(Size)_{pt-1} + \varepsilon_{p,t} \quad \textbf{(8)}$$

The results in Table 2.4 confirm those of the previous studies, such as Brennan and Subrahmanyam (1996) and Amihud (2002). Φ_{3t} is always significantly positive, which implies that illiquid stocks show higher returns. The results, however, are not expected in the CAPM framework. The inter-link among illiquidity, beta, and returns is not supported.

The result is interpreted as follows. The CAPM, where only beta explains returns, does not explain why illiquid stocks whose betas are lower than liquid stocks have higher returns. Therefore the attempt to explain illiquidity in the CAPM framework (Acharya and Pedersen, 2005) is not supported by the evidence of this study. That illiquid stocks have lower betas but still show higher returns, implies that liquidity might be an additional risk factor as in Pastor and Stambaugh (2003). It is argued that the results of Acharya and Pedersen (2005) are affected by the size effect when Amihud’s measure is used.

2.4. Discussions and Conclusions

In this study, the focus is on the relation between beta and liquidity. One of the main purposes of this study is to reveal the impact of illiquidity on beta. Although Acharya and Pedersen (2005) show that illiquid stocks have high betas, this study however find opposite results. It is shown that the illiquidity measure of Amihud (2002) is not ideal given its high association with size. By either using a size/liquidity two-dimensional sorting procedure or using this study's relative liquidity proxy, it is shown that illiquidity is negatively related to beta.

The implications of the study's findings are summarised as follows. First, Amihud's measure appears to be popular in empirical studies, but caution should be exercised when this liquidity proxy is chosen given its high correlation with size, especially in investigating the cross-correlation between liquidity and other assets' characteristics. Second, after size is controlled, both Amihud's illiquidity measure and this study's size-free relative liquidity measure yield consistent results, e.g., illiquid stocks have lower systematic risk. This, together with the evidence that excess returns of illiquid stocks exist only within the small-stock family, naturally raises a couple of important questions: how is illiquidity priced? Or is liquidity at least pervasive? Even among small stocks this negative link between illiquidity and beta contradicts with the risk-return theory. This certainly suggests that illiquidity is not priced through betas.

Liquid stocks have higher betas than illiquid stocks, which seem odd at first glance given that people generally perceive illiquid stocks should have higher risk therefore higher beta. The results, nonetheless, are consistent with Pastor and Stambaugh (2003) who argue that investors require higher expected returns on assets whose returns have higher sensitivities to market-wide liquidity, i.e., high liquidity beta. They demonstrate that illiquid stocks tend to have high liquidity beta and low market beta. Secondly, our empirical results could be explained in terms of risk-averse investors' trading behaviour. The model of Holden and Subrahmanyam (1996) suggests that investors would focus exclusively on the short term if they are sufficiently risk averse. In their model, different information signals get reflected in price at different points in time, and the increase of liquidity, in equilibrium, causes a greater proportion of investors to focus on the short-term signal, which decreases the information-ness of prices about the long run. Therefore, risk-averse investors might disfavour holding risky (high beta) stocks so that they trade the risky stocks much more often than the low beta stocks. This is confirmed in Panel B of Table 2.1 where liquid stocks have high turnovers.

Last but not least, this empirical study shows that liquidity does affect returns, but not within the CAPM framework as suggested by Acharya and Pedersen (2005). Nevertheless the existence of cross-sectional return difference related to liquidity does imply that liquidity might be priced within a multifactor model as in Brennan and Subrahmanyam (1996) and Pastor and Stambaugh (2003).

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3. Too Many Factors! Do We Need Them All?

3.1. Introduction

Earlier tests on the CAPM show that alphas are positive and betas are not priced (see Black, Jensen, and Scholes, 1972; Blume and Friend, 1973; and Fama and MacBeth, 1973; among many others). Some researchers try to find answers to the failure of CAPM from different risk measures in the rational framework, for example, coskewness (Kraus and Litzenberger, 1976; and Harvey and Siddique, 2000) or downside beta (Harlow and Rao, 1989). Others show that firm characteristics such as size, book-to-market, and momentum explain cross-sectional asset returns (Banz, 1981; Fama and French, 1992, 1993 and 1996a; Jegadeesh and Titman, 1993; and Lakonishok, Shleifer and Vishny, 1994). The success of these firm characteristics has accelerated the efforts of academics and practitioners in search of new firm characteristics that produce a large cross-sectional return difference that is robust to well known existing factors, such as, the famous Fama-French three factors and momentum. These efforts have produced more than a dozen factors in both the finance and the accounting spectra, most of which can be replicated with data readily available.

When factors are constructed by taking long and short positions on firm characteristics or risk measures as in Fama and French (1993 and 1996a), they could capture the variation in cross-sectional asset returns. These factors (or subsets of these factors) are assumed to be proxies for the underlying risk factors or state variables that capture the stochastic opportunity set (Merton, 1973 and Ross, 1976). Fama and French (1996a) claim that their two firm characteristics based factors (i.e., size and book-to-market) are indeed the ones that 'mimic' combinations of underlying risk factors or state variables (page 57). However, the debate as to whether the two factors outlined by Fama and French (1996a) are risk factors continues. For example, Daniel and Titman (1997) suggest it is firm characteristics, i.e., size or book-to-market ratios, that appears to explain the cross-sectional variation in stocks returns rather than the characteristics being proxies for non-diversifiable risk.

The question addressed in this study is that the number of firm characteristics or risk measures that are claimed to be useful in cross-sectional asset pricing seems to be too large. Although the theory of multifactor models does not specify how many factors are needed to explain asset returns, the number certainly should not be large. Early empirical studies on multifactor models, such as Roll and Ross (1980), Lehmann and Modest (1988), Connor and Korajczyk (1988, 1993), among others, suggest three to six factors. Compared with these figures, the number of factors that have been introduced in the empirical studies is well above a dozen. This difference suggests that either many empirically identified firm characteristics are the result of data-snooping bias due to portfolio grouping and are thus redundant, or that the number of factors is truly larger than those suggested by the early studies on multifactor models in the 1980s.

In this study, among the many different factors that have been proposed in the literature, specific factors are identified to explain asset returns. These factors should be included in linear asset pricing models. The study, however, does not answer whether or not these factors are associated with risk. For example, the well-documented value premium could reflect investors' incorrect extrapolation of the past earnings growth of firms (Lakonishok, Shleifer and Vishny, 1994), the distress of firms (Fama and French, 1993 and 1995), or risk related to costly reversibility of value firms (Zhang, 2005). The focus in this study is to empirically identify the pervasive factors out of the many proposed factors, which could best explain asset returns.

For this purpose, a total number of eighteen factors that have been proposed in the literature, are tested:[19] eight are formed on non-risk firm characteristics, five on risk-related variables, and five are principal factors used in Connor and Korajczyk (1988, CK factors hereafter). The classification of the three groups is in line with MacKinlay (1995), and Brennan, Chordia and Subrahmanyam (1998). For instance, MacKinlay (1995) claims that risk-based factors are developed under the assumptions of investor rationality and perfect capital markets; while the non-risk based factors are stimulated by the biases in the empirical methodology. Analogously, Brennan, Chordia and Subrahmanyam (1998) empirically investigate the relation between stock returns and non-risk stock characteristics, such as book-to-market, size, and risk measures[20].

In order to avoid data-snooping bias in empirically testing asset pricing models, thousands of individual stocks were used without grouping. The conventional *F* test developed by Gibbons, Ross, and Shanken (1989) is not possible when the number of assets tested is larger than the number of time series observations; and hence, in this study we use the average *F* test proposed by Hwang and Satchell (2007). Hwang and Satchell (2007) show that the new test has more power than the conventional *F* test in a variety of situations, and that it is also robust with respect to leptokurtic data.

In time-series regression analysis, the performance of different sets of factors are investigated using 7 non-overlapping 5-year intervals starting from January 1972 to December 2006 to allow the time variation in linear factor models. Ultimately it is believed that the set of pervasive factors should explain asset returns equally well in different sample periods.

We find that a four-factor model (comprised of the market portfolio, coskewness, downside risk and liquidity) performs equally well to the famous Fama-French three factor model with momentum, which is widely used as a

[19] The factors considered (i.e., firm characteristics or risk measures) have been shown in major financial journals to have explanatory power with respect to cross-sectional asset returns. The study results show that the factors not tested in the study are not likely to change the conclusions.

[20] They classify the risk measures as betas or factor loadings, where benchmark factors are those in either Fama and French (1993) or Connor and Korajczyk (1988).

benchmark model in much empirical research. More importantly, the three factors, coskewness, downside risk, and liquidity are economically better motivated than the non-risk firm characteristics related factors such as the famous Fama-French factors (*SMB*, *HML*), momentum factor of Jegadeesh and Titman (1993) and others.

The results of the study have several implications for the asset pricing literature. First, many additional factors other than market return have been proposed due to the desire for a CAPM replacement, e.g., Fama-French factors and others. Since these factors are claimed to be successful in explaining cross-sectional returns, the return differences related to these factors are expected to disappear or at least decrease to some extent given the existence of institutional investors, hedge funds in particular. Among the factors examined in this study, many of them are found to be highly correlated with each other, and evidence is also provided that many of these factors are not pervasive when data sample are more updated than that are used in the original studies.

More importantly, some light is cast upon the controversy over empirical asset pricing models, where the debate centres on whether firm-specific attributes should be used to predict returns. For instance, Lakonishok, Shleifer and Vishny (1994) and Daniel and Titman (1997) argue that these variables may be used to find securities that are systematically mis-priced by the market. Others argue that these measures are proxies for underlying economic risk factors (Fama and French, 1993, 1995, and 1996a). There is also a third view that suggests the observed return-characteristics relations suffer from data-snooping biases (MacKinlay, 1995; and Chan, Jegadeesh and Lakonishok, 1995). By controlling the data-snooping biases, the results demonstrate that risk-related factors that are better motivated than the firm-specific attributes perform as well as firm-characteristics based factors in explaining individual stock returns.

The rest of the paper is organised as follows. In the next section, we describe the factors considered in this study. Section 3.2 discusses the potential drawbacks of the conventional asset pricing test and describes the study's test method, i.e., the average F test. In section 3.4, the data and empirical results are presented. The last section concludes.

3.2. Factor Specifications

Among the many firm-specific characteristics and risk measures (hereafter 'factors') that have been proposed in the literature, those that are widely cited in the literature have been selected. Other factors could be included, but as demonstrated in the tests, the factors other than those considered in the study do not seem to change the study conclusion. In this section the factors used in the study are divided into three groups and described.

3.2.1. Risk Related Factors

Five factors are identified that are economically better motivated than the other factors. First, market return is probably the most widely used factor in the literature. Despite little empirical evidence that supports the CAPM (see Black, Jensen, and Scholes, 1972; Blume and Friend, 1973; and Fama and MacBeth, 1973; among others), in particular, in the presence of size (Fama and French, 1992 and 1996b), the excess market return is still considered to be one of the most important factors in testing asset pricing theory. Fama and French (1996a) argue that the excess market return is required for the positive equity premium although it does not explain cross-sectional average returns.

Second, it is difficult to rationally object that liquidity matters in asset pricing (see Amihud and Mendelson, 1986). Brennan and Subrahmanyam (1996) show that there is a statistically significant positive relationship between expected returns and illiquidity, even after taking the Fama-French three factors into account. Additionally, Chordia, Subrahmanyam and Anshuman (2001) argue that liquidity does need to be accounted for individually, after controlling for size, book-to-market and momentum. Pastor and Stambaugh (2003) further demonstrate that half of the profits from a momentum strategy are attributable to the liquidity risk.

Three more factors are then included that are closely related to the distribution of asset returns. When asset returns are not normal and investors' utility functions are not quadratic, asymmetry or fat-tails are priced. In particular, when investors have a decreasing marginal utility of wealth and decreasing absolute risk aversion, as in Arrow (1971), then we expect investors to dislike fat-tails and downside risk but prefer positive skewness. Kraus and Litzenberger (1976) show that higher moment such as coskewness is priced. Harvey and Siddique (2000) claim that conditional skewness helps explain cross-sectional variation of expected returns across assets; and its significance does not disappear even when factors based on size and book-to-market are included. They also provide evidence that the momentum effect of Jegadeesh and Titman (1993) is related to systematic skewness. Furthermore, we also use cokurtosis as Hwang and Satchell (1999) report that cokurtosis could also explain the dynamics of equity returns when asset returns have fat-tails. Finally, motivated by the studies of Bawa and Lindenberg (1977) and Harlow and Rao (1989), Ang, Chen and Xing (2006) investigate whether or not equities that are sensitive to downside market movements require a premium. They show that this downside risk premium exists and that it is not explained by various characteristics, such as size, book-to-market, momentum, volume, coskewness and liquidity effects.

3.2.2. Factors Formed on Firm Characteristics

Eight factors are identified based on firm-specific characteristics in this section. Although many of these factors explain asset returns well with significant cross-sectional return differences, debates on why these factors explain cross-sectional asset returns still continue and there is little conclusive evidence that these are risk factors. In particular, debates on value/growth, momentum, and idiosyncratic volatility, have attracted extensive interest in the recent literature.

Banz (1981) and Rosenberg, Reid and Lanstein (1985), as well as a series of studies by Fama and French (1992, 1993, 1996a and 1996b), show that size and book-to-market equity are able to explain a significant amount of the common variation in stock returns. Fama and French (1993) create the well-known *SMB* (small size portfolio returns minus big size portfolio returns) and *HML* (high book-to-market portfolio returns minus low book-to-market portfolio returns).

A recent study of Cooper, Gulen and Schill (2006) suggests that a stock's annual asset growth rate is more important than other accounting variables in predicting cross-sectional returns. They further demonstrate that the forecasting ability of asset growth is above other well known characteristics, such as book-to-market, size, and lagged returns. Parallel studies in the accounting literature show that accruals[21] also can be used in explaining asset returns. Sloan (1996) documents that firms with high accruals earn abnormally lower returns on average than firms with low accruals. Richardson, Sloan, Soliman and Tuna (2005) develop a comprehensive balance sheet categorization of accruals and show that less reliable accruals lead to lower earnings persistence and abnormally lower average returns.

A series of studies show that returns are predictable because of investors' over- and under- reaction to information. Earlier studies, such as De Bondt and Thaler (1985), Fama and French (1988a) and Poterba and Summers (1988), report negative autocorrelations in the long-run and positive autocorrelations in the short run. Jegadeesh and Titman (1993) document that past winners consistently outperform past losers over a 3 to 12-month holding period. They argue that this strategy of buying winners and selling losers is profitable, and is not due to systematic risk or delayed stock price reactions to common factors. In addition, Fama and French (1996a) suggest that most of the stock characteristics-related anomalies are largely dissipated in their three factor model except for this short-term momentum profit. Jegadeesh and Titman (2001) show that the short

[21] Accruals are commonly defined as the change in non-cash working capital less depreciation expense. Detailed calculations can be found in Appendix.

term momentum continues but past winners consistently underperform past losers over a 13 to 60-month holding period, suggesting the phenomenon of long-term reversal.

Gervais, Kaniel and Mingelgrin (2001) find that stocks with unusually high trading volume over a day or a week tend to appreciate over the following month. They argue that their results are consistent with a "visibility" story: shocks in the trading activity of a stock affect its visibility, and in turn the subsequent demand and price for that stock. They conclude that the volume premium cannot be accounted for by return autocorrelations, firm announcements, market risks, and liquidity.

Finally, Ang, Hodrick, Xing and Zhang (2006) show that idiosyncratic volatility is priced. They find that stocks with high idiosyncratic volatility from the Fama-French three factor model have low average returns, and that this phenomenon cannot be explained by size, book-to-market, momentum, volume and liquidity effects.

3.2.3. Principal Component Factors

Despite the empirical success of the above factors, most of them are not well motivated from an economic point of view (see Daniel and Titman, 1997; and Ferson, Sarkissian and Simin, 1999). The Arbitrage Pricing Theory (APT) implies that the risk factors should be those which capture the variations in large well-diversified portfolios. Following Connor and Korajczyk (1988), we use principal components techniques to estimate the pervasive factors for asset returns. They provide evidence that their five-factor version of APT explains returns better than the CAPM. Therefore, the first five principal component factors (PCA factors, hereafter) are also used in this study, and grouped in the third category.

3.2.4. The Factors Tested in This Study

In summary, we have eighteen factors altogether. These are the excess market return (*ERM*), coskewness (*COSK*), cokurtosis (*COKT*), downside risk (*DNSD*), liquidity (*LIQ*), *HML*, *SMB*, asset growth (*ASG*), accrual (*ACRU*), long-term reversal *(LTRV*), momentum (*MOM*), idiosyncratic volatility (*IDSN*), trading volume (*VO*), and five CK factors (PCA1 to PCA5).[22] Among the eighteen factors, *ERM*, *COSK*, *COKT*, *DNSD* and *LIQ* as well as the PCA factors are theoretically motivated. On the other hand, it is still controversial whether the firm-characteristics based factors (such as *SMB*, *HML*, *ASG*, *LTRV*, *MOM*, *IDSN* and *VO*) are priced factors.

3.3. Testing Method

Two popular methods for testing asset pricing models are the two-step cross-sectional regression (Black, Jensen and Scholes, 1972; and Fama and Macbeth, 1973) and the multivariate *F* tests in the time-series approach (Gibbons, Ross, and Shanken, 1989). For both methods, it is a common practice to group stocks into portfolios using some criteria (e.g., firm characteristics) to reduce the cross-sectional dimension of the joint distribution of returns and the measurement errors in the betas. However this grouping leads to loss of information (Roll, 1977; Litzenberger and Ramaswamy, 1979) and can cause a data-snooping bias (Lo and MacKinlay, 1990). When portfolios are formed on empirically motivated characteristics, the conventional test will reject the model too often in the presence of grouping (Lo and MacKinlay, 1990; and Lewellen, Nagel and Shanken, 2006).

A direct and more effective method to avoid this problem is to use individual stocks rather than portfolios. For example, Kim (1995) proposes a method for

[22] Short-term reversal (from Professor Kenneth French' data library) and upside risk (Ang, Chen and Xing, 2006), were also used in this study, both of which do not play any meaningful role in asset pricing in the presence of the other factors considered in this study.

testing asset pricing models using individual stocks in the two-step cross-sectional regression. However, the approach seems to be too complicated to be used in empirical finance. A simple but appealing approach is the average *F* test proposed by Hwang and Satchell (2008). They show that the assumption does not decrease the power of the test and the size and power of the average *F* test is generally better than the conventional *F* test. The advantages of the average *F* test are that it can be used even when the number of stocks (*N*) is larger than the number of observations in time horizon (*T*), and that it is robust to elliptical distributions of returns. Therefore, the test makes it possible to assess thousands of individual stocks and thus avoid the problems that arise from grouping.

Assume that the linear factor model is

$$R_t = \alpha + \beta F_t + \varepsilon_t$$

where R_t is a (*N* by 1) vector of excess returns for *N* assets, F_t is a (*K* by 1) vector of factor portfolio returns, $\alpha \equiv (\alpha_1, \alpha_2, ..., \alpha_N)'$ is a vector of intercepts, $\beta \equiv (\beta_1, \beta_2, ..., \beta_N)'$ is an (*N* by *K*) matrix of factor sensitivities, and $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, ..., \varepsilon_{N,t})'$ is an (*N* by 1) vector of normally distributed idiosyncratic errors for which the variance-covariance matrix is $E\left(\varepsilon_t \varepsilon_t{}'\right) = \Sigma$. For the null hypothesis of $H_0^\alpha : \alpha = 0$, against the alternative hypothesis $H_1^\alpha : \alpha \neq 0$, the average *F* statistic to test linear asset pricing model is

$$S = \frac{Tc}{N} \sum_{j=1}^{N} \frac{\hat{\alpha}_j^2}{\sum_{t=1}^{T} \left(r_{j,t} - \hat{\alpha}_j - \hat{\beta}_j F_t \right)^2 / (T - K - 1)}$$

$$\sim \frac{1}{N} \sum_{j=1}^{N} F_j (1, T - K - 1)$$

where ~ means “distributed as”; and

$$c = \left(1 + \hat{\mu}_K{}' \, \hat{\Omega}_K^{-1} \, \hat{\mu}_K \right)^{-1},$$

$$\hat{\mu}_K = \frac{1}{T} \sum_{t=1}^{T} F_t ,$$

$$\hat{\Omega}_K = \frac{1}{T} \sum_{t=1}^{T} \left(F_t - \hat{\mu}_K \right) \left(F_t - \hat{\mu}_K \right)',$$

and $\hat{\alpha}$ and $\hat{\beta}$ are the maximum likelihood estimators of α and β. The analytic function of the average *F* statistic is not known and thus in this study the statistics are obtained via Monte Carlo simulations with 10,000 replications. Throughout this study, we choose 5% of the simulated test statistics as benchmarks to test the linear factor models. For robustness, we compared the results with those of the conventional *F* test using bootstrapping.

3.4. Empirical Results

3.4.1. Data and Calculating Factor Returns

The Fama-French three factors, momentum (*MOM*), and long-term reversal *(LTRV*) are from Professor Kenneth French's data library. Other firm characteristic factors are calculated as follows. Following the method used by Fama and French (1992), a factor related to a specific characteristic is computed as the out-of-sample (post-formation) return difference between the lowest 30% and the highest 30% portfolios formed on the characteristic. When forming portfolios, stocks with share price below $5 are removed to minimise the impact of extremely large returns associated with market microstructure biases and thin trading.[23] The portfolio returns are calculated with value weights.[24] All nonfinancial firms listed in the NYSE, AMEX, and NASDAQ markets were used

[23] Acharya and Pedersen (2005), Amihud (2002), and Pastor and Stambaugh (2003) have similar requirements.
[24] Factor returns with equal weights are also calculated, and it is found that the results with equal weights are not different from those with value weights. Thus in the study results are reported with factors that are calculated with value weights.

from the CRSP monthly return files and the Compustat annual industrial files from 1963 to 2006. The detailed calculation methods for the factors are explained in the Appendix.

3.4.2. Preliminary Analysis

3.4.2.1. Properties of Factor Returns

Table 3.1 displays the properties of eighteen factors. The first two rows of Panel A describe the average monthly returns and their standard errors. Some of the average returns are not significant; this could be because the study's sample period is not the same as those used by previous studies, or the study's factor construction method (the return difference between the lowest 30% and highest 30% in our study) is not necessarily the same as those used by the studies which introduce these factors. For example, high volume stocks have higher returns than low volume stocks, as in Gervais, Kaniel and Mingelgrin (2001), but the factor *VO* formed on volume shows an insignificant average return of 0.04%. The insignificance could be explained by the fact that Gervais, Kaniel and Mingelgrin (2001) use NYSE stocks while this study uses all CRSP nonfinancial firms. Another difference can be found in the performance of downside risk premium (*DNSN*). Ang, Chen and Xing (2006) suggest that stocks whose downside betas are high have higher returns than those whose downside betas are low. However, this study did not find a significant difference in returns between high and low downside betas. The reason for the difference in results would be that post-formation returns are used in our study, whereas Ang, Chen and Xing (2006) use pre-formation returns. The factors formed on size, coskewness and idiosyncratic errors, also do not show significance. As is well documented, the effects of size become weaker after the early 1980s. The empirical evidence of coskewness in cross-sectional asset returns is mixed and depends on the sample periods (Kraus and Litzenberger, 1976; and Friend and Westerfield, 1980).

Idiosyncratic errors are not significant, which could be the result of the study's calculation using nonfinancial firms, whereas Ang, Hodrick, Xing and Zhang (2006) use all the available stocks.[25]

Among these factors, momentum (*MOM*) shows the most significant monthly average return, i.e., 0.81%. Liquidity (*LIQ*) has the second largest average monthly return, which is -0.51% per month.[26] Clearly illiquid stocks show higher returns than liquid stocks, which is consistent with most previous studies, such as Amihud (2002), among others. This study reports a 0.41% monthly average return for asset growth (*ASG*), which is smaller than the 7.9% per annum reported by Cooper, Gulen and Schill (2006). The difference can be explained by the portfolio construction method; a higher return difference can be obtained by calculating *ASG* returns using the lowest and highest asset growth decile portfolios as in Cooper, Gulen and Schill (2006).[27]

The difference in the performance between the factors that were obtained using the top and bottom 30% with all CRSP nonfinancial firms and those proposed in the previous literature indicates that the performance of many factors include in the study is sensitive to the portfolio construction methods and thus may not be robust. Different sets of factors are likely to be selected for different sample periods or for different exchanges. Consistent with many previous studies that tested the Fama-French three factors and momentum in various ways (Fama and French, 1996a, and many others), the study also found that these factors are significant except for *SMB*. On the other hand, only the liquidity factor is significant among risk-related factors, and none of the PCA factors are. The poor

[25] Ang, Hodrick, Xing and Zhang (2006) report a negative return (-0.02%) for portfolio 5 (containing the highest volatility stocks), where this portfolio accounts for just 1.9% of the whole market capitalization (Panel B of Table VI, Page 285). In an unreported table, the study's calculations are repeated using their sample period, from 1963 to 2000. Similar results are found for low idiosyncratic risk portfolios 1 (containing the lowest volatility stocks) to 4. Portfolio 5 in the study's calculation, however, has a positive average return (1.09%) and represents 3.3% of the whole market capitalization. This difference is mainly the result of excluding financial firms. The reason for this difference is beyond the scope of the study. Nonetheless, it is certainly an interesting issue to explore in future.

[26] The Appendix shows the formulas for calculating the liquidity proxies. By construction, lower values of the liquidity proxies imply more liquidity. Therefore, the negative sign suggests that liquid stocks have a lower return than illiquid stocks.

[27] Indeed, the average monthly return difference between the lowest and highest asset growth decile portfolios in the study is 0.7%, which is close to the annual average of 7.9% reported in Cooper, Gulen and Schill (2006).

performance of these factors is one of the major reasons why they are not used in the empirical studies, despite their strong theoretical support.

Panel B of Table 3.1 displays the correlation coefficients among these factors. These factors are grouped into three sub-groups as indicated by the lines. Not surprisingly, downside risk is highly correlated with excess market return since downside risk is constructed conditional upon market performance. Liquidity is highly correlated with size factor, which is due to the close association between firm size and liquidity (Hwang and Lu, 2007). As expected, accounting variables related factors are highly correlated. For example, *ASG* and *HML*, both of which could be interpreted as value/growth factors, are highly correlated (0.68); and the correlation coefficient between *ACRU* and *ASG* (*HML* and *ACRU*) is 0.63 (0.57). Interestingly long-term reversal and momentum show low correlations with other factors. While behaviourists argue that these factors are driven by investors' irrational behaviours, many researches argue that these factors are likely to be connected to the business cycle.[28] Notably, the idiosyncratic factor is significantly correlated with many other factors, for instance *ERM*, *DNSD*, *SMB*, *HML* and *ASG*. The high correlations of the idiosyncratic factor with other factors indicate that the idiosyncratic factor could be a proxy for many other firm specific characteristics. This result is also consistent with that of Brennan, Chordia and Subrahmanyam (1998).[29]

The first PCA factor displays high association with other factors, for example, -0.66 with idiosyncratic factor, and 0.57 with *SMB*. Market return has correlation coefficients of 0.43 and 0.41 with *PCA1* and *PCA3*. However, there is no significant association between the remaining three PCA factors and other risk-related and firm characteristics based factors.

[28] See Chan, Jegadeesh and Lakonishok (1996), Daniel, Hirshleifer and Subrahmanyam (1998), Hong and Stein (1999), and Zhang (2006), who explain momentum from investors' irrational behaviour,. Others that attempt to explain momentum with changes in fundamentals include Conrad and Kaul (1998), Berk, Green and Naik (1999), Chordia and Shivakumar (2002), Johnson (2002), and Liu, Warner and Zhang (2005).

[29] They find that returns after adjusted by Fama-French factors are still significantly with other firm-characteristics.

3.4.4.2. Do We Need All of These Factors?

The correlation matrix in Table 3.1 suggests that the factors in the literature are not mutually exclusive or equally important in asset pricing. Given that early studies on multi-factor models suggest up to six factors, we hypothesize that many of these factors are redundant in asset pricing. In this section we perform some preliminary tests to evaluate this hypothesis.

Following many previous studies, we first regress factor returns on the Fama-French (FF) three factors and momentum, as these factors are known to explain cross-sectional returns. If these FF factors and momentum (four factors) explain the other factors considered in the study, then these other factors can be constructed by combining the four factors. Panel A of Table 3.2 shows that the majority of the factor loadings on Fama-French factors and momentum are significant. For example, *HML* is significant for 8 out of 9 factors except for *COSK*. The alphas of the factors where average returns are significant (Table 3.1), i.e., *ASG*, *LTRV* and *LIQ*, become insignificant in the presence of Fama-French factors and momentum. For example, despite the argument by Cooper, Gulen and Schill (2006), the study found that *ASG* is explained by both the Fama-French three factors with momentum because the pricing error (intercept) of asset growth becomes statistically insignificant.

In parallel, we also use PCA factors to explain the same factor returns. The first PCA factor is statistically significant in explaining all 9 factors, and the remaining 4 PCA factors also have significant factor loadings in some regression specifications. For example, when the first 3 PCA factors together are to explain *COKT*, the pricing error becomes insignificant. However, the four factors, i.e., *LIQ*, *ASG*, *LTRV*, and *IDSN*, are not explained by the PCA factors, while only one factor, i.e., IDSN, is not explained by the FF three factors and momentum. The results indicate that the FF three factors and momentum performs better in explaining asset returns than the PCA factors. The outperformance of the FF factors with momentum relative to the PCA factors is in fact consistent with the results of Brennan, Chordia, and Subrahmanyam (1998).

In Panel B, *SMB*, *HML* and *MOM* are regressed on other factors. The study found that the intercept for *SMB* and *HML* becomes insignificant. Although the alpha for *MOM* still remains significant, its magnitude has been significantly reduced from 0.81% to 0.7%. The evidence in Panels A and B implies that there are many correspondences among these factors, and thus some of them might be redundant if they are used together to explain stock returns.

Panel B of Table 3.2 displays the results of the Principal Component Analysis of the 5 risk-based and 8 firm-attributes related factors. The first four components explain approximately 80% of the total variance, and the first nine components explain about 95% of the variation in the thirteen factor returns.

The simple exercises in this section suggest that the number of factors needed, among the 13 risk and firm-specific related factors, could be smaller than those proposed in the literature. In the following subsection we investigate these factors in a more rigorous way.

3.4.3. Which Factors We Need?

Although the previous section indicates that all of these factors may not be needed, and the Fama-French three factors and momentum explain most of the other factors proposed in the literature, it does not clearly identify which factors are empirically 'most' relevant for the explanation of asset returns. There are two important motivations for this study, namely identifying factors, or sets of factors, that best explain asset returns of individual stocks; and investigating the possibility that a set of economically better motivated factors can replace the empirical factors based on firm characteristics, such as the Fama-French three factors (FF factors, hereafter) and momentum.

One of the studies that is closely related to the present research is Brennan, Chordia and Subrahmanyam (1998), who investigated the relation between individual stock returns, measure of risk and non-risk characteristics, where Fama-French factors or CK factors are employed as proxies of risk measures. Under the assumption that expected returns are determined by risk factors, which are proxies either by CK factors or Fama-French factors, they find that non-risk characteristics are significantly related to returns even after risk-adjusted by CK factors and FF factors, for example, return momentum effect still persists.

However, this study has a different focus and uses different methods. First, the study does not explicitly assume a set of factors that should be used to explain asset returns; instead the factors are grouped into three categories: risk-based, firm-characteristics related and CK factors. By examining the performance of different combinations of factors within each group, we can directly answer the following question, which factors, firm-characteristics or risk based factors, have more marginal explanatory power?

Second, a series of papers by Fama and French (1992, 1993, 1996a, and 1996b) shows that FF factors can explain most of asset return anomalies except for momentum. One of the study's null hypotheses is that the pervasive factor returns (characteristics sorted portfolios, e.g., Fama-French factors, *SMB*, *HML*) should explain asset returns in time-series regressions if they are really the proxies for underlying risk factors. Using Average F-Test method can enable the examination of the performance of the factors using individual stocks to avoid the loss of information due to grouping; and it is also applicable when the number of stocks (N) is larger than the number of observations (T). The number of stocks (second column of Table 3.3), which is indeed large, ranges from 1741 in the early 1970s to 4300 in the late 1990s, and is significantly larger than the number of months, i.e. the 420 months from January 1972 to December 2006.

Finally, it is also interesting to examine the validity of different asset pricing models in different sample periods. For example, if Fama-French's *SMB* and *HML* and momentum are really pervasive and proxies for the underlying risk factors, it is not likely that these factors lose their explanatory power in asset pricing within different sample periods unless the risks related to these factors disappear during the periods. For this reason, we use seven non-overlapping 5-year sub-periods to allow the time variation in linear factor models. Moreover using sub-periods reduces survivorship bias; for example, the number of stocks that have survived for the last 35 years is very small, i.e., only 381 in our sample. It is also possible to investigate which factors matter during which sub-periods.

The study's sample covers all the nonfinancial stocks in the NYSE, AMEX, and NASDAQ return files from the CRSP. Average *F*-test is applied to all these stocks in the 7 non-overlapping 5-year intervals from January 1972 to December 2006, because the CRSP only started to record NASDAQ stocks from December 1972. At the start of each interval, a stock must have share price equal to or above \$5; and during each 5-year interval it must have at least 24 observations.[30] Using a shorter sub-period (5-year) would minimise the effects of time-varying factor loadings (Ferson and Harvey; 1999). The empirical tests in this study start with single factor models. Table 3.3 reports the results of seven sub-sample periods using the average *F* test. The third column represents the simulated Average *F* test statistics at the 5% significance level; and any number larger than these statistics would imply the rejection of the model (i.e. the null hypothesis that alphas are zero is rejected). The last row of Table 3.3 (Titled "NOR") counts the number of sub-periods, in which one factor model is rejected. Although the number of sub-periods in which the model is rejected is a crude measure, it summarizes the performance of these models in a straightforward way.

As expected, single-factor models do not explain asset returns well. For instance, similar to the results of Fama and French (1992 and 1996b), the excess market return (*ERM*) is rejected in five out of seven sub-periods. Interestingly, most of the factors that were tested performed equally well or better than *ERM*. For example, two factors, *COSK* and *PCA1*, are rejected only three out of seven sub-periods. Over the entire 35 years, three 5-year sub-periods (1982 to 1986,

[30] The study also applies the Average *F*-test in the period from January 1967 to December 1971; and it was found that most of the factor models examined in this study do not explain individual stock returns over this period. This might be the effect of the smaller number of stocks in the sample because NASDAQ stocks are not included. Nonetheless, the conclusions in this study do not change if this period is included.

1992 to 1996, and 2002 to 2006) remain the most challenging periods for single factor models, because none of the single factors considered in this study can explain asset returns.

Table 3.3 clearly suggests that the one factor models have some difficult periods in explaining stock returns. Since the market return is required for the positive equity premium although it does not explain cross-sectional average returns (Fama and French, 1996a), the study next investigates the marginal explanatory power of an additional factor in addition to the *ERM*. Besides, the study also evaluates the performance of any combinations of two CK factors in parallel. Panel A of Table 3.4 suggests that two CK factors do not increase the explanatory power of a single PCA factor. For instance, PCA1 and PCA2 have 3 and 4 rejected sub-periods on standalone basis respectively (Table 3.3); but combining these two still displays 3 rejected sub-periods (Model 1 of Table 3.4); and any other mixtures of two PCA factors do not seem to outperform Model 1.

The results of adding either one risk related or characteristics related factor are reported in Panel B and C. Among the total 12 factors, liquidity (Model 4 of Panel B), long-term reversal, and momentum (Models 5 and 6 of Panel C) can improve the performance of CAPM by two periods. The best two-factor model is the one that includes *ERM* with *HML* (Model 2 of Panel C), which is rejected in only two sub-periods. Similar to the one factor models, the two factor models show significant pricing errors during the 10-year period from 1977 to 1986 and the last 5-year interval.

The study repeated the same exercise to include the 3rd and 4th factors and report the results in Table 3.5 and 3.6. Panel A of both Table 3.5 and 3.6 shows that the explanatory power of CK factors does not increase with the number of factors included. For example, the first 3 PCA factors have 3 rejected periods (Model 1, Panel A of Table 3.5); whereas the first 4 PCA factors together also have 3 rejected periods (Model 1, Panel A of Table 3.6), which performs no better than just the first two PCA factors (Model 1, Panel A of Table 3.4).

However, by adding more factors, the risk related factor models improve significantly. When number of factors is 3, there are 3 models which only have 2 rejected sub-periods: *ERM*, *COSK* and *LIQ*; *ERM*, *COKT* and *LIQ*; and *ERM*, *DNSD* and *LIQ* (Models 3, 5 and 6 in Panel B of Table 3.5). This implies that coskewness, cokurtosis and downside risk can improve the two factor model of *ERM* and *LIQ* which has 3 rejected periods (Model 4 in Panel B of Table 3.4). Indeed, the number of rejected sub-periods reduces to 1 with the four risk related factor model, e.g., *ERM*, *LIQ*, *COSK* and *DNSD* (Model 4 in Panel B of Table 3.6); and no other combinations can outperform these four factors.

Panel C of Table 3.5 displays the performance of three factor models whose factors are firm-characteristics based. None of the combinations outperform the risk-based three-factor combinations, i.e., have less than 2 rejected periods, but there are 4 models, i.e., Models 1, 8, 10, and 11, which have 2 rejected sub-periods. Among these four models, it is interesting to observe that the two rejected sub-periods of the Fama-French three factor model (Model 1) are all within the first 20 years of the sample period. Fama and French (1993) argue that their factors can explain stock returns. The study results, obtained by using individual stocks instead of portfolio returns, imply that their seemingly successful results might be the outcome of information loss (Roll, 1977; Litzenberger and Ramaswamy, 1979) or data-snooping biases (Lo and MacKinlay, 1990; and Berk, 2000) due to portfolio grouping. When the number of factors is 4, there are 56 different factor specifications (Panel C of Table 3.6). As in Fama and French (1996a), we find that Fama-French factors together with momentum explain stock returns better than the FF three factor model. However, only one sub-period requires momentum and the contribution of momentum for the other sub-periods is limited.

To sum up the results so far, the study has been unable to find a set of factors that can explain individual stock returns over the 35-year period. Nonetheless, one may still draw the following conclusions. First, CK-type PCA factors underperform risk-related and firm-characteristics related factors[31], as the least number of rejected periods is 3. Second, the set of economically better motivated risk-related factors which shows the least number of rejections are, market portfolio, coskewness, downside risk and liquidity. Third, among the firm-specific information related factors, Fama-French and momentum outperform all the other alternatives. While the firm characteristics related factors, such as Fama-French and momentum, remain controversial in asset pricing, coskewness, downside risk and liquidity are well and economically better motivated. The study found these three factors together with market return explaining individual stock returns no worse than firm-characteristics sorted factors, e.g., size, book-to-market, and past return.

During the five-year period from January 1982 to December 1986, almost all the models investigated in this study fail to explain individual stock returns. This might be related to macroeconomic conditions, because the US economy was in contraction over this period and the interest rate was at a historical peak. Figure 3.1 and Figure 3.2 plot the one-month T-bill and NBER business cycles from December 1966 to December 2006. It is evident that the average yield is higher in the first half than the second half of the sample period, especially during the early 80s with an average yield of over 8%. This implies a higher cost of capital for firms, which in turn requires high expected returns. In addition, there are four contraction periods in the first half of the sample period; in contrast, there are only two short-lived contractions in the remaining period. Chordia and Shivakumar (2002) show that time-series patterns in returns are strongly linked to business cycle, and they find that the most intriguing momentum payoff can be explained by a set of lagged macroeconomic variables. They provide evidence that momentum returns are only positive during expansionary periods, whereas, they are negative during recessions.

[31] Brennan, Chordia and Subrahmanyam (1998) also provide empirical evidence that Fama-French factors outperform CK factors.

3.4.4. Robustness Tests

In this section, a number of robustness exercises are performed. First, the number of the factors is increased to 5; and the results do not seem to be improved. Second, the results reported above are obtained with non-penny stocks whose prices are at least \$5. In order to examine the robustness of the findings when penny stocks or small stocks are included, the Average *F*-test is applied to the two four-factor models identified in the previous section using all the stocks. Panel A of Table 3.7 suggests that the result remains unchanged when penny stocks are included.

A further question is whether or not the study results are significantly different from those obtained using the conventional *F* test. The conventional *F* test cannot be used when the number of stocks is much larger than the number of monthly observations. Thus the bootstrapping method is used to conduct the conventional *F*-test as follows. For each sub-period (T=60), 10 stocks (N=10) are randomly selected with replacement, and then tested to see if alphas are significant at the 5% level. By randomly selecting 10 stocks with replacement and repeating the procedure 10,000 times, any bias from grouping stocks may be minimised. Panel B of Table 3.7 compares the results from using the Average and Conventional *F*-test for the two most successful four-factor models identified in the previous section. Once again similar results were obtained.

3.5. Concluding Remarks

Given the empirical failure of CAPM, one common response is to use returns of firm-characteristics sorted portfolios in a multi-beta model. Many factor returns have been proposed in the literature; they are all claimed to explain cross-sectional asset returns. However the number of factors seems to be too large. Hence, a total 18 widely cited factors were grouped into three categories and investigated. By examining the performance of these three types of factors in explaining individual returns, we identify a set of risk-related factors, market return, coskewness, downside risk and liquidity, which work as well as the controversial Fama-French factors and momentum. However, it is not claimed that these firm-characteristics are not the proxies for the underlying risk factors. Nevertheless, the study results do imply that the economically better motivated factors could serve as a replacement for the controversial Fama-French and Momentum factors.

Appendix

The data sets are from the Centre for Research in Security Prices (CRSP) and Compustat. The firm characteristics and other risk measures are defined and calculated as follows:

1) Asset Growth (*ASG*): Asset growth rate is calculated as in Cooper, Gulen and Schill (2006). The annual firm asset growth rate is calculated using year-on-year percentage change in total assets (Compustat Data Item 6). The firm asset growth rate for year *y* is defined as the percentage change in total assets from fiscal year ending in calendar year *y-2* to year ending in calendar *y-1*, that is,

$$Asset\_Growth(y) = \frac{Data6(y-1) - Data6(y-2)}{Data6(y-2)}$$

Using this asset growth rate, in June of year *y*, stocks are assigned into portfolios. Asset-growth factor (*ASG*) is the value-weighted hedge portfolio return (the return difference between lowest 30% minus highest 30% asset-growth portfolios) in the next 12 months. Portfolios are rebalanced at the end of June every year.

2) Accrual (*ACRU*): The comprehensive accrual definition of Richardson et al. (2005) is used, where accrual consists of the change in non-cash working capital, the change in non-current operating assets and the change in net financial assets[32].

3) Volume (*VO*): The volume factor (*VO*) is calculated following Gervais, Kaniel and Mingelgrin (2001), where the past 50 days trading interval is used to classify the high- (low-) volume stock. This 50-day interval is split into a reference period (first 49 days) and formation period (the last day of the interval). Using the daily number of shares traded during the first 49 days, a stock is classified as a high- (low-) volume stock if its formation period volume is among the top (bottom) 10 percent for that trading interval. Then the one-month holding period returns are calculated for these 10 decile volume portfolios. Volume factor (*VO*) is the return

[32] Detailed calculations can be found in page 446 of Richard et al. (2005)

difference between the lowest and highest trading volume portfolio. Portfolios are rebalanced very month.

4) Liquidity (*LIQ*): The illiquidity measure of Amihud (2002) is calculated;

$$\gamma_{i,y} = \frac{1}{D_{i,y}} \sum_{d=1}^{D_{i,y}} \frac{\left| r_{i,y,d} \right|}{v_{i,y,d}}$$

where $D_{i,y}$ is the number of days for which data are available for stock i in year y, $r_{i,y,d}$ is the return on stock i on day d of year y, and $v_{i,y,d}$ is the dollar trading volume for stock i on day d of year y. Analogous to Amihud (2002), a stock must have return and volume data for at least 200 days in order to calculate this illiquidity proxy. The liquidity factor (*LIQ*) is computed similar to that of *ASG*. The relative illiquidity measure of Hwang and Lu (2007) is also used, but the results are not better than those with Amihud (2002).

5) Idiosyncratic risk (*IDSN*): the method followed is as in Ang, Hodrick, Xing and Zhang (2006). Specifically, idiosyncratic risk is defined as $\sqrt{\operatorname{var}(\varepsilon_t^i)}$ in the following Fama-French three factor model

$$r_t^i = \alpha^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_t^i$$

At month t, idiosyncratic volatility is computed using 1 month daily data. Then all the available stocks are assigned to decile portfolios according to their $\sqrt{\operatorname{var}(\hat{\varepsilon}_t^i)}$ and held for the next month. The procedure is repeated every month. The factor construction of *IDSN* is analogous to *VO*.

6) Coskewness, cokurtosis, and downside risk measure are defined as below

$$\text{coskewness} = \frac{E\left[(r_i - \mu_i)(r_m - \mu_m)^2\right]}{\sqrt{\operatorname{var}(r_i)}\operatorname{var}(r_m)}$$

$$\text{cokurtosis} = \frac{E\left[(r_i - \mu_i)(r_m - \mu_m)^3\right]}{\sqrt{\operatorname{var}(r_i)}\operatorname{var}(r_m)^{3/2}}$$

$$\beta^- = \frac{\operatorname{cov}(r_i, r_m | r_m < \mu_m)}{\operatorname{var}(r_m | r_m < \mu_m)}$$

where $r_i(r_m)$ is security *i*'s (the market's) excess return, and μ_m is the average market excess return. Coskewness and cokurtosis are calculated at end of every month following Harvey and Siddique (2000), and Ang, Chen, Xing (2006) where at least 24 out of the past 60 monthly returns are used. Then the following month return is recorded for the coskewness- (cokurtosis-) sorted portfolios. For the downside beta, Chen and Xing (2006) sort stocks into portfolios based on the realised β^- at the beginning of the 12-month period *t*, and then they examine the relationship between downside beta and return from time *t+1* to *t+12*. This study however forms portfolios with downside betas calculated with past daily returns and hold them for the next month. Specifically, at the end of every month we use past 1-year daily data to compute downside beta and then use post-formation return in the following month. The computations of factors, *COSK*, *COKT*, and *DNSD* are parallel to *VO* and *IDSN*.

Summarizing, firm characteristics: volume, idiosyncratic volatility, coskewness, cokurtosis and downside risk are calculated at the end of every month. Therefore, the corresponding factor returns: VO, IDSN, COSK, COKT, and DNSD are computed and rebalanced every month. As asset growth, accrual and liquidity level are calculated annually, factors ASG, ACRU and LIQ are rebalanced in June of every year. All the factor returns and portfolios are value-weighted. Our choice of value-weighting portfolios is consistent with other studies33 (see Harvey and Siddique (2000) and Ang, Chen and Xing (2006) for example).

[33] Ang, Chen and Xing (2006) suggest that the relationship between factors and returns should hold for both an average stock (equal-weighting) and an average dollar (value-weighting). Furthermore, as advised by Kothari, Shanken and Sloan (1995), The CAPM implies that the portfolio of stocks that has maximum correlation with the true market portfolio is efficient. Therefore, equally weighted returns can be dominated by the significant number of small stocks, resulting in an unrepresentative picture of the importance of the portfolio returns (Fama and French, 2006).

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4. Is Share Price Relevant?

4.1. Introduction

Financial theory suggests that share prices do no affect the value of firms in frictionless markets. However, there is considerable empirical evidence that the share price of a firm is not entirely irrelevant. For instance, Bhardwaj and Brooks (1992) conclude that the well-documented January effect is primarily a low-share price effect. They also document that after-transaction-cost raw and excess January returns are lower on low-price stocks than on high-price stocks. Angel (1997) provides international evidence that share prices vary substantially across countries; and Dyl and Elliott (2006) report that there are substantial price variations in US stock markets due to firms selecting particular price ranges for their shares. They claim that firms manage share price levels to increase the value of the firm.

A topic closely related to share price is stock splits. The work of Benartzi, Michaely, Thaler and Weld (2006) suggests that the average nominal share price in the US has remained remarkably constant at around $30 in spite of inflation since the Great Depression as a result of stock splits. A considerable number of hypotheses have been proposed to answer the question of why firms split their stocks. There are at least three possible categories of explanations. One is signalling, in which firms keep their share prices low, despite the increased brokerage commissions, to signal that they are higher quality firms (Brennan and Copeland, 1988 and Ikenberry, Rankine and Stice, 1996). A second hypothesis is to increase the ownership base of the firm, and this is sometimes known as the optimal trading-range hypothesis. Although this is one of the most popular explanations (surveyed in Baker and Gallagher, 1980), the empirical evidence is mixed. For example, both Lamourex and Poon (1987) and Mukherji, Kim and Walker (1997) find the number of shareholders increases after a stock split; however, Mukherji, Kim and Walker (1997) find that the proportion of institutional ownership remains unchanged following a stock split. In addition, this hypothesis cannot explain why open-end mutual funds split since individuals can buy fractional shares. A third explanation is related to the liquidity issue. After firms lower their share prices via stock splits, more investors would be able to own it and liquidity should increase (Baker and Gallagher, 1980; Muscarella and Vetsuypens, 1996; Schultz, 2000 and among others). Benartzi, Michaely, Thaler and Weld (2006) examine these hypotheses and conclude that none of the existing theories is satisfactory in explaining the stock splits phenomena. The debate continues.

In this study, evidence is first shown that share price *per se* is relevant in cross-sectional asset pricing. Share prices are inversely related to returns. Low share price stocks (penny stocks, less than or equal to $5) have higher average returns than high price stocks (more than $20). The strategy of buying low price stocks and selling high price stocks can generate significant positive returns: on average, 53 basis points a month over the period from 1963 to 2006. Secondly, our investigation confirms the result of Bhardwaj and Brooks (1992) after replication. However, by using extra 20 years data, we, contrary to their early result, demonstrate that the profitability of this price strategy persists after 2 years even after considering a full round of transaction costs. Last but not least, the profitability of this strategy is robust in the presence of other effects such as size, liquidity, book-to-market equity, earning/price ratio, and past performance. Fama-MacBeth cross-sectional regressions suggest that the price effect is robust and not subsumed by other firm-specific characteristics.

The excess return of penny stocks to high price stocks could be explained by so-called "*Nominal Price Illusion*". This illusion arises when investors have valuation difficulties in noisy markets. Consider a situation with two identical stocks except for share prices, the same return for the two stocks implies that the absolute amount of share price increase would be higher for the high price stock than that of the low price stock. Naïve investors would interpret that the high price stocks simply become too expensive, therefore they would expect a higher return for the low price stock. Using this illusion, an explanation is proposed as to why firm managers split stocks: If firm managers know that lower prices may generate higher returns, they would keep share prices lower through stock splits to maximize shareholders', and thus their own, utilities.

The rest of this paper is organized as follows: The next section reviews the background of penny stocks. In Section 4.3, evidence is provided for the notion that the strategy of buying low and selling high share price stocks is profitable. It is also demonstrated that the profitability of this strategy is robust in the presence of size, book-to-market equity, liquidity and other firm-specific characteristics. Section 4.4 shows that the return patterns associated with nominal share price are not explained by the existing factors such as Fama and French three factors and momentum; and it is also suggested that "*Nominal Price Illusion*" can be used to explain why firms split their stocks regardless of brokerage commissions. Finally, the last section concludes.

4.2. Penny Stocks

The term "penny stock" is defined differently depending on the context. In the US, a penny stock is a common stock that trades for less than $5 a share and is traded over the counter (OTC) through quotation services such as OTC Bulletin Board or the Pink Sheets. However, the official SEC definition[34] of a penny stock is low-priced, speculative security of a very small company, regardless of market capitalization or whether it trades on a securitized exchange (e.g. NYSE or NASDAQ) or an OTC listing service.

The market for penny stocks has changed dramatically over the last few decades. Prior to the development of the NASDAQ market in 1971, penny stocks were typically traded over the counter or on regional exchanges, often with very limited disclosure requirements. In particular, before the Penny Stock Reform Act of 1990, the penny stock market was plagued by unscrupulous broker-dealers and underwriters. Previous researches on penny stocks were mainly within the spectrum of Initial Public Offering market, for example, Beatty and Kadiyala (2003); Bradley et al (2006), among others.

In this study, penny stocks (whose prices are $5 or less) traded on the securitized exchanges, i.e., NYSE, AMEX or NASDAQ, are investigated in the perspective of cross-sectional asset pricing. Figure 4.1 plots the number of stocks traded in these three markets from December 1925 to December 2006, obtained from the CRSP data file. There are two significant adjustments over this period: the inclusion of AMEX and NASDAQ stocks into the CRSP database on July 2, 1962 and December 14, 1972, respectively. Analogous to Bhardwaj and Brooks (1992), 5 price groups are created: less than or equal to $5, $5 to $10, $10 to $15, $15 to $20, and more than $20. It is evident that there were not many penny stocks publicly traded before 1962. However, after NASAQ stocks are included, penny stocks have represented on average 28% of the total stocks traded over the period from 1972 to 2006 with its peak of 48% at December 1974. It is also worth noting that the number of common stocks traded, peaks at the end of 1997 and decreases sharply during the following bear market.

[34] SEC (2006-02-02), Penny Stock Rules, US Securities and Exchange Commission.

4.3. Does Share Price Matter in the Cross-Sectional Asset Pricing?

Financial theory suggests that share price should not affect a firm's value, because a firm can change its share price by splitting or reverse splitting its shares. For example, a $10 million market value equity can be packaged as 1 million shares at $10 per share, or 2 million shares at $5 per share. In this section, evidence is provided that share price *per se* is relevant in cross-sectional returns. Low price stocks show higher returns than high price stocks.

4.3.1. Data and Construction of Portfolios Based on Prices

The sample used in this study covers all NYSE, AMEX, and NASDAQ common stocks included in the CRSP monthly return files and the Compustat annual industrial files from July 1963 through December 2006. Stocks are grouped into 5 price range portfolios at the end of June each year and are held for the next *K* years. In addition, following Jegadeesh and Titman (1993), overlapping holding periods are used to increase the power of the tests. That is, in any given year *t*, the strategies hold a series of portfolios that are selected in the current year as well as in the previous *K* - 1 year.[35] The portfolios are equally-weighted and rebalanced at the end of June each year.[36]

Column six of Table 4.1 shows the number of stocks for portfolios in each price range. It is clear that the majority of the penny stocks are traded in NASDAQ; and these penny stocks have higher delisted probabilities than high price stocks as implied by the transition matrices in Table 4.1. Shumway (1997) documents a delisting bias in the stock return database maintained by CRSP. He suggests that delists for bankruptcy and other negative reasons are generally *surprises* and that correct delisting returns are not available for most of the stocks

[35] The empirical exercises are conducted without using the overlapping method, and the results are similar. These results are available from the authors upon request.
[36] Using value-weighted portfolios do not change the conclusions.

that have been delisted for negative reasons[37] since 1962. This bias is more severe in the NASDAQ data than in the AMEX/NYSE files. To avoid any potential distortion this bias could cause, Shumway's method is followed to avoid this delisting bias. Specifically, a delisting return of -30% is given to a stock if it has CRSP delisting codes of 500, 520, 551 to 573, 574, and 580 to 584.[38]

4.3.2. Performance of the 5 Price Range Portfolios

4.3.2.1 Share Price and Expected Return

Table 4.1 documents the average monthly returns in the following 12-month holding period and characteristics of the 5 portfolios formed on price. Panel A reports the results that are obtained using NYSE and AMEX stocks only from July 1926 to December 2006; in Panels B and C, the entire sample period is divided into two: pre- and post- July 1963 periods; and finally Panel D examines NASDAQ separately given the fact that the number of stocks below $5 is significantly larger in this exchange.

Panel A shows that penny stocks, clearly, have higher returns than nonpenny stocks in the following 12 months. The return difference between penny (P1) and more than $20 share price portfolio (P5) is 0.83% per month over the entire 81 years. The return difference is 1.31% in the first 35 years (Panel B), although the number of penny stocks in this period is significantly less than that in the post-1963 period, with on average only 41 stocks being less than or equal to $5. Although penny stocks still outperform high priced stocks by almost 40 basis points in the post-1963 period, it is statistically insignificant. Therefore the outperformance of penny stocks is prominent during the pre-1963 period.

[37] Shumway (1997) suggests that the negative reasons include bankruptcy, insufficient capital, and other performance-related reasons.

[38] It is worth noting that assigning -30% return for these stocks can only enable the estimation more conservative.

The right hand side of Table 4.1 presents the migrations of these price range portfolios over one-year period. Each row shows the average transition vector for a particular portfolio. There are several interesting results that can be drawn from the table. First, as expected, penny stocks and more than $20 stocks that belong to the two extreme portfolios (P1 and P5) are more likely to stay in the same portfolio one year later than the middle price stocks. For instance, in Panel C, 69% (83%) of penny (more than $20) stocks stay in same portfolio, while only 35% of $15 to $20 stocks remain in the same rank after 12 months. The migration is the most frequent for middle price range stocks, in particular, P4 ($15 to $20). For instance 30% of stocks in NASDAQ P4 portfolios remain in the same rank; about 32% of them move to the more than $20 range; and 20% of them are shifted into the $10 to $20 range. Second, penny stocks are more prone to migrate into the higher price range than high price stocks migrate into the lower price range. For example, more than 16% of penny stocks move into the $5 to $10 range for NYSE and AMEX stocks during the post-1963 period (Panel C), while only 8.2% of the more than $20 stocks are relocated in the next price range. The last column of Table 4.1 shows the percentage of surviving firms in 12 months time. It is obvious that NASDAQ firms have a higher delisting probability than NYSE and AMEX; and the pre-1963 period has the lowest delisting stocks. This is the reason the delisting bias is controlled using the method of Shumway (1997).

Since Panels C and D of Table 4.1 display similar return and characteristics pattern, and the number of penny stocks during the pre-1963 period is too small to get meaningful conclusions, we use all the stocks traded in the three exchanges from July 1963 to December 2006 as our sample hereafter.

4.3.2.2. Share Price, Transaction Costs and January Effect

Panel A of Table 4.2 reports the properties of price level sorted portfolios using the stocks in the three exchanges. Penny stocks, on average, outperform high price stocks by 53 basis points per month with the t-statistic of 1.94. Panel B of

Table 4.2 presents the average monthly buy-and-hold returns when holding period is 1 year and up to 5 years. It is evident that the price strategy of long penny stocks and short high price stocks (P1-P5) remains profitable up to 2 years. For example, when the holding horizon is two years, the average monthly return difference between penny (P1) and more than $20 (P5) is more than 58 basis points a month, which is equivalent to a 15% holding period return. It is worth noting that the performance of this strategy tends to be negative after two years. For instance, the average monthly return of P1-P5 becomes 50 basis points when the holding period is five years, relative to the 55 basis points when the holding period is three years.

One of the natural concerns of this strategy is the transaction cost. Bhardwaj and Brooks (1992) randomly select 5 trading days from each year of the 1982 through 1986 period, and then on each of these five days, they obtain the bid and ask prices and derive the commission rate from Francis Emory Fitch Inc's Daily Market Publication. They report that the median bid-ask spread for penny stocks (and stocks with price more than $20) is 5.1% (and 0.8%); and the median commission rate is 7.4% (and 1.3%). Therefore, when a penny stock is acquired, its transaction cost would be (5.1%+7.4%)/2=6.3%. Likewise, when a stock with price higher than $20 is acquired, the transaction would be 1%. In Panel A of Table 4.2, the 1.6% monthly return of penny stocks can be translated into an annualized return of 21.2% before transaction costs. Therefore, penny stocks have, on average, 14.9% annual returns after transaction costs. Similarly, the after transaction costs returns for stocks with prices higher than $20 are 12.9%. Hence penny stocks outperform high price stocks by 2% after transaction costs in one year. However, after round-trip transaction costs, penny stocks underperform high price stocks by 3.3%, which is consistent with the result of Bhardwaj and Brooks (1992) who report 3.2% underperformance. They also claim that there is an underperformance of 1.8% when the holding period is two years. The results of the present study do not match those of Bhardwaj and Brooks. The two-year buy-and-hold returns before transaction costs for penny and high price stocks are

48.3% and 29.1% respectively, compared to their calculation of 38.6% and 40.4%. This is primarily due to the different sample selection in the present study. Their study uses NYSE and AMEX stocks from January 1967 to December 1986. The present study repeats this exercise using their sample and finds similar results. Therefore, by using a 20 year longer period, it is demonstrated that penny stocks outperform high price stocks by 8.6% within two years of the round trip transactions, although this is not the case when the investment horizon is one year.

Although it seems that penny stocks need to be held for two years to outperform high stocks after the round trip transaction costs assumptions suggested by Bhardwaj and Brooks (1992), this is not necessarily the case with the transaction cost calculations of other researchers. For example, Hasbrouck (2006), using the Gibbs estimation method, suggests that the effective transaction costs for low price stock are never higher than 4% for US stocks over the period from 1926 to 2005 (Hasbrouck, 2006, Figure 3). Both Jones (2002) and Hasbrouck (2006) document the decline of the commission and effective transaction costs in the US, although the effective costs can rise during market turbulence. According to their calculation, the average effective transaction costs for penny and high price stocks over this study’s sample periods are 2% and 0.5% respectively. Based on these assumptions, penny stocks would outperform high price stocks by 4.3% (16.2%) in one- (two-) year period after the round trip transaction costs.

In similar fashion to Bhardwaj and Brooks (1992), this study also separates January returns from the rest of the year and reports them in Panel B. In line with the January effect studies, January returns are considerably higher for all the stocks than the non-January returns. Consistent with the observation of Bhardwaj and Brooks (1992), it is also found that the excess returns of penny stocks over non-penny stocks are mainly attributable to the significant abnormal returns in January. When the holding period is one year, the monthly return difference between penny and high price stock is on average 11% in January, compared to the insignificant -0.4% returns in other months of the year.

4.3.3.3. Robustness of the Price Strategy

The outperformance of penny stocks relative to high price stocks, however, could be explained by size, as Table 4.1 shows that size is positively related to price. Since Banz (1981) documents that small firms outperform large firms, the size effect has been subjected to extensive research (Fama and French, 1992, 1993 and among many others). The performance of small relative to large firms, particularly in January, has also been investigated by many other authors. Many researchers have proposed different explanations. For example, Kross (1985) concludes that the size effect is primarily a price effect. Jaffe, Keim and Westerfield (1989) find share prices significant in explaining abnormal January returns after control for size effect. However, Bhardwaj and Brooks (1992) conclude that low share price, rather than size, is primarily responsible for the January effect. The empirical evidence in the previous section indicates that share price matters in the cross-section of average stock returns. In this subsection, we first investigate whether the outperformance of penny over high price stocks is due to size effect.

Panel A of Table 4.3 displays the results of the two dimensional sorts for the period from July 1963 to December 2006. At the end of June each year, all the available stocks are firstly ranked into quintiles based upon firm's size (Market Equity, which is defined as the product of share price and the number of shares outstanding), and then they are sub-grouped into 5 price range portfolios. These 25 portfolios are rebalanced at the end of June each year.

Panel A of Table 4.3 shows penny stocks outperform high price stocks only for small stocks. For example, the return difference between the smallest penny (S1P1) and smallest high price stocks (S1P5) is 0.9% per month. On the other hand, the difference between P1 and P5 within other size-quintile is negative although not significant. It is interesting to note that the excess return of penny stocks over high price stocks is not related to size in January. For example, P1-P5 is 6.6% even for the largest 20% of the stocks. In other months of the year, penny stocks significantly underperform high price stocks except for the small stocks.

The same exercise is applied to construct 25 liquidity[39] and price portfolios, since penny stocks are generally small and illiquid and hence the abnormal returns of penny stocks could be explained by liquidity. Panel C of Table 4.3 shows that there is no outperformance of penny stocks over high price stocks within each liquidity quintile. However, similar to the 25 size and price portfolios, significant abnormal returns are found for penny stocks in January irrespective of liquidity.

The similarity between liquidity/price portfolios and size/price portfolios, however, is not completely unexpected since size and liquidity are highly associated with each other. The right hand side of Panel B shows the average number of stocks for the 25 Size-Price portfolios. More than 72% of small stocks have a share price not larger than \$5 (portfolio S1P1, which has on average 739 stocks over this period); while more than 78% of the big firms are priced over \$20 (portfolio S5P5, which has on average 869 stocks over this period). These two portfolios together represent 30% of the total available stocks in the market. The return difference between these two portfolios is highly significant, 1% (t-statistic of 3.20) per month, in which a significant 12% (t-statistic of 9.56) in January, and -0.03% (t-statistic of -0.11) in other months. The results in Panel D show that the share distribution of the 25 liquidity/price portfolios displays a similar picture to that of the size/price portfolios. For example, in the most liquid quintile, the majority of stocks have a share price higher than \$20 (556 stocks in portfolio L1P5 out of the total 704 stocks in the most liquid quintile); conversely, more than half of the stocks in the most illiquid quintile are penny stocks. The return difference between these two portfolios (i.e., L5P1-L1P5) is 1% (t-statistic of 3.08)

[39] The illiquidity measure of Amihud (2002) is employed, and detail explanation of this liquidity proxy can be found in chapter one.

per month, in which a highly significant 13.19% (t-statistic of 9.99) in January, and -0.09% (t-statistic of -0.31) in other months.

We also perform the same two-dimensional sorts using other firm characteristics, such as past returns, BE/ME and E/P, as previous researches report that there are cross-sectional return regularities associated with these firm attributes (Jegadeesh and Titman, 1993; Fama and French, 1993, 1996 and among others). Since the calculations of these firm attributes need share price as one of the inputs, which implies that share price is inevitably linked with these variables, one might suspect that the high abnormal returns of low price stocks could be the effect of these well-documented firm characteristics. For example, Miller and Scholes (1982) hypothesize that firms with low prices are often in financial distress, therefore the higher returns for the low price stocks might be the compensation for the distress risk. Fama and French (1995) on the other hand argue that high BE/ME signals poor earnings and *HML* (defined as the return difference between the high and low BE/ME stocks) proxies firms' financial distress risk. Therefore, if distress risk is the underlying factor which drives the higher returns of low price stocks, we would not expect the presence of a price effect within each BE/ME quintile. Using the Compustat data file, we calculate BE/ME as in Davis, Fama and French (2000), in which Book equity (BE) is defined as a stock holders' book equity, plus balance sheet deferred taxes and investment tax credit, minus book value of preferred stock. Market equity (ME) is the product of prices and the number of shares outstanding. All firms with negative book values are excluded. A firm's average past 6 month return is used to form the past performance quintile. Earning per share (EPS) data is from Compustat, and E/P is defined as the ratio between EPS and price.

Tables 4.4, 4.5 and 4.6 show the results of two-dimensional portfolio sorts using share price and past return, BE/ME and E/P. In contrast to the high correlations between share price, size and liquidity, the correlations between price, past return, BE/ME and E/P are less prominent because Panel B of each of these three tables shows that stocks are much more evenly distributed among different portfolios. A similar pattern is observed for these additional three portfolio forming methods; i.e., the excess return of penny stocks over high price stocks is significantly positive, with exceptionally high abnormal performance in January and insignificantly different from zero in other months of the year. For example when portfolios are firstly sorted by BE/ME then by sub-grouped by price range (Table 4.5), within the middle BE/ME group (quintile 3) P1-P5 shows a statistically significant 0.67% return per month throughout the year with 11.81% in January and an insignificant -0.034% in other months.

The results in this subsection can be summarized as follows: i) when the two-dimensional portfolios are constructed first by size or liquidity, penny stocks are mostly small and illiquid; ii) the two dimensional sorts suggest that the price strategy of long penny and short high price stocks is profitable even after controlling the effects of BE/ME, Momentum and E/P; and iii) this excess return is primarily driven by the exceptional abnormal January returns of penny stocks.

Due to these high associations between share price, size and liquidity, the size and liquidity effects cannot be separated from the price effect in this portfolio formation method. Fama and French (2008) suggest that the main advantage of portfolio sorts is to present a simple picture of how average returns vary across the spectrum of an anomaly variable; the major disadvantage, however, is that sorts are difficult for drawing inferences about which anomaly variables have unique information about average return. Following their suggestion, the widely used Fama and MacBeth (1973) cross-sectional regressions are employed to measure the marginal effects of share price relative to many other explanatory variables.

4.3.3.4. How Strong is Share Price Compared to Other Important Determinants of the Cross-Section?

As the empirical results above show that the return difference between penny and high price stocks varies with other characteristics, there is a need to examine whether the price effect can be subsumed by the other multiple determinants of cross-section of returns. Bhardwaj and Brooks (1992, page 553) state "*Transaction costs, degree of neglect, misassessment of risk, infrequent trading have been shown to partially explain the positive abnormal returns on small firm stocks. These characteristics are equally, if not more, applicable to low-price stocks.*" If the price-return association is the by-product of other, or combinations of other characteristics, the coefficients on price should be statistically insignificant in the presence of other characteristics.

The assets to be explained are monthly individual stock returns. To be included in the regression, firms must have non-missing observations for all the variables that are used in that model. There are 6 explanatory variables: previous month's share price, size (market equity), average previous 6 months return, BE/ME, E/P and liquidity. Among which, liquidity is annually updated and the others are monthly updated. Seven models are estimated and their results are reported in Panel A of Table 4.7. In all the models estimated, share price is statistically significant in explaining cross-sectional return difference in the presence of other firm characteristics such as size, past return, BE/ME and others. Moreover, the R-square values with other additional characteristics variables do not increase significantly. Only the inclusion of firm size, past return and liquidity can improve the model marginally. For example, Model 2, which has size as an additional explanatory variable, only increases the R-squared to 3.8% from 3%. The inclusion of liquidity in the regression decreases the significance of share price effect, but share price still remains significant at the 10% level.

Panels B and C repeat the same exercise but distinguish January from the other months of the year. It is found that the results in Panel C which exclude January are not different from the results of Panel A where all months are included. However, hardly any of the firm characteristics considered in this study are significant in explaining returns in January except for share price (significant at the 10% level when used alone, Model 1 in Panel B; and significant at the 5% level when used together with past return, Model 3 of Panel B). Nevertheless, the estimated coefficients on share price are all negative in January as they are in other months of the year.[40]

In short, the Fama-MacBeth cross-sectional regression strongly suggests that share price is not irrelevant of cross-sectional returns. Low share price can predict high future returns. More importantly, the effect of share price is not subsumed by other firm characteristics such as size, BE/ME and liquidity.

4.4. Explaining the Profitability of the Price Strategy

4.4.1. Seasonality of the Price Strategy

Thus far it is demonstrated that the share price is inversely related to the cross-sectional returns. The strategy of buying penny and selling high price stocks can generate a significant premium. However, the exceptionally high abnormal returns in January, as shown in the previous sections, suggest that this strategy might have a seasonal pattern. Figure 4.2 plots the average monthly returns for three price strategies: buying penny stocks and selling stocks with share price above $20 (P1-P5), buying small penny stocks and selling big high price stocks (S1P1-S5P5), and buying illiquid penny stocks and selling liquid high price stocks (L5P1-L1P5). There is clearly a seasonal pattern for all these price strategies: significant positive returns in the first quarter of the year and negative returns in the last quarter. In the following section, it is investigated whether this seasonality and the profitability of the price strategies are explainable by the widely used common factors such as Fama-French's *SMB*, *HML* and Momentum factors.

4.4.2. Time Series Regressions

In this section the robustness of price effect is examined using, arguably, one of the most widely used factor models in empirical finance: Fama-French factors and

[40] The study's sample includes 522 monthly observations from July 1963 to December 2006; therefore there are 43 observations in January and 479 observations in non-January months. The significance of estimated coefficients could also be due to estimation errors as suggested by Shanken (1992).

the momentum factor of Jegadeesh and Titman (1993). The purpose of this time-series regression is to investigate whether the profitability and seasonality of the price strategy can be explained by this four-factor model.

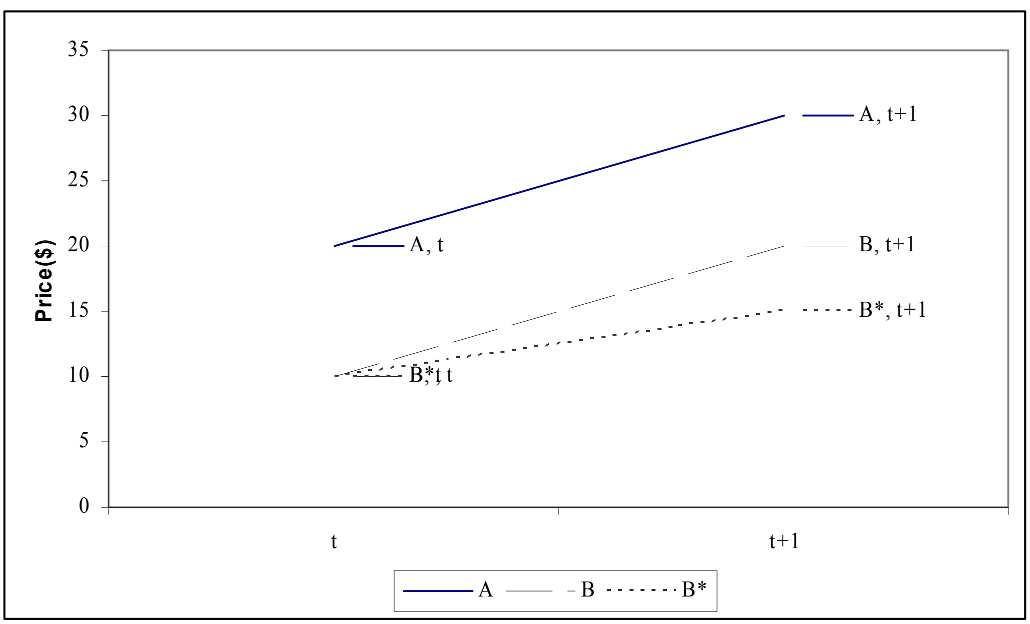
The assets to be explained are the 3 hedge portfolios defined in the previous section: (P1-P5), (S1P1-S5P5), and (L5P1-L1P5). In order to examine the seasonality, 12 dummy variables (*JANDM*, *FEBDM*, … , *DECDM*) are included which indicate the months of the year. For example *JANDM* is the dummy variable for January, which is unity in January and zero in other months. The last row of Table 4.8 reports the Wald F-statistics for the test of the coefficients on *JANDM*, *FEBDM*, … , *DECDM* are jointly zero.

It is not surprising to observe that the factor loading on *SMB* is significantly positive, since low price stocks are small as in Panel B of Table 4.3. On the other hand, *HML* and *MOM* are significant only in 1 out 3 cases. The Wald test shows that the seasonal pattern of these price strategies remains even in the presence of these four factors. Figure 4.3 displays a similar seasonal pattern to the unadjusted price strategies payoff as in Figure 4.2, i.e., we continue to observe the positive returns in the first quarter and negative returns in the last quarter of the year. Although the magnitude of these price strategies is reduced in some months (for example, the January return of the hedge portfolio (P1-P5) is 11% and 9% before and after adjusted by Fama-French and Momentum factors.), the total returns in the whole year for these price strategies still remain significantly positive.

4.4.3. Share Price Illusion and Stock Splits

The evidence in this study suggests that low price stocks have higher returns than the high price stocks, and this outperformance is not explained by other well known firm characteristics or factors. How does this abnormal return arise? The abnormal return of penny stocks would be evidence of "*Nominal Price Illusion*" in noisy markets, which can be demonstrated in the following simple exercise and the figure below. Suppose that there are two stocks: A and B, which have the same fundamental value except for their prices, and investors do not know whether or not they have the same values due to the difficulties in valuation; at time *t*, their prices are $P_{A,t} = 20$ with 100 shares and $P_{B,t} = 10$ with 200 shares. At time *t*+1 when $P_{A,t+1} = 30$, rational asset pricing theory suggests the price of stock B should be $P^*_{B,t+1} = 15$ (the dotted line in the figure) since these two stocks' fundamentals are not different, i.e., the returns would be the same for these two stocks $r_{A,t+1} = r^*_{B,t+1} = 0.5$. The same return for different price levels, however, will widen the price difference at time *t* + 1, and naïve investors, without knowing the real values of stocks A and B, may believe that stock A simply becomes too expensive compared with stock B. In other words, in noisy markets, we could observe price $P_{B,t+1} > 15$, i.e., $r_{A,t+1} < r_{B,t+1} = 1$ when $P_{A,t+1} = 30$ in our example (the dashed line in the figure).

When investors know that the fundamentals of the two firms are the same, the price illusion would not occur. However, because of noises in the market, fundamental values of firms are not known, and the simple price comparison would drive higher returns for lower price stocks. The upward bias in return would be higher for lower price stocks.



Our empirical evidence of the higher return of B over A generally supports the existence of this illusion.[41] This may be directly tested by examining the performance of companies with publicly traded dual class shares in the US, because "*financial theory suggest that two assets promising the same payoff in every state of nature must sell for the same price, therefore the voting rights would be worthless and we should expect the same market price for the two classes of stocks*" (Levy, 1982).

The typical dual class company offers one class of common stock with superior voting rights and one class of common stock with inferior voting rights. It is not uncommon to observe that the same company issues two classes shares ("A" and "B") in the US. The two classes usually indicate different voting rights and dividend payment policies.[42] A famous example is the A and B class shares of Berkshire and Hathaway. The difference between A and B class shares is well-known to investors: 1) a share of Class B common stocks have the rights of 1/30th of a share of Class A common stock except that a Class B share has 1/200th of the voting rights of a Class A share (rather than 1/30th of the vote); 2) Each share of a Class A is convertible at any time, at the holder's option, into 30 shares of Class B, but not the opposite direction.[43] The B class share can never sell for anything more than a tiny fraction above 1/30th of the price of A share. When it rises above 1/30th, arbitrage takes place in which someone, perhaps an NYSE specialist can buy the A and converts into B. This will push the prices back into a 1:30 ratio.[44]

For our purposes, we focus on whether investors can generate a profit by investing on the price gap between a company's two share classes. To do this, a search is conducted for the companies with dual class common stocks in the

[41] The tendency of think in terms of nominal rather than real monetary values is known as "Money Illusion" in economics. The recognition of the illusion has a long tradition, which can be traced back to 80 years ago. For example, Irving Fisher devoted an entire book to it (The Money Illusion, 1928). The existence of money illusion is well recognized in the economy (Shafir, Diamond and Tversky, 1997), therefore our proposal of share price illusion might simply be the special case of this money illusion.
[42] More details in Gompers, Ishii and Metrick (2004)
[43] Source: http://www.berkshirehathaway.com/compab.html
[44] Source: http://www.berkshirehathaway.com/compab.html

CRSP database at the end of December 2001, and it is found that a total of 46 companies have both A- and B- class shares. In order to control the effect of voting power associated with the share class, the voting rights of these companies are manually discovered from their annual report. The final sample covers 20 companies (40 stocks).

The second column of Table 4.9 displays the voting rights ratio between the two share classes of a company.[45] The fifth (labelled "B-A") and sixth column show the average share price differences and the t-statistics from January 2002 to December 2007.[46] It is clear that the nominal share prices between the two share classes are significantly different from each other. The returns for the two classes (the 9th column) are however not different from each other. More importantly, this return difference does not seem to be related to voting rights. For example, from the first company in Table 4.9, Kelly Services Inc, to the last company, Berkshire Hathaway Inc, the voting rights of A-share increase. However there is no return pattern associated with this increase.

For our purpose, we construct two strategies based on share price: one is long only; and another is zero-financing long/short. The column "Payoff 1" in Table 4.9 is the average monthly return for the long only price strategy. This strategy only buys the low price class stocks at the end of each month, and then they are held for the next month. It is found that 15 out of 20 companies have "payoff 1" higher than both of the two classes, and the remaining 5 companies have "Payoff 1" higher than at least one share class. This implies that investors of companies with dual-class shares can have better payoff by investing on the low price class if their investment motivations are not to control the voting powers of the companies.

The column "Payoff 2" is the average monthly return for the zero-cost price strategy, which long the low price class and short the high price class stock at the

[45] The notation, "A" and "B", in this study does not necessarily coincide with the company's "A" and "B" shares. In this study, we normalize "B" share as the class of share which has 1 voting right, and "A" as another share class which has all other voting rights.
[46] The price difference for Berkshire Hathaway is calculated as the difference between 30 times of B share price and A share price.

end of each month and are held for the next month. It is observed that all the 20 companies have a positive payoff, among which half of them are statistically significant at 95% confidence level.

Hence, higher returns are likely for low price stocks among the 20 companies with dual-class shares. These results are consistent with the "*Nominal Price Illusion*". It might be this type of behavioural illusion which results in the high return of low price stocks. The proposal of this study is also consistent with Dyl and Elliott (2006) who claim that firms manage share price levels to increase the value of the firm, because firm managers would prefer to split stocks to maximize shareholders' utility since they know that lower price will generate higher returns in future.

4.4.4. The Impact of Minimum Price Increment (Tick Size)

This study demonstrates that penny stocks outperform high price stocks. However, one of the concerns is that the minimum price increment might account for part of the abnormal high returns for penny stocks as this minimum price increment has larger impact on penny stocks than that on high price stocks. If this is the case, we would expect a lower than average return for price strategy P1-P5 after the decimalization. However, P1-P5 displays a monthly average return of 0.40% (t-statistics of 1.35) and 1.35% (t-statistics of 1.98) before and after 2001. Secondly, Ikenberry and Weston (2003) present empirical evidence that there is a widespread and persistent of price clustering at increments of five and ten cents (i.e., larger than the minimum tick size) even after the US equity market transitioned from the trading in multiples of one sixteenth and one eighth to one hundredth of a dollar in early 2001. In addition, Huang and Stoll (2001) investigate the impact of market characteristics, such as tick size, bid-ask spread and market depth on the market structure. After comparing the stocks traded on the London Stock Exchange (there is no minimum tick for quotes) and New York

Stock Exchanges (a dealer market and the existence of minimum tick size), they conclude that these characteristics are endogenous to the market structure, i.e., the minimum tick size regulation is not related to transaction prices. We, therefore, conclude that this minimum tick size is unlikely to have major impact to the conclusion in the current study.

4.5. Conclusions

In this study, empirical evidence is provided against the financial theory which suggests that share price is independent of returns; and we demonstrate that cross-sectional returns are significantly linked to their nominal share prices. Low price stocks have higher average returns than high price stocks; and this return difference is robust in the presence of other firm-specific effects such as size, liquidity, BE/ME, E/P and momentum. The well-known existing factors such as Fama-French and momentum factors cannot explain this cross-sectional return difference associated with share price. However, it is recognized that there is an evident seasonal pattern associated with the price strategy.

In the US, publicly traded penny stocks have accounted for more than a quarter of total number of stocks in the three national exchanges. This study suggests that investors can acquire significant returns by investing in penny stocks. The fact that the exceptionally high returns for pennies in the first quarter of the year suggests investors can realize even larger returns by forming portfolios in the last quarter and liquidating in the second quarter of next year. This study also casts some light on the stock split phenomenon. Firm managers may lower their share prices to generate higher expected returns by splitting their stocks.

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Figures and Tables

Figure 1.1

Monthly Average Amihud's Illiquidity Level in the UK

The market liquidity is the average of individual stock's illiquidity, where the illiquidity measure is based on Amihud's (2002) measure.

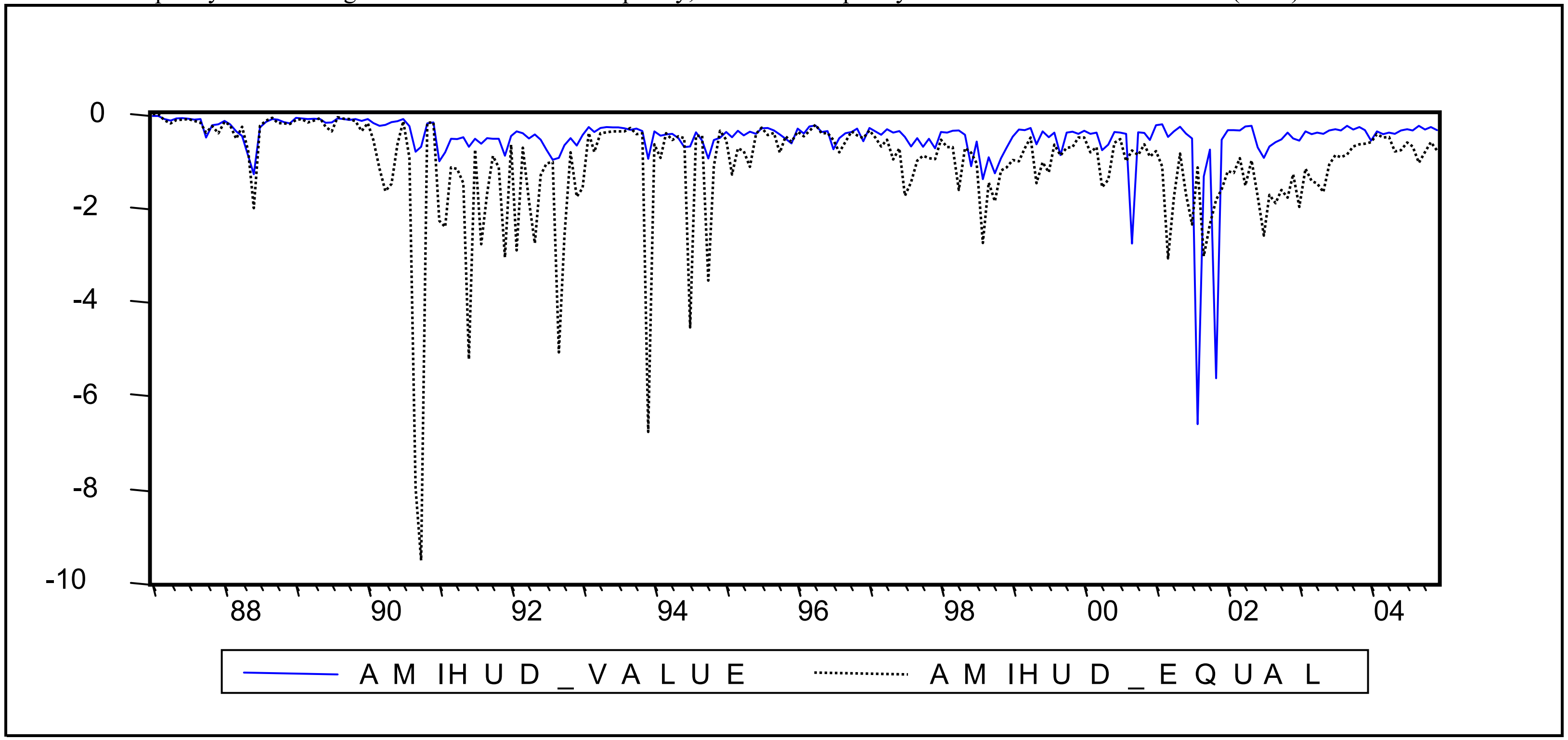

Figure 1.2
Monthly Average Relative Illiquidity Level in the UK

The market liquidity is the average of individual stock's illiquidity, where the liquidity measure is based on the new relative measure proposed in this study.

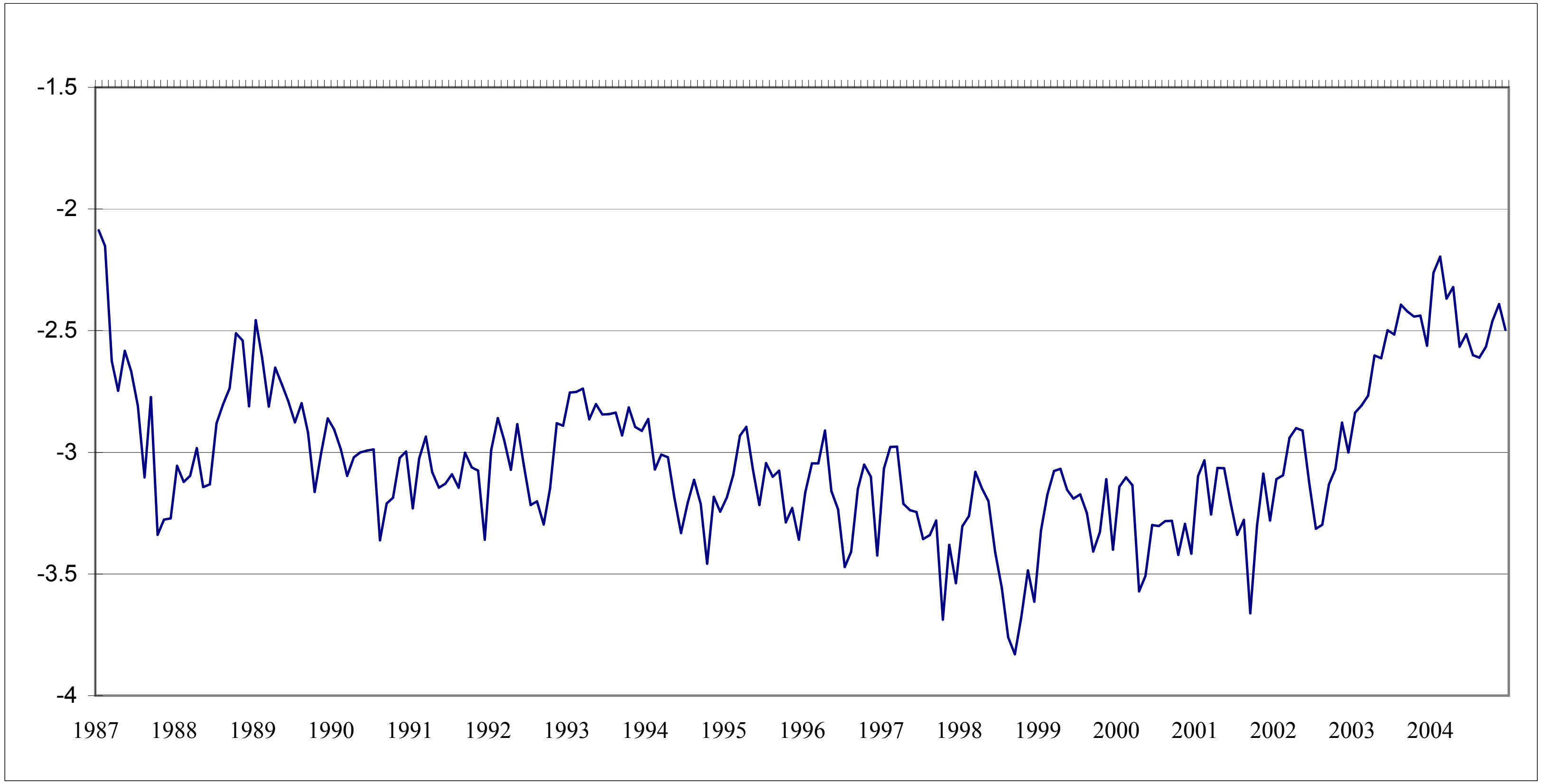

Figure 1.3
Monthly SMB in the UK and US (Percentage)

The UK SMB is calculated as follows: at the end of June in year t, two portfolios are formed on stocks' ranked market value and held for the next 12 months. The breakpoint is the 70th percentile of the ranked market equity.The return difference of these two portfolios is SMB. Portfolios are rebalanced every year. The US SMB is downloaded from Kenneth French Website.

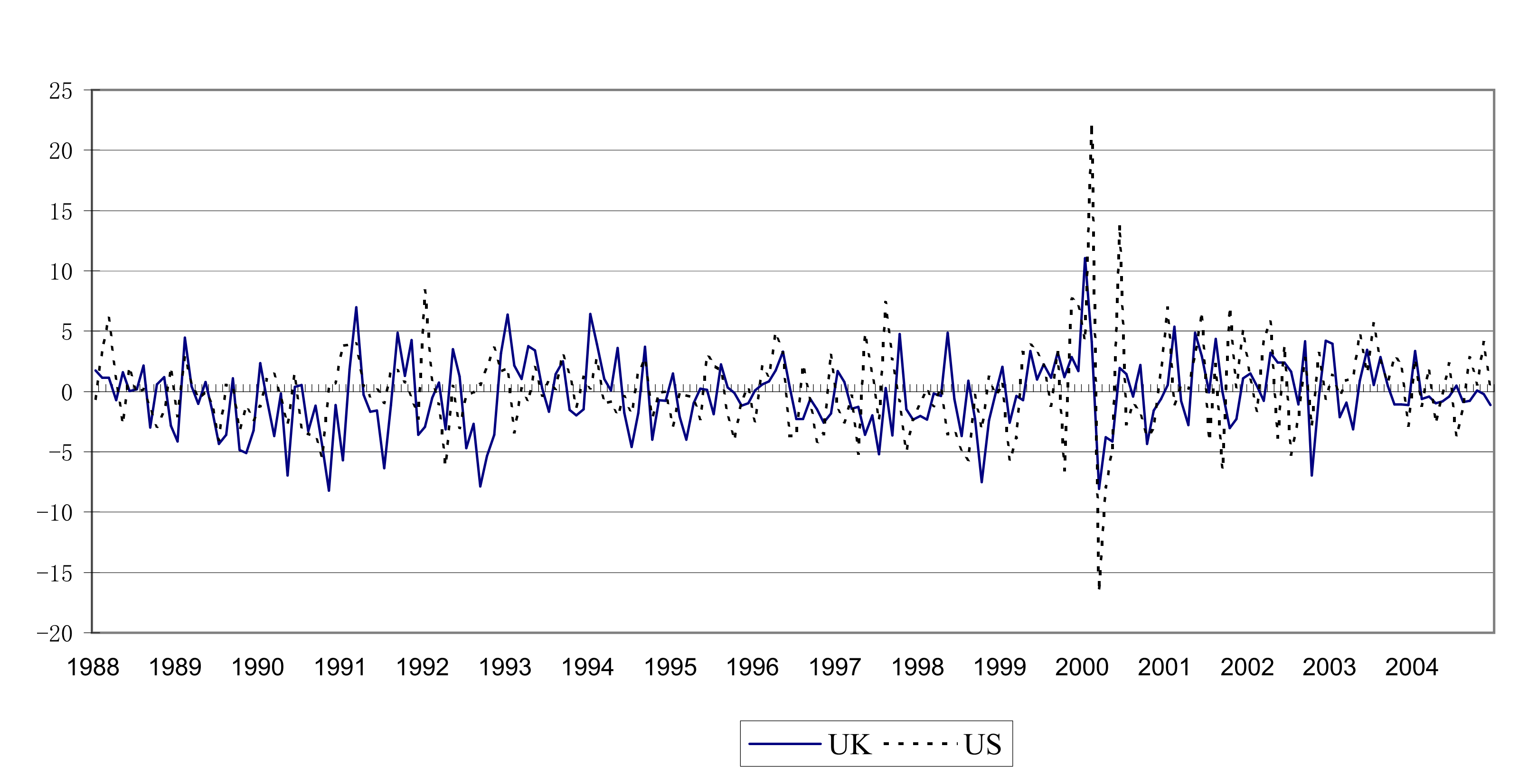

Figure 1.4
Monthly HML in the UK an US (Percentage)

The UK HML is calculated as follows. At the end of December in year t, two portfolios are formed on stocks' ranked book-to-market value and held for the next 12 months. The breakpoints are the 40th and 60th percentile of the ranked book-to-market equity. The return difference of these two portfolios is the HML. Portfolios are rebalanced every year. The US HML is downloaded from Kenneth French Website.

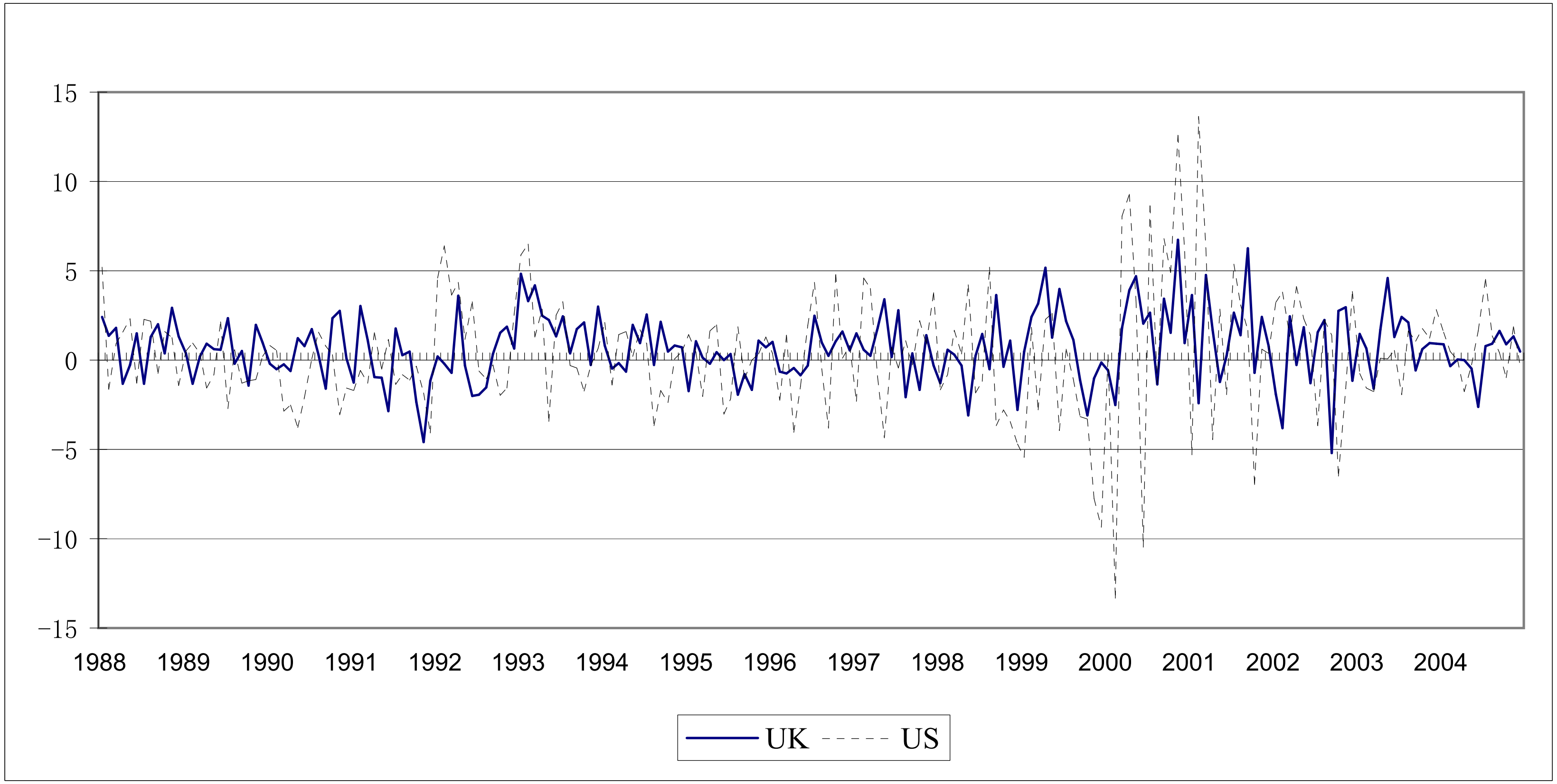

Table 1.1

Liquidity Properties of the UK Stock Market over Time (Annual Average)

The market liquidity is the average of individual stock's illiquidity. The first two rows are aggregate market liquidity based on Amihud's (2002) measure. The third row is the aggregate market liquidity based on the new relative liquidity measure proposed in this study.

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
$\gamma_{i,m}$ **(Value weighted)**	-0.160	-0.380	-0.130	-0.290	-0.650	-0.620	-0.390	-0.560	-0.430	-0.420	-0.500	-0.750	-0.460	-0.670	-1.460	-0.510	-0.380	-0.380
$\gamma_{i,m}$ **(Equally weighted)**	-0.180	-0.430	-0.180	-2.060	-2.010	-1.880	-1.060	-1.180	-0.670	-0.470	-0.910	-1.220	-0.880	-0.870	-1.810	-1.560	-1.130	-0.680
$\psi_{i,m}$	-2.786	-2.901	-2.805	-3.064	-3.107	-3.037	-2.832	-3.158	-3.124	-3.181	-3.275	-3.444	-3.221	-3.313	-3.223	-3.065	-2.575	-2.446
No. of Stocks	96	179	183	184	576	577	712	826	832	798	974	1003	1060	1118	1325	1367	1382	1459

Table 1.2

Performance of Size-Sorted Portfolios

At the end of June in year t, 10 size decile portfolios are formed on stocks' ranked market value and held for the next 12 months. Every portfolio represents 10 percentile of the ranked ME. Portfolios are rebalanced every year. SMB is the mimicking factor for size. The breakpoint is the 70th percentile of the ranked market equity. The data for the US is from Kenneth French's Website.

Panel A: Properties for 10 Decile Size Portfolios (in percentage) January 1988 to December 2004

	Small	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Big**	***SMB***
Average MV/Total MV (%)	0.060	0.160	0.300	0.490	0.810	1.320	2.240	4.050	9.290	81.290	
Average Annual Return	1.310	0.890	0.500	0.810	2.600	2.500	2.340	2.790	4.000	7.050	**-4.080**
Average Monthly Return	0.110	0.070	0.040	0.070	0.210	0.210	0.190	0.230	0.330	0.570	**-0.350**
Monthly Return SD	3.320	3.520	3.510	3.810	4.070	3.890	4.000	3.910	4.040	3.900	**2.720**

Panel B: Statistical Properties for Monthly SMB in the UK and US

	SMB_US	***SMB_UK***
Mean	0.002	-0.004
Median	0.002	-0.004
Std. Dev.	0.037	0.027
t-test	0.656	-0.248

Table 1.3
Performance of BE/ME-Sorted Portfolios

At the end of December in year t, 10 value decile portfolios are formed on stocks' ranked book-to-market value and held for the next 12 months. Every portfolio represents 10 percentile of the ranked book-to-market stocks. Portfolios are rebalanced every year. HML is the mimicking factor for value. The breakpoints are the 40th and 60th percentile of the ranked book-to-market equity. The data for the US is from Kenneth French's Website.

Panel A: Properties for 10 Decile Book-to-Market Portfolios (in percentage) January 1988 to December 2004

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	***HML***
Average MV/Total MV (%)	17.280	14.560	17.300	16.530	9.960	7.740	5.530	4.070	3.130	3.900	
Average Annual Return	2.080	1.340	6.080	7.490	4.220	6.930	6.120	8.020	9.620	12.270	**3.870**
Average Monthly Return	0.170	0.110	0.490	0.600	0.340	0.560	0.500	0.640	0.770	0.960	**0.320**
Monthly Return SD	3.830	4.480	3.930	4.210	4.360	4.680	5.460	5.030	4.830	4.940	**2.500**

Panel B: Statistical Properties for Monthly HML in the UK and US

	HML_US	***HML_UK***
Mean	0.003	0.003
Median	0.003	0.002
Std. Dev.	0.034	0.025
t-test	4.424	4.525

Table 1.4
Performance of Liquidity-Sorted Portfolios

At the end of December in year t, 10 liquidity decile portfolios are formed on stocks' ranked Amihud's (or the relative) liquidity measure and held for the next 12 months. Every portfolio represents 10 percentile of the ranked stocks. Portfolios are rebalanced every year. LIQ is the mimicking liquidity factor, which is the average return difference between the portfolios of the most illiquid 50 percent and the most liquid 50 percent of stocks.

Panel A: Properties for 10 Decile Liquidity Portfolios Sorted by $\gamma_{i,m}$ 1988 to 2004 (in percentage)

	Illiquid	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Liquid**	***LIQ***
Average MV/Total MV (%)	0.740	0.780	1.070	1.360	1.730	2.340	3.170	5.150	11.190	72.470	
Average Annual Return	-13.740	-2.670	-3.440	1.760	1.750	-0.030	1.880	7.030	3.640	8.740	**-7.850**
Average Monthly Return	-1.230	-0.230	-0.290	0.150	0.140	0.000	0.160	0.570	0.300	0.700	**-0.680**
Monthly Return SD	6.860	5.650	5.450	5.230	5.360	5.200	5.190	5.030	5.290	4.450	**2.920**

Panel B: Properties for 10 Decile Liquidity Portfolios Sorted by $\psi_{i,m}$ 1988 to 2004 (in percentage)

	Illiquid	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Liquid**	***LIQ***
Average MV/Total MV (%)	9.010	6.570	9.260	10.790	13.480	15.800	13.080	10.870	8.590	2.560	
Average Annual Return	-6.550	-0.980	3.580	4.110	6.010	9.100	7.270	6.800	11.960	11.370	**-7.527**
Average Monthly Return	-0.560	-0.080	0.290	0.340	0.490	0.730	0.590	0.550	0.940	0.900	**-0.650**
Monthly Return SD	6.090	4.980	4.690	5.160	4.850	4.630	4.370	5.070	5.180	7.030	**2.020**

Table 1.5
Statistical Properties of the Factors

RM is the market return on the FTSE-all share index. SMB is the return difference between the 70th percentile of the ranked ME at the end of June each year t, and HML is the return spread between 40th and 60th percentiles of (BE/ME) at the end of December each year t. At the end of each year, Amihud's illiquidity measure and the relative liquidity mearsure are calculated for all stocks. The two portfolios are created based on these ranked measures. The breakpoint is the median of each liquidity measure. The return difference of these two portfolios in the next 12 months is the mimicking liquidity factor (LIQ and LIQ_AMIHUD).

Panel A: Correlation Matrix (204 Monthly Observations)

	LIQ	*LIQ_AMIHUD*	*RM*	*HML*	*SMB*
LIQ	1				
LIQ_AMIHUD	0.010	1			
RM	-0.080	-0.120	1		
HML	-0.240	0.030	0.200	1	
SMB	-0.080	0.750	-0.330	0.020	1

Panel B: Statistical Properties for All Factors in the UK

	LIQ	*LIQ_AMIHUD*	*RM*	*HML*	*SMB*
Monthly Mean	-0.007	-0.007	0.008	0.003	-0.004
Monthly Std. Dev.	0.020	0.029	0.042	0.025	0.027
Historical Sharpe Ratio	-0.651	-0.462	0.034	0.010	-0.312

Table 1.6
Size, Book-to-Market, Liquidity and Returns

S-B (H-L) is the hedge portfolio for long the smallest (highest book-to-market) and short the biggest (lowest book-to-market). ILLIQ-LIQ is the hedge portfolio for long the most illiquid and short most liquid. _D, _Q and _P stand for decile, quintile and 30%/40%/30% breakpoints. RM is the market return on the FTSE-all share index. T-bill is the monthly rate for UK one month Treasury bill. S-B (H-L) is the hedge portfolio for long the smallest (highest book-to-market) and short the biggest (lowest book-to-market). ILLIQ-LIQ is the hedge portfolio for long the most illiquid and short the most liquid. _D, _Q and _P stand for the decile, quintile and 30%/40%/30% breakpoints. The numbers in italic are t-statistics. Portfolios are rebalanced every year. The estimations are justified in the presence of both heteroskedasticity and autocorrelation of unknown forms according to Newey and West (1987).

Panel A: Monthly Statistical Properties of Different Hedge Portfolios

	S-B				***H-L***				***ILLIQ-LIQ***		
	S-B_D	**S-B_Q**	**S-B_P**		**H-L_D**	**H-L_Q**	**H-L_P**		**ILLIQ-LIQ_D**	**ILLIQ-LIQ_Q**	**ILLIQ-LIQ_P**
Mean	-0.003	-0.003	-0.003		0.008	0.008	0.005		-0.009	-0.012	-0.015
Std. Dev.	0.038	0.034	0.031		0.044	0.033	0.027		0.032	0.041	0.064
t-test	-0.922	-0.980	-1.046		2.431	3.001	2.641		-3.259	-4.349	-4.048

Panel B: CAPM of SMB, HML and ILLIQ-LIQ from 1991 to 2004

	S-B				***H-L***				***ILLIQ-LIQ***		
	S-B_D	**S-B_Q**	**S-B_P**		**H-L_D**	**H-L_Q**	**H-L_P**		**ILLIQ-LIQ_D**	**ILLIQ-LIQ_Q**	**ILLIQ-LIQ_P**
C	-0.001	-0.001	-0.001		0.008	0.008	0.005		-0.010	-0.010	-0.007
	-0.346	*-0.443*	*-0.508*		*2.028*	*2.402*	*1.956*		*-2.183*	*-3.405*	*-3.123*
RM-Tbill	-0.546	-0.439	-0.395		0.047	0.004	0.068		-0.461	-0.330	-0.276
	-7.988	*-6.807*	*-6.659*		*0.382*	*0.036*	*0.862*		*-3.446*	*-3.567*	*-3.981*
R-squared	0.348	0.282	0.273		0.002	0.000	0.011		0.114	0.126	0.135

Table 1.7
Liquidity Effects over Size (SMB) and Book-to-Market Strategy (HML)

RM is the market return on the FTSE-all share index. T-bill is the monthly rate for the UK one month Treasury bill. S-B(H-L) is the hedge portfolio for long the smallest (highest book-to-market) and short the biggest (lowest book-to-market). _D, _Q and _P stand for the decile, quintile and 30%/40%/30% breakpoints. LIQ is the liquidity mimicking factor based on the relative liquidity measure proposed in this study. The numbers in italic are t-statistics. Portfolios are rebalanced every year. The estimations are justified in the presence of both heteroskedasticity and autocorrelation of unknown forms according to Newey and West (1987).

	S-B				***H-L***		
	S-B_D	**S-B_Q**	**S-B_P**		**H-L_D**	**H-L_Q**	**H-L_P**
C	-0.003	-0.003	-0.003		0.005	0.005	0.003
	-1.146	*-1.151*	*-1.307*		*1.503*	*1.609*	*1.083*
Rm-Tbill	-0.586	-0.474	-0.432		-0.006	-0.053	0.014
	-8.315	*-6.957*	*-7.170*		*-0.051*	*-0.498*	*0.184*
LIQ	-0.358	-0.321	-0.343		-0.489	-0.511	-0.488
	-2.502	*-2.061*	*-2.664*		*-2.859*	*-4.073*	*-4.994*
Wald test of LIQ (F-stats)	6.261	4.246	7.095		8.176	16.591	24.937
R-squared	0.381	0.315	0.318		0.049	0.091	0.136

Table 1.8
Robustness of Liquidity Effects

RM is the market return on the FTSE-all share index. T-bill is the monthly rate for the UK one month Treasury bill. H-L is the hedge portfolio for long the highest book-to-market and short the lowest book-to-market. _D, _Q and _P stand for the decile, quintile and 30%/40%/30% breakpoints. LIQ is the liquidity mimicking factor based on the relative liquidity measure proposed in this study. The distress factor is a mimicking factor for distress risk, obtained from Agarwal and Taffler (2005). The numbers in italic are t-statistics. Portfolios are rebalanced every year. The estimations are justified in the presence of both heteroskedasticity and autocorrelation of unknown forms according to Newey and West (1987).

Panel A: Financial Distress Factor over Book-to-Market Strategy

H-L	**H-L_D**	**H-L_Q**	**H-L_P**
C	0.009	0.008	0.006
	1.954	*2.349*	*2.026*
Rm-Tbill	*0.074*	-0.012	0.039
	0.566	*-0.108*	*0.511*
Distress_Factor	-0.096	0.137	0.184
	-0.468	*0.871*	*1.451*
R-squared	0.005	0.007	0.028

Panel B: Robustness of Liquidity effects over Book-to-Market Strategy

H-L	**H-L_D**	**H-L_Q**	**H-L_P**
C	0.006	0.005	0.003
	1.369	*1.563*	*1.193*
Rm-Tbill	0.027	-0.056	-0.002
	0.206	*-0.524*	*-0.029*
LIQ	-0.543	-0.520	-0.480
	-3.150	*-3.970*	*-4.791*
Distress_Factor	-0.173	0.064	0.117
	-0.914	*0.477*	*1.109*
Wald test of LIQ(F-stats)	9.922	15.761	22.952
R-squared	0.059	0.094	0.143

Table 1.9
Robustness of Liquidity Effects over Macroeconomic Variables

RM is the market return on the FTSE-all share index. T-bill is the monthly rate for the UK one month Treasury bill. H-L is the hedge portfolio for long the highest book-to-market and short the lowest book-to-market. _D, _Q and _P stand for the decile, quintile and 30%/40%/30% breakpoints. LIQ is the liquidity mimicking factor based on the relative liquidity measure proposed in this study. The macroeconomic variables are all downloaded from Datastream. Among these macroeconomic variables, the industrial production is the increase in the rate of the seasonally adjusted UK industrial production volume index. CPI is the changes of the UK comsumer price index. Term spread is the yield difference between the 10-year government bond and one month T-bill. Corporate spread is the return difference between the Merrill Lynch UK BBB and AAA bond index. Money supply is the increase rate of the broad money supply.The numbers in italic are t-statistics. Portfolios are rebalanced every year. The estimations are justified in the presence of both heteroskedasticity and autocorrelation of unknown forms according to Newey and West (1987).

HML	**H-L_D**	**H-L_Q**	**H-L_P**
C	*0.013*	0.015	0.005
	1.664	*2.753*	*1.051*
Rm-Tbill	-0.027	-0.140	-0.088
	-0.131	*-0.863*	*-0.784*
LIQ	-0.343	-0.332	-0.389
	-1.878	*-2.440*	*-3.580*
Industrial Production	-0.191	0.260	0.116
	-0.382	*0.743*	*0.412*
CPI	1.225	0.582	0.400
	0.782	*0.495*	*0.444*
Term Spread	7.261	3.514	2.147
	1.113	*0.645*	*0.440*
Corporate Spread	-0.538	-0.186	0.271
	-0.612	*-0.296*	*0.590*
Momey Supply (M2)	-1.084	-1.206	-0.358
	-1.344	*-1.964*	*-0.613*
Wald test of LIQ(F-stats)	3.527	5.953	12.816
R-squared	0.051	0.106	0.118

Table 1.10

Different Factor Models for Illiquid minus Liquid Portfolios

RM is the market return on the FTSE-all share index. T-bill is the monthly rate for the UK one month Treasury bill. ILLIQ-lLIQ_d is the return difference between the most illiquid and liquid decile portfolios. SMB and HML are mimicking factors for size and value. The distress factor is a mimicking factor for distress risk, obtained from Agarwal and Taffler (2005). WML is a 6 by 6 momentum factor as in Jegadeesh and Titman (1993). The numbers in italic are t-statistics. Portfolios are rebalanced every year. The estimations are justified in the presence of both heteroskedasticity and autocorrelation of unknown forms according to Newey and West (1987).

Dependent variables: ILLIQ-LIQ_D					
C	-0.010	-0.012	-0.014	-0.01468	-0.016
	-2.183	*-2.543*	*-2.622*	*-2.702*	*-2.846*
RM-TBILL	-0.461	-0.614	-0.552	-0.560	-0.504
	-3.446	*-4.845*	*-4.506*	*-3.844*	*-3.730*
SMB		-0.478	-0.361	-0.435	-0.338
		-3.776	*-2.499*	*-2.933*	*-2.109*
HML		0.401	0.444	0.412	0.452
		2.216	*2.443*	*2.282*	*2.497*
Distress_Factor			-0.227		-0.145
			-0.973		*-0.583*
WML				0.157	0.179
				1.091	*1.134*
R-squared	0.114	0.190	0.198	0.197	0.207

Table 2.1

Betas, Average Returns, Liquidity and Other Characteristics on 20 Liquidity-ranked Portfolios Over the Period 1962 to 2005

At the end of each year, from 1962 to 2004, all the available non-financial AMEX/NYSE stocks with price greater than 5 dollars from CRSP are ranked into 20 portfolios based on their liquidity level. Portfolio 1 (20) in each year consists of the most liquid (illiquid) 5 percent stocks. Portfolios are rebalanced every year. The post-ranking betas use the full sample of post-ranking returns for each portfolio. The market returns are equally-weighted. In order to minimise the effects of nonsynchronous trading on the estimate of beta (Scholes and Williams, 1977; Dimson, 1979), betas are estimated as the sum of the slopes in the regression of excess returns on the current and prior month's excess market returns. An annual, equally-weighted buy-and-hold return on each portfolio in the next 12 months is calculated.

A time-series of 44 postranking-year returns for each portfolio from year 1962 to 2005 is constructed. Two illiquidity measures are reported: Amihud's (2002) absolute illiquidity measure (Amihud) and the relative liquidity measure (reAmihud). Amihud measures liquidity as the ratio of absolute return to dollar trading volume. The relative illiquidity measure (reAmihud) is the natural logarithm of Amihud's measure scaled by market capitalization. By this construction, high value suggests low liquidity. Size is the average market value of equity in millions of dollars on June 30 of each year. Volume is measued as the total dollar trading volume in each year. Turnover is defined as the ratio of Volume to Size. Price is the annual year-end price level in dollars. Panel A (B) presents the results based on Amihud's (reAmihud) illiquidity measure.

Panel A. Illiquidity Measure of Amihud

Portfolio	Postranking Betas	Postranking Returns (%)	Illiquidity	ln(Size)	ln(Volume)	Turnover	Price
1 (Liquid)	0.88	9.82	-5.10	16.86	14.75	0.14	59.45
2	0.79	10.77	-4.19	15.46	13.91	0.21	46.07
3	0.77	11.07	-3.68	14.96	13.52	0.24	40.50
4	0.82	11.46	-3.24	14.60	13.25	0.28	37.33
5	0.80	12.10	-2.77	14.26	13.04	0.30	33.99
6	0.85	12.88	-2.39	13.98	12.79	0.32	32.80
7	0.88	11.80	-2.04	13.74	12.51	0.32	32.62
8	0.80	13.62	-1.73	13.48	12.24	0.33	30.24
9	0.86	12.89	-1.37	13.26	12.09	0.35	27.66
10	0.85	13.81	-1.08	13.07	11.86	0.34	26.52
11	0.88	14.90	-0.70	12.86	11.67	0.34	25.10
12	0.86	15.63	-0.40	12.67	11.46	0.35	23.73
13	0.86	14.80	-0.14	12.46	11.14	0.33	22.48
14	0.82	16.30	0.22	12.26	10.87	0.33	21.31
15	0.89	16.47	0.69	12.06	10.75	0.33	20.83
16	0.82	17.70	1.09	11.79	10.35	0.32	18.69
17	0.74	19.22	1.53	11.58	10.32	0.32	18.47
18	0.69	19.77	2.09	11.24	9.87	0.32	16.59
19	0.79	21.93	2.86	10.76	9.23	0.29	14.02
20 (Illiquid)	0.62	28.09	4.14	10.29	8.85	0.32	10.99

Table 2.1----*Continued*

Panel B. Relative Illiquidity Measure							
Portfolio	**Postranking Betas**	**Postranking Returns (%)**	**Illiquidity**	**ln(Size)**	**ln(Volume)**	**Turnover**	**Price**
1 (Liquid)	1.04	10.63	8.60	14.55	13.72	0.64	34.10
2	0.99	11.66	8.83	14.72	13.46	0.46	32.96
3	0.88	12.61	8.94	14.83	13.40	0.40	33.05
4	0.92	13.41	9.05	14.81	13.25	0.36	32.92
5	0.88	14.78	9.14	14.91	13.26	0.32	32.08
6	0.96	12.62	9.20	14.84	13.22	0.32	30.23
7	0.84	13.93	9.29	14.97	13.12	0.30	31.22
8	0.84	14.60	9.36	14.94	13.22	0.30	30.50
9	0.87	14.65	9.44	14.94	13.03	0.29	29.59
10	0.86	14.71	9.51	14.94	13.03	0.28	29.37
11	0.84	15.13	9.61	14.90	12.87	0.28	28.66
12	0.75	15.19	9.71	14.97	12.78	0.28	26.23
13	0.85	15.57	9.83	14.23	12.14	0.27	26.78
14	0.76	16.18	9.95	14.33	12.14	0.26	26.49
15	0.72	16.26	10.08	13.48	11.36	0.24	24.35
16	0.78	16.78	10.19	13.20	11.11	0.24	24.06
17	0.72	16.25	10.36	12.90	10.68	0.22	24.03
18	0.65	17.78	10.56	12.98	10.41	0.20	23.95
19	0.68	18.70	10.84	12.93	10.16	0.18	23.67
20 (Illiquid)	0.70	19.40	11.38	12.79	10.03	0.15	23.93

Table 2.2
Holding Period Betas, Average Returns and Size on 100 Size/Liquidity-ranked Portfolios Over the Period 1962 to 2005

At the end of each year, from 1962 to 2004, all the available non-financial AMEX/NYSE stocks with price greater than 5 dollars from CRSP are firstly ranked into 10 portfolios based on their market value. Then within each size-decile, stocks are subdivided into 10 liquidity portfolios. Portfolios are rebalanced every year. The post-ranking betas use the full sample of post-ranking returns for each portfolio. The market returns are equally-weighted. In order to minimise the effects of nonsynchronous trading on the estimate of beta (Scholes and Williams, 1977; Dimson, 1979), betas are estimated as the sum of the slopes in the regression of excess returns on the current and prior month's excess market returns. An annual, equally-weighted buy-and-hold return on each portfolio in the next 12 months is calculated.
A time-series of 44 postranking-year returns for each portfolio from year 1962 to 2005 is constructed. Turnover is defined as the ratio of dollar trading volume to market capitalization. Two illiquidity measures are reported: Amihud's (2002) absolute illiquidity measure (Amihud) and the relative illiquidity measure (reAmihud). Amihud measures liquidity as the ratio of absolute return to dollar trading volume. The relative illiquidity measure (reAmihud) is the natural logarithm of Amihud's measure scaled by market capitalization. By this construction, high value suggests low liquidity. Panel A (B) presents the results based on Amihud's (reAmihud) illiquidity measure.

Panel A. Illiquidity Measure of Amihud

Portfolio	Small	2	3	4	5	6	7	8	9	Big	*Small-Big*	*s.e.*
					Postranking Betas							
LIQ	0.80	1.11	0.81	1.11	1.07	0.99	0.94	0.85	0.92	0.90	*-0.10*	*0.19*
2	0.77	0.70	1.07	1.06	0.89	0.97	0.97	0.86	0.81	0.99	*-0.23*	*0.20*
3	0.85	0.79	0.78	0.98	0.98	0.96	0.85	0.81	0.67	0.82	*0.03*	*0.22*
4	0.96	1.03	0.98	0.90	0.96	0.82	0.97	0.75	0.76	0.82	*0.13*	*0.16*
5	0.68	0.75	0.99	1.03	0.86	0.88	0.88	0.74	0.76	0.76	*-0.08*	*0.18*
6	0.72	0.79	0.71	0.97	0.89	0.76	0.73	0.79	0.73	0.70	*0.02*	*0.18*
7	0.64	0.59	0.64	0.81	0.83	0.79	0.76	0.84	0.73	0.75	*-0.11*	*0.19*
8	0.73	0.55	0.75	0.90	0.77	0.77	0.76	0.73	0.75	0.75	*-0.02*	*0.17*
9	0.53	0.84	0.67	0.84	0.67	0.69	0.75	0.73	0.73	0.75	*-0.22*	*0.21*
ILLIQ	0.40	0.78	0.82	0.70	0.80	0.74	0.80	0.79	0.80	0.62	*-0.22*	*0.20*
ILLIQ-LIQ	*-0.40*	*-0.34*	*0.01*	*-0.40*	*-0.27*	*-0.25*	*-0.14*	*-0.06*	*-0.13*	*-0.28*		
s.e.	*0.20*	*0.20*	*0.14*	*0.14*	*0.19*	*0.14*	*0.15*	*0.14*	*0.15*	*0.08*		
					Average Annual Returns							
LIQ	0.21	0.17	0.15	0.11	0.11	0.10	0.09	0.13	0.10	0.09	*0.12*	*0.03*
2	0.18	0.16	0.16	0.15	0.12	0.14	0.15	0.12	0.10	0.10	*0.09*	*0.03*
3	0.18	0.20	0.18	0.18	0.14	0.16	0.14	0.13	0.11	0.11	*0.07*	*0.04*
4	0.20	0.18	0.18	0.16	0.12	0.13	0.13	0.14	0.12	0.10	*0.10*	*0.03*
5	0.25	0.22	0.14	0.17	0.16	0.14	0.12	0.11	0.12	0.09	*0.16*	*0.03*
6	0.24	0.19	0.19	0.16	0.15	0.15	0.13	0.13	0.12	0.11	*0.13*	*0.03*
7	0.26	0.21	0.19	0.16	0.15	0.14	0.12	0.14	0.12	0.10	*0.16*	*0.03*
8	0.26	0.20	0.18	0.15	0.15	0.13	0.15	0.11	0.13	0.11	*0.15*	*0.03*
9	0.32	0.24	0.19	0.14	0.16	0.14	0.13	0.11	0.11	0.10	*0.22*	*0.04*
ILLIQ	0.36	0.22	0.23	0.17	0.17	0.13	0.16	0.12	0.11	0.10	*0.26*	*0.03*
ILLIQ-LIQ	*0.15*	*0.05*	*0.08*	*0.06*	*0.06*	*0.03*	*0.07*	*0.00*	*0.00*	*0.01*		
s.e.	*0.04*	*0.03*	*0.02*	*0.03*	*0.03*	*0.02*	*0.02*	*0.02*	*0.03*	*0.02*		

Panel A-Table 2.2----*Continued*

	Average ln(Size)											
LIQ	10.44	11.23	11.78	12.21	12.71	13.13	13.63	14.20	14.94	17.70	*-7.26*	*0.05*
2	10.32	11.09	11.73	12.29	12.65	13.16	13.67	14.15	14.86	16.89	*-6.57*	*0.07*
3	10.22	11.15	11.78	12.23	12.68	13.12	13.59	14.15	14.84	16.52	*-6.30*	*0.09*
4	10.17	11.10	11.79	12.21	12.61	13.10	13.60	14.10	14.84	16.17	*-6.00*	*0.08*
5	10.14	11.11	11.68	12.22	12.65	13.15	13.54	14.08	14.77	15.95	*-5.81*	*0.08*
6	10.06	11.02	11.70	12.17	12.62	13.07	13.52	14.06	14.77	15.74	*-5.68*	*0.07*
7	10.00	11.04	11.66	12.19	12.57	13.05	13.50	14.08	14.74	15.70	*-5.71*	*0.07*
8	9.95	11.01	11.64	12.15	12.57	13.05	13.52	14.01	14.66	15.52	*-5.57*	*0.07*
9	9.84	11.04	11.65	12.11	12.62	13.01	13.50	14.00	14.59	15.43	*-5.60*	*0.08*
ILLIQ	9.61	10.99	11.69	12.15	12.61	13.00	13.52	13.99	14.58	15.37	*-5.76*	*0.08*
ILLIQ-LIQ	*-0.83*	*-0.24*	*-0.09*	*-0.06*	*-0.10*	*-0.14*	*-0.11*	*-0.21*	*-0.37*	*-2.33*		
s.e.	*0.06*	*0.05*	*0.03*	*0.03*	*0.03*	*0.03*	*0.03*	*0.03*	*0.03*	*0.03*		
	Average Turnover											
LIQ	0.58	0.76	0.79	0.87	0.74	0.75	0.61	0.47	0.33	0.09	*0.49*	*0.04*
2	0.47	0.56	0.51	0.56	0.47	0.51	0.39	0.36	0.28	0.11	*0.36*	*0.03*
3	0.42	0.48	0.43	0.46	0.41	0.37	0.36	0.30	0.23	0.12	*0.29*	*0.03*
4	0.38	0.42	0.39	0.42	0.39	0.31	0.30	0.26	0.22	0.15	*0.23*	*0.04*
5	0.31	0.37	0.36	0.34	0.31	0.31	0.24	0.24	0.19	0.17	*0.14*	*0.04*
6	0.34	0.35	0.32	0.31	0.27	0.27	0.21	0.24	0.19	0.15	*0.19*	*0.03*
7	0.33	0.30	0.29	0.28	0.24	0.22	0.21	0.19	0.19	0.15	*0.18*	*0.04*
8	0.32	0.30	0.24	0.25	0.21	0.21	0.19	0.18	0.16	0.14	*0.18*	*0.03*
9	0.32	0.25	0.22	0.21	0.18	0.18	0.16	0.15	0.17	0.14	*0.18*	*0.03*
ILLIQ	0.49	0.24	0.20	0.16	0.14	0.13	0.12	0.10	0.10	0.11	*0.38*	*0.14*
ILLIQ-LIQ	*-0.09*	*-0.53*	*-0.59*	*-0.70*	*-0.60*	*-0.62*	*-0.49*	*-0.37*	*-0.23*	*0.01*		
s.e.	*0.14*	*0.05*	*0.05*	*0.08*	*0.06*	*0.05*	*0.04*	*0.04*	*0.02*	*0.01*		

Table 2.2----*Continued*

Panel B. Relative Illiquidity Measure

Portfolio	Small	2	3	4	5	6	7	8	9	Big	*Small-Big*	*s.e.*
						Postranking Betas						
LIQ	0.79	1.02	0.81	1.15	0.99	1.09	0.98	1.01	1.03	0.91	*-0.13*	*0.17*
2	0.56	0.76	1.02	0.93	1.01	0.93	0.92	0.81	0.77	0.79	*-0.23*	*0.18*
3	0.89	0.85	0.80	1.08	0.80	0.98	0.83	0.80	0.68	0.79	*0.11*	*0.16*
4	0.81	0.86	1.00	1.00	0.93	0.80	0.93	0.77	0.75	0.82	*-0.01*	*0.19*
5	0.86	0.76	1.00	0.87	0.96	0.91	0.89	0.82	0.75	0.78	*0.08*	*0.20*
6	0.83	0.75	0.71	0.91	0.88	0.77	0.72	0.74	0.70	0.71	*0.11*	*0.18*
7	0.85	0.67	0.83	0.87	0.90	0.75	0.81	0.72	0.74	0.81	*0.04*	*0.16*
8	0.64	0.82	0.70	0.87	0.68	0.72	0.75	0.80	0.66	0.80	*-0.16*	*0.23*
9	0.55	0.65	0.58	0.83	0.78	0.69	0.78	0.72	0.81	0.71	*-0.16*	*0.21*
ILLIQ	0.46	0.78	0.84	0.76	0.76	0.75	0.76	0.75	0.78	0.73	*-0.27*	*0.19*
ILLIQ-LIQ	*-0.33*	*-0.23*	*0.04*	*-0.39*	*-0.23*	*-0.33*	*-0.22*	*-0.26*	*-0.25*	*-0.19*		
s.e.	*0.15*	*0.19*	*0.16*	*0.14*	*0.20*	*0.15*	*0.16*	*0.14*	*0.16*	*0.11*		
						Average Annual Returns						
LIQ	0.21	0.16	0.17	0.12	0.11	0.12	0.11	0.13	0.09	0.09	*0.13*	*0.03*
2	0.20	0.18	0.15	0.15	0.13	0.14	0.14	0.11	0.09	0.10	*0.10*	*0.03*
3	0.21	0.19	0.17	0.17	0.13	0.13	0.13	0.14	0.11	0.10	*0.11*	*0.03*
4	0.22	0.20	0.18	0.17	0.15	0.13	0.13	0.13	0.12	0.10	*0.12*	*0.03*
5	0.23	0.18	0.18	0.14	0.13	0.16	0.14	0.12	0.14	0.10	*0.13*	*0.03*
6	0.25	0.21	0.18	0.17	0.16	0.15	0.14	0.14	0.13	0.10	*0.15*	*0.03*
7	0.26	0.20	0.17	0.15	0.16	0.13	0.12	0.12	0.11	0.10	*0.15*	*0.03*
8	0.26	0.21	0.18	0.16	0.15	0.14	0.14	0.12	0.12	0.11	*0.15*	*0.04*
9	0.30	0.22	0.20	0.15	0.16	0.14	0.14	0.11	0.12	0.10	*0.19*	*0.04*
ILLIQ	0.29	0.22	0.23	0.17	0.17	0.13	0.16	0.11	0.10	0.10	*0.19*	*0.03*
ILLIQ-LIQ	*0.08*	*0.06*	*0.06*	*0.05*	*0.06*	*0.01*	*0.05*	*-0.02*	*0.01*	*0.02*		
s.e.	*0.03*	*0.03*	*0.03*	*0.03*	*0.03*	*0.03*	*0.03*	*0.02*	*0.03*	*0.02*		

Panel B-Table 2.2----*Continued*

Average ln(Size)												
LIQ	10.20	11.13	11.76	12.18	12.68	13.11	13.60	14.12	14.76	15.88	*-5.68*	*0.07*
2	10.15	11.08	11.68	12.29	12.63	13.11	13.59	14.07	14.72	16.00	*-5.85*	*0.08*
3	10.02	11.04	11.72	12.19	12.64	13.08	13.57	14.12	14.75	15.96	*-5.94*	*0.08*
4	10.06	11.08	11.78	12.19	12.64	13.09	13.58	14.13	14.75	16.22	*-6.16*	*0.08*
5	10.07	11.12	11.74	12.20	12.61	13.12	13.57	14.07	14.82	16.22	*-6.14*	*0.09*
6	10.07	11.15	11.68	12.19	12.64	13.10	13.53	14.09	14.79	16.30	*-6.23*	*0.09*
7	10.12	11.02	11.65	12.16	12.62	13.04	13.52	14.06	14.73	16.48	*-6.36*	*0.07*
8	9.97	11.04	11.70	12.21	12.59	13.08	13.54	14.08	14.77	16.49	*-6.52*	*0.08*
9	10.10	11.06	11.66	12.13	12.64	13.05	13.56	14.03	14.81	16.86	*-6.76*	*0.09*
ILLIQ	10.24	11.08	11.74	12.18	12.65	13.03	13.55	14.03	14.73	17.08	*-6.84*	*0.12*
ILLIQ-LIQ	*0.04*	*-0.05*	*-0.03*	*0.00*	*-0.03*	*-0.08*	*-0.05*	*-0.08*	*-0.03*	*1.20*		
s.e.	*0.05*	*0.04*	*0.03*	*0.03*	*0.04*	*0.03*	*0.03*	*0.03*	*0.03*	*0.10*		
Average Turnover												
LIQ	0.61	0.79	0.79	0.88	0.75	0.76	0.61	0.51	0.41	0.23	*0.38*	*0.05*
2	0.46	0.57	0.56	0.56	0.50	0.51	0.44	0.38	0.29	0.17	*0.29*	*0.03*
3	0.42	0.46	0.45	0.47	0.39	0.39	0.33	0.27	0.25	0.14	*0.28*	*0.03*
4	0.41	0.42	0.39	0.41	0.38	0.33	0.30	0.26	0.21	0.15	*0.26*	*0.05*
5	0.36	0.36	0.36	0.35	0.33	0.28	0.23	0.25	0.18	0.13	*0.23*	*0.03*
6	0.34	0.36	0.33	0.30	0.26	0.27	0.22	0.22	0.17	0.13	*0.22*	*0.03*
7	0.31	0.32	0.25	0.28	0.23	0.21	0.21	0.20	0.16	0.12	*0.19*	*0.03*
8	0.28	0.26	0.23	0.24	0.21	0.20	0.19	0.18	0.17	0.11	*0.18*	*0.03*
9	0.38	0.27	0.23	0.22	0.17	0.17	0.15	0.15	0.14	0.09	*0.29*	*0.08*
ILLIQ	0.32	0.23	0.20	0.15	0.14	0.14	0.11	0.10	0.10	0.07	*0.24*	*0.03*
ILLIQ-LIQ	*-0.30*	*-0.56*	*-0.58*	*-0.73*	*-0.61*	*-0.62*	*-0.50*	*-0.41*	*-0.31*	*-0.16*		
s.e.	*0.04*	*0.06*	*0.06*	*0.08*	*0.06*	*0.05*	*0.04*	*0.04*	*0.04*	*0.03*		

Table 2.3
Cross-Sectional Regression of Betas on Liquidity and Size Over the Period 1962 to 2005

Time-series averages of estimated coefficients from the following annual cross-sectional regressions from 1962 to 2005. Associated t-statistics and R-squares are reported (with and without Size/Liquidity being included in the regressions).

$$\boxed{\beta_{pt} = \Phi_{1t} + \Phi_{2t} ILLIQ_{pt-1} + \Phi_{3t} Size_{pt-1} + \varepsilon_{pt}}$$

where βpt is the postranking beta for portfolio p from July 1 of year t to June 30 of year t+1. ILLIQpt-1 and Sizept-1 are the liquidity level and natural logarithm of the average market capitalization in millions of dollars for portfolio p at the end of year t. Both these two series are cross-sectionally demeaned every year. Φ1t, Φ2t, and Φ3t are regression parameters; and εpt is the regression error. Portfolios are formed in two different ways. (i) 20(100) portfolios by grouping on liquidity alone; (ii) ranking stocks first on size into 5(10) portfolios and then on liquidity within each size group into 5(10) portfolios.The post-ranking betas use the full sample of post-formation returns for each portfolio.

Two illiquidity measures are reported: Amihud's (2002) absolute illiquidity measure (Amihud) and the relative illiquidity measure (reAmihud). Amihud measures liquidity as the ratio of absolute return to dollar trading volume. The relative illiquidity measure (reAmihud) is the natural logarithm of Amihud's measure scaled by market capitalization. By this construction, high value suggests low liquidity. Panel A (B) presents the results based on Amihud's (reAmihud) illiquidity measure.

Panel A. Illiquidity Measure of Amihud

Portfolios	Φ_{1t} t-statistics	Φ_{2t} t-statistics	Φ_{3t} t-statistics	R^2
20 liquidity ranked	0.79	-0.04		0.54
	980.43	*-12.48*		
	0.79		0.02	0.20
	173.56		*94.39*	
	0.79	-0.04	0.00	0.54
	88.26	*-14.17*	*-2.02*	
25, first size, then liquidity ranked	0.87	0.00		0.00
	4379.29	*2.79*		
	0.87		-0.03	0.18
	530.19		*-78.58*	
	0.87	-0.04	-0.05	0.27
	185.57	*-15.07*	*-47.17*	
100 liquidity ranked	0.96	0.04		0.51
	161.95	*25.33*		
	0.96		-0.05	0.47
	165.31		*-59.06*	
	0.96	0.09	0.07	0.54
	4.10	*19.64*	*12.60*	
100, first size, then liquidity ranked	0.81	-0.01		0.06
	327.39	*-19.54*		
	0.81		0.00	0.00
	247.33		*23.22*	
	0.81	-0.09	-0.10	0.27
	97.20	*-43.13*	*-58.60*	

Table 2.3----*Continued*

Panel B. Relative Illiquidity Measure				
20 liquidity ranked	0.80	-0.11		0.81
	49.58	*-35.31*		
	0.80		0.02	0.56
	2.84		*1.62*	
	0.80	-0.10	0.00	0.82
	31.14	*-33.39*	*-0.80*	
25, first size, then liquidity ranked	0.87	-0.08		0.26
	20.17	*-10.00*		
	0.87		-0.04	0.28
	444.68		*-88.98*	
	0.87	-0.13	-0.06	0.80
	75.25	*-52.65*	*-19.47*	
100 liquidity ranked	0.96	-0.04		0.12
	61.98	*-19.39*		
	0.96		0.01	0.09
	16.26		*2.31*	
	0.96	-0.03	0.01	0.14
	15.69	*-7.88*	*1.71*	
100, first size, then liquidity ranked	0.82	-0.08		0.25
	42.71	*-23.23*		
	0.82		0.00	0.00
	462.08		*-8.40*	
	0.82	-0.10	-0.02	0.33
	108.14	*-60.48*	*-7.11*	

Table 2.4

Cross-Sectional Regression of Portfolio Returns on Betas, Liquidity and Size Over the Period 1962 to 2005

Time-series averages of estimated coefficients from the following annual cross-sectional regressions from 1962 to 2005. Associated *t*-statistics and R-squares are reported (with and without Size/Liquidity being included in the regressions).

$$r_{pt} = \Phi_{1t} + \Phi_{2t}\beta_{pt} + \Phi_{3t} ILLIQ_{pt-1} + \Phi_{4t}\ln(Size_{pt-1}) + \varepsilon_{pt}$$

where rpt is the portfolio holding period return; βpt is the post-formation beta for portfolio p from July 1 of year t to June 30 of year t+1. ILLIQpt-1 and ln(Size)pt-1 are the liquidity level and natural logarithm of the average market capitalization in millions of dollars for portfolio p at the end of year t. Φ1t, Φ2t, Φ3t and Φ4t are regression parameters; and εpt is the regression error. Portfolios are formed in two different ways. (i) 20(100) portfolios by grouping on liquidity alone; (ii) ranking stocks first on size into 5(10) portfolios and then on liquidity within each size group into 5(10) portfolios.Postranking beta for each portfolio is the beta estimate in the one-year buy-and-hold period.

Two illiquidity measures are reported: Amihud's (2002) absolute illiquidity measure (Amihud) and the relative illiquidity measure (reAmihud). Amihud measures liquidity as the ratio of absolute return to dollar trading volume. The relative illiquidity measure (reAmihud) is the natural logarithm of Amihud's measure scaled by market capitalization. By this construction, high value suggests low liquidity. Panel A (B) presents the results based on Amihud's (reAmihud) illiquidity measure.

Panel A. Illiquidity Measure of Amihud

	Φ_{1t}	Φ_{2t}	Φ_{3t}	Φ_{4t}	
Portfolios	*t*-statistics	*t*-statistics	*t*-statistics	*t*-statistics	R^2
20 liquidity ranked	0.49	-0.43			0.21
	9.70	*-7.64*			
	0.16	-0.01	0.02		0.38
	4.11	*-0.24*	*6.48*		
	0.33	-0.22		-0.02	0.51
	11.16	*-5.40*		*-4.70*	
	0.17	-0.02	0.02	-0.01	0.61
	5.14	*-0.57*	*3.62*	*-3.19*	
100 liquidity ranked	*0.18*	*-0.05*			0.25
	5.24	*-0.80*			
	0.18	*-0.05*	*0.01*		0.40
	5.33	*-0.85*	*2.21*		
	0.25	*-0.13*		*-0.01*	0.51
	9.31	*-2.98*		*-2.94*	
	0.23	*-0.11*	*0.01*	*-0.01*	0.56
	8.63	*-2.55*	*2.35*	*-2.18*	
25, first size, then liquidity ranked	*-0.11*	*0.27*			0.17
	-2.16	*3.86*			
	0.03	*0.13*	*0.00*		0.27
	0.73	*2.13*	*4.10*		
	0.00	*0.16*		*-0.01*	0.28
	-0.04	*3.49*		*-2.41*	
	0.10	*0.06*	*0.00*	*-0.01*	0.37
	2.96	*1.44*	*4.68*	*-1.78*	
100, first size, then liquidity ranked	*0.26*	*-0.13*			0.08
	11.37	*-3.63*			
	0.15	0.01	0.02		0.21
	6.51	*0.22*	*6.74*		
	0.25	-0.12		-0.02	0.29
	10.97	*-3.10*		*-4.86*	
	0.18	-0.04	0.02	-0.01	0.34
	8.27	*-1.12*	*4.86*	*-3.03*	

Table 2.4----*Continued*

Panel B. Relative Illiquidity Measure					
20 liquidity ranked	0.31	-0.20			0.31
	8.25	*-3.90*			
	0.17	-0.03	0.02		0.39
	5.72	*-0.63*	*3.33*		
	0.26	-0.13		-0.01	0.39
	7.75	*-2.98*		*-2.71*	
	0.18	-0.04	0.02	0.00	0.45
	6.17	*-1.03*	*2.57*	*-1.20*	
100 liquidity ranked	*0.18*	*-0.05*			0.29
	4.66	*-0.86*			
	0.11	*0.03*	*0.03*		0.45
	2.07	*0.38*	*3.49*		
	0.28	*-0.16*		*-0.02*	0.53
	8.87	*-3.51*		*-3.28*	
	0.28	*-0.16*	*0.00*	*-0.01*	0.56
	8.25	*-3.67*	*0.09*	*-2.90*	
25, first size, then liquidity ranked	*0.25*	*-0.10*			0.06
	7.37	*-2.70*			
	0.14	*0.01*	*0.04*		0.23
	4.72	*0.25*	*5.10*		
	0.18	*-0.03*		*-0.01*	0.17
	5.97	*-0.83*		*-2.28*	
	0.14	*0.02*	*0.04*	*0.00*	0.25
	4.59	*0.41*	*5.64*	*0.79*	
100, first size, then liquidity ranked	*0.23*	*-0.10*			0.08
	9.53	*-2.41*			
	0.17	-0.02	0.02		0.15
	6.74	*-0.42*	*3.70*		
	0.24	-0.10		-0.02	0.29
	9.69	*-2.64*		*-4.85*	
	0.21	-0.07	0.01	-0.02	0.32
	9.98	*-2.22*	*1.98*	*-4.28*	

Figure 3.1: One Month T-bill

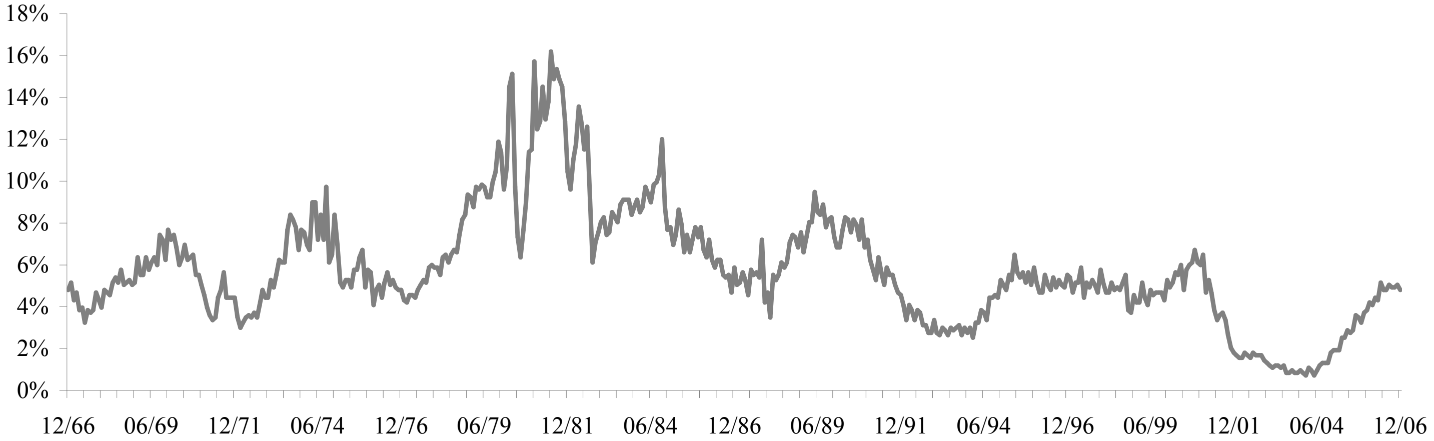

Figure 3.2: NBER Business Cycle

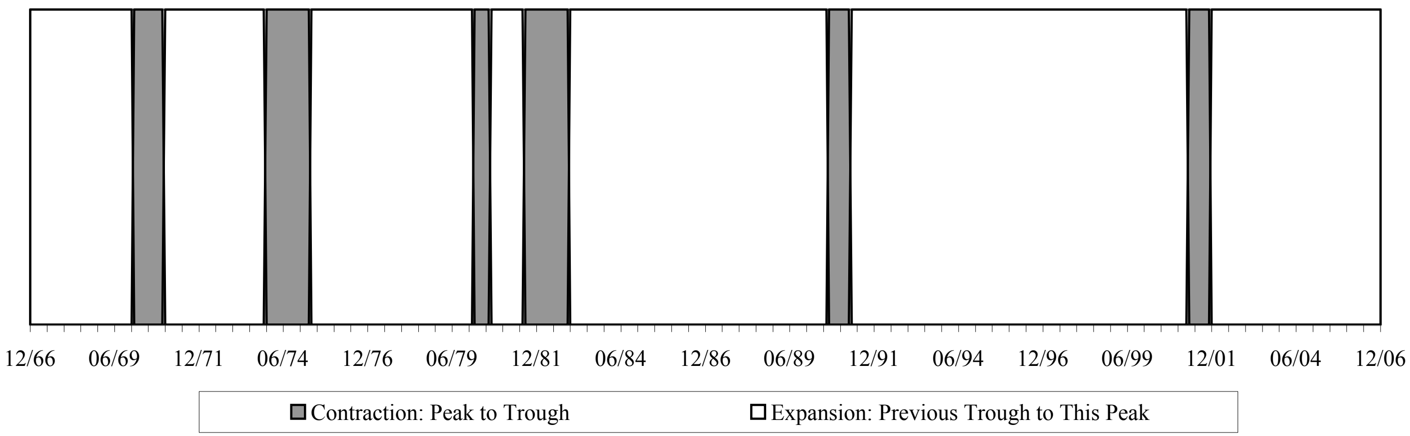

Table 3.1

Descriptive Statistics of Different Factors (Value-Weighted) from January 1967 to December 2006

We use all the NYSE, AMEX, and NASDAQ nonfinancial firms which have traded at prices at least 5 dollars listed on the CRSP daily and monthly stock return files and the Compustat annual industrial files from 1963 to 2006. The data of Fama and French (1993) factors, momentum factors (MOM) and long-term reversal (LTRV) are from Professor Kenneth French's data library. Asset growth factor (ASG) is calculated as in Cooper, Gulen and Schill (2006). Accrual factor (ACRU) is calculated as in Richardson, Sloan, Soliman and Tuna (2005). Other firm characteristic factors are calculated as follows. We follow the method used by Fama and French (1993). A mimicking factor related to one specific characteristic is computed as the out-of-sample return difference between the lowest 30% and the highest 30% characteristic-sorted portfolios using past information. Asset growth rate is calculated as in Cooper, Gulen and Schill (2006). Specifically, the annual firm asset growth rate is calculated using year-on-year percentage change in total assets (Compustat Data Item 6). The firm asset growth rate for year y is defined as the percentage change in total assets from fiscal year ending in calendar year y-2 to year ending in calendar y-1.

We calculate our volume factor (VO) following the principal of Gervais, Kaniel and Mingelgrin (2001), where the past 50 days trading interval is used to classify the high- (low-) volume stock. This 50-day interval is split into a reference period (first 49 days) and formation period (the last day of the interval). Using daily number of trade in this 50-day interval, a stock is classified as high- (low-) volume stock if its formation period volume is among the top (bottom) 10 percent for that trading interval. Liquidity factor (LIQ) is calculated using the illiquidity measure of Amihud's (2002). We calculate coskewness and cokurtosis following Harvey and Siddique (2000), where at least 24 out of past 60 monthly returns are used. Then the 61st month return is recorded for the coskewness- (cokurtosis-) sorted portfolios. For the downside beta, Ang, Chen and Xing (2006) sort stocks into portfolios based on the realised downside beta at the beginning of the one-year period t, and then they examine the relationship between downside beta and return from time t to t+12.

We however form our downside-beta sorted portfolios consistent with other characteristic-sorted portfolios. That is, we use past 1-year daily data to compute downside-beta, and then use postformation return in the following month. VO, IDSN, COSK, COKT, DNSD, are rebalanced every month. ASG, LIQ are rebalanced in June of each year. All the factor returns are value weighted.

Panel A: Descriptive Statistics

	ERM	COSK	COKT	DNSD	LIQ	SMB	HML	ASG	ACRU	LTRV	MOM	IDSN	VO	PCA1	PCA2	PCA3	PCA4	PCA5
Mean	**0.487**	0.157	0.176	0.025	**-0.510**	0.245	**0.461**	**0.407**	0.175	**0.351**	**0.806**	0.328	-0.036	0.082	0.055	-0.004	0.058	-0.042
(Std Err)	(0.206)	(0.117)	(0.132)	(0.227)	(0.159)	(0.151)	(0.137)	(0.152)	(0.141)	(0.116)	(0.187)	(0.284)	(0.092)	(0.163)	(0.071)	(0.078)	(0.064)	(0.053)
Skewness	-0.496	0.239	0.180	0.494	-0.422	0.573	0.014	-0.183	-0.048	0.796	-0.630	0.046	-0.286	1.445	1.066	0.445	2.559	1.714
Kurtosis	4.947	6.248	5.201	7.451	5.019	8.539	5.385	6.367	4.665	6.086	8.273	8.873	6.613	10.267	12.353	11.589	23.012	17.291
Jarque-Bera	95.5	215.6	99.5	415.7	95.8	640.0	113.7	229.4	55.6	241.2	587.8	690.1	267.7	1223.2	1840.4	1491.4	8533.1	4319.5

Panel B: Correlation Matrix

	ERM	COSK	COKT	DNSD	LIQ	SMB	HML	ASG	ACRU	LTRV	MOM	IDSN	VO	PCA1	PCA2	PCA3	PCA4	PCA5
ERM	1													**0.431**	0.270	**0.407**	0.143	0.163
COSK	0.293	1												0.242	0.033	0.184	0.151	0.012
COKT	-0.323	-0.374	1											-0.246	-0.197	-0.140	-0.031	-0.049
DNSD	**-0.643**	-0.361	0.478	1										**-0.525**	-0.167	-0.247	-0.093	-0.028
LIQ	0.082	0.080	-0.310	-0.100	1									-0.332	-0.009	0.164	-0.125	-0.056
SMB	0.306	0.033	0.058	-0.289	**-0.786**	1								**0.574**	0.073	0.055	0.151	0.077
HML	-0.429	-0.104	0.380	**0.665**	-0.131	-0.289	1							-0.390	-0.147	-0.115	0.030	0.077
ASG	-0.432	-0.187	0.395	**0.627**	-0.153	-0.231	**0.680**	1						-0.394	-0.176	-0.199	-0.042	0.060
ACRU	-0.291	-0.238	0.329	0.460	-0.117	-0.161	**0.570**	**0.625**	1					-0.250	-0.152	-0.104	-0.065	0.068
LTRV	-0.107	-0.168	0.225	0.311	-0.343	0.248	0.388	0.288	0.309	1				0.105	-0.017	0.001	-0.001	-0.021
MOM	-0.075	-0.154	0.206	-0.037	-0.076	-0.004	-0.116	0.079	-0.062	-0.032	1			-0.047	-0.181	-0.158	-0.165	-0.089
IDSN	**-0.600**	-0.246	0.286	**0.734**	0.285	**-0.674**	**0.604**	**0.550**	0.357	0.045	0.020	1		**-0.664**	-0.107	-0.226	-0.115	-0.065
VO	-0.089	-0.065	0.090	0.123	-0.021	-0.010	0.126	0.057	0.071	0.017	-0.020	0.101	1	-0.119	-0.067	-0.089	-0.015	-0.058

Table 3.2

Regression and Principal Component Analysis of Different Factors from January 1967 to December 2006

The definitions of the factors are explained in Table 3.1. The numbers in the parentheses are White heteroskedasticity adjusted t-statistics. Bold numbers represent significance at 5% level. Principal component analysis is applied using covariance matrix.

A. Regression Analysis

Dependent Factors	Constant	ERM	SMB	HML	MOM	Adj R-Sqr	Constant	PCA1	PCA2	PCA3	PCA4	PCA5	Adj R-Sqr
COSK	0.002	**0.170**	-0.047	-0.008	**-0.083**	0.099	0.001	**0.175**	0.054	**0.277**	**0.278**	0.026	0.107
	(1.327)	**(6.014)**	-(1.311)	-(0.181)	**-(3.022)**		(1.136)	**(5.614)**	(0.766)	**(4.256)**	**(3.493)**	(0.279)	
COKT	-0.001	**-0.136**	**0.205**	**0.370**	**0.166**	0.271	0.002	**-0.200**	**-0.365**	**-0.238**	-0.066	-0.121	0.114
	-(0.942)	**-(4.758)**	**(5.645)**	**(8.636)**	**(5.940)**		(1.692)	**-(5.733)**	**-(4.595)**	**-(3.260)**	-(0.742)	-(1.135)	
DNSD	-0.001	**-0.481**	-0.030	**0.778**	-0.018	0.597	0.001	**-0.731**	**-0.532**	**-0.720**	**-0.333**	-0.115	0.367
	-(0.506)	**-(13.171)**	-(0.634)	**(14.203)**	-(0.514)		(0.699)	**-(14.439)**	**-(4.603)**	**-(6.800)**	**-(2.569)**	-(0.743)	
LIQ	-0.001	**0.176**	**-1.002**	**-0.371**	**-0.085**	0.812	**-0.005**	**-0.325**	-0.020	**0.337**	**-0.314**	-0.166	0.147
	-(1.504)	**(10.052)**	**-(44.783)**	**-(14.087)**	**-(4.980)**		**-(3.183)**	**-(7.861)**	-(0.213)	**(3.891)**	**-(2.969)**	-(1.317)	
ASG	0.000	**-0.110**	-0.003	**0.701**	**0.114**	0.502	**0.005**	**-0.368**	**-0.376**	**-0.388**	-0.101	0.174	0.223
	(0.403)	**-(4.046)**	-(0.076)	**(17.157)**	**(4.296)**		**(3.497)**	**-(9.784)**	**-(4.375)**	**-(4.928)**	-(1.051)	(1.512)	
ACRU	-0.001	-0.042	0.015	**0.565**	-0.002	0.322	0.002	**-0.218**	**-0.301**	**-0.189**	-0.145	0.182	0.096
	-(0.541)	-(1.410)	(0.400)	**(12.758)**	-(0.086)		(1.671)	**-(5.770)**	**-(3.497)**	**-(2.402)**	-(1.501)	(1.584)	
LTRV	0.001	-0.006	**0.303**	**0.422**	0.017	0.286	**0.003**	**0.074**	-0.027	0.002	-0.001	-0.045	0.001
	(0.684)	-(0.247)	**(9.600)**	**(11.361)**	(0.692)		**(2.973)**	**(2.289)**	-(0.364)	(0.023)	-(0.014)	-(0.453)	
IDSN	**0.004**	**-0.421**	**-0.911**	**0.702**	0.052	0.711	**0.005**	**-1.162**	**-0.431**	**-0.825**	**-0.519**	**-0.341**	0.516
	(2.403)	**-(10.844)**	**-(18.423)**	**(12.054)**	(1.383)		**(2.317)**	**-(20.910)**	**-(3.401)**	**-(7.098)**	**-(3.654)**	**-(2.008)**	
VO	-0.001	-0.024	0.024	**0.077**	-0.005	0.011	0.000	**-0.068**	-0.087	-0.105	-0.022	-0.101	0.020
	-(0.635)	-(1.018)	(0.803)	**(2.187)**	-(0.225)		-(0.322)	**-(2.636)**	-(1.478)	-(1.957)	-(0.335)	-(1.287)	

B. Regression Analysis

Dependent Factors	Constant	ERM	COSK	COKT	DNSD	LIQ	ASG	ACRU	LTRV	IDSN	VO	Adj R-Sqr
SMB	0.000	**0.094**	**-0.058**	-0.004	**0.042**	**-0.636**	**-0.085**	**-0.073**	**0.089**	**-0.210**	0.042	0.860
	-(0.494)	**(5.418)**	**-(2.359)**	-(0.167)	**(1.925)**	**-29.796**	**-(3.236)**	**-(3.029)**	**(3.435)**	**-(12.098)**	(1.488)	
HML	0.001	0.028	**0.213**	0.054	**0.104**	**-0.085**	**0.191**	**0.190**	**0.219**	**0.175**	0.072	0.655
	(1.362)	(1.134)	**(6.046)**	(1.547)	**(3.313)**	**-2.803**	**(5.098)**	**(5.524)**	**(5.960)**	**(7.054)**	(1.781)	
MOM	**0.007**	-0.096	**-0.252**	**0.346**	**-0.330**	-0.056	**0.280**	**-0.270**	-0.038	0.070	-0.044	0.116
	(3.938)	-(1.762)	**-(3.263)**	**(4.549)**	**-(4.824)**	-0.842	**(3.419)**	**-(3.598)**	-(0.469)	(1.296)	-(0.503)	

C. Principal Component Analysis

	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6	Comp 7	Comp 8	Comp 9	Comp 10	Comp 11	Comp 12	Comp 13
Eigenvalue	0.0083	0.0028	0.0018	0.0012	0.0008	0.0007	0.0005	0.0004	0.0004	0.0004	0.0003	0.0002	0.0001
Variance Prop.	0.467	0.155	0.102	0.066	0.042	0.037	0.028	0.023	0.023	0.022	0.017	0.013	0.005
Cumulative Prop.	0.467	0.622	0.724	0.790	0.832	0.869	0.897	0.921	0.944	0.966	0.982	0.995	1.000

Table 3.3

Average F-test of Factor Pricing Models with T=60 and K=1

We use all the NYSE, AMEX, and NASDAQ nonfinancial firms which have traded at prices at least $5 listed on the CRSP daily and monthly stock return files and the Compustat annual industrial files from 1972 to 2006. For explanations of the factors, see Table 3.1. For each subsample period, we apply the average F-test proposed by Hwang and Satchell (2007). The third column is the average F-test statistic for 5% significance level. The bold numbers indicate that they are significantly different from the 5% signfiicant level. 'NOR' means number of rejection period.

Sample Preiod T=60	No of Stocks N	5%	K=1																	
			ERM	COSK	COKT	DNSD	LIQ	SMB	HML	ASG	ACRU	MOM	LTRV	IDSN	VO	PCA1	PCA2	PCA3	PCA4	PCA5
Jan 1972 - Dec 1976	1741	1.096	0.640	0.432	0.428	0.614	0.525	0.699	0.699	0.533	0.459	**1.232**	1.088	0.755	0.404	0.638	0.435	0.463	0.417	0.406
Jan 1977 - Dec 1981	2752	1.084	**1.348**	0.868	**1.248**	**1.107**	**1.451**	**1.349**	**1.372**	**1.252**	**1.255**	0.682	**1.336**	0.908	**1.396**	0.757	**1.289**	**1.150**	0.998	**1.965**
Jan 1982 - Dec 1986	2809	1.084	**1.634**	**2.152**	**2.349**	**3.018**	**2.137**	**2.173**	**3.916**	**3.239**	**2.524**	**2.001**	**2.021**	**3.532**	**2.034**	**1.791**	**1.689**	**2.196**	**2.133**	**2.140**
Jan 1987 - Dec 1991	3365	1.080	**1.088**	0.984	1.005	0.810	0.857	**1.264**	0.862	**1.355**	0.977	0.804	1.055	**1.661**	0.985	1.015	0.926	1.027	**1.106**	1.010
Jan 1992 - Dec 1996	3682	1.076	**1.152**	**1.907**	**1.932**	**2.066**	**1.835**	**1.945**	**1.948**	**2.004**	**1.977**	**1.503**	**1.647**	**2.317**	**2.038**	**2.029**	**1.518**	**1.911**	**1.589**	**1.991**
Jan 1997 - Dec 2001	4300	1.074	0.742	0.864	0.816	0.956	0.878	0.859	1.027	0.879	0.867	0.972	1.051	**1.091**	0.870	0.879	0.873	0.746	0.896	0.856
Jan 2002 - Dec 2006	3990	1.075	**1.676**	**1.887**	**2.245**	**2.345**	**1.865**	**1.511**	**1.930**	**2.017**	**1.942**	**2.270**	**1.706**	**1.889**	**2.030**	**2.652**	**2.038**	**1.413**	**2.064**	**2.189**
Pre 1992 NOR			3	1	2	2	2	3	2	3	2	2	2	2	2	1	2	2	2	2
Post 1992 NOR			2	2	2	2	2	2	2	2	2	2	2	3	2	2	2	2	2	2
Total NOR			5	3	4	4	4	5	4	5	4	4	4	5	4	3	4	4	4	4

Table 3.4

Number of Rejections: Average F-test of Factor Pricing Models with T=60 and K=2

We use all the NYSE, AMEX, and NASDAQ nonfinancial firms which have traded at prices at least $5 listed on the CRSP daily and monthly stock return files and the Compustat annual industrial files from 1972 to 2006. For explanation of the factors, see Table 3.1. For each subsample period, we apply the average F-test proposed by Hwang and Satchell (2007). The third row is the average F-test statistic for the 5% significance level. The bold numbers indicate that they are significantly different from 5% signfiicant level. 'NOR' means number of rejection period.

Models		Jan 72 - Dec 76	Jan 77 - Dec 81	Jan 82 - Dec 86	Jan 87 - Dec 91	Jan 92 - Dec 96	Jan 97 - Dec 01	Jan 02 - Dec 06	Total NOR	Pre-92 NOR	Post-92 NOR
	Number of Stocks	1741	2752	2809	3365	3682	4300	3990			
	5% Average F-test	1.097	1.084	1.083	1.080	1.078	1.075	1.076			
	Panel A: PCA Factors										
1	PCA1, PCA2	0.651	0.818	**1.125**	0.865	**1.598**	0.904	**2.628**	3	1	2
2	PCA1, PCA3	0.685	0.771	**1.842**	1.013	**2.023**	0.793	**1.784**	3	1	2
3	PCA1, PCA4	0.598	0.729	**1.802**	0.950	**1.672**	0.943	**2.633**	3	1	2
4	PCA1, PCA5	0.595	**1.093**	**1.808**	1.031	**2.099**	0.902	**2.833**	4	2	2
5	PCA2, PCA3	0.469	**1.272**	**1.753**	0.961	**1.496**	0.775	**1.382**	4	2	2
6	PCA2, PCA4	0.422	**1.100**	**1.701**	1.043	**1.203**	0.946	**2.027**	4	2	2
7	PCA2, PCA5	0.411	**2.202**	**1.708**	0.934	**1.575**	0.903	**2.150**	4	2	2
8	PCA3, PCA4	0.456	1.002	**2.208**	**1.139**	**1.574**	0.796	**1.388**	4	2	2
9	PCA3, PCA5	0.438	**1.912**	**2.216**	1.034	**1.976**	0.756	**1.488**	4	2	2
10	PCA4, PCA5	0.396	**1.659**	**2.150**	**1.114**	**1.642**	0.922	**2.175**	5	3	2
	Panel B: Risk-Related Factors										
1	ERM, COSK	0.676	**1.527**	**1.608**	**1.102**	**1.138**	0.728	**1.689**	5	3	2
2	ERM, COKT	0.618	**1.192**	**1.426**	**1.094**	**1.153**	0.747	**1.467**	5	3	2
3	ERM, DNSD	0.715	**1.405**	**1.391**	1.032	**1.106**	0.744	**1.528**	4	2	2
4	ERM, LIQ	0.751	**1.315**	**1.713**	1.014	1.065	0.757	**1.088**	3	2	1
	Panel C: Firm Characteristics Based Factors										
1	ERM, SMB	0.823	**1.163**	**1.698**	1.013	**1.193**	0.776	**1.477**	4	2	2
2	ERM, HML	1.066	**1.371**	**1.590**	1.056	0.977	0.808	1.074	2	2	0
3	ERM, ASG	0.629	**1.307**	**1.348**	**1.102**	1.070	0.743	**1.391**	4	3	1
4	ERM, ACRU	0.610	**1.346**	**1.444**	**1.103**	**1.148**	0.739	**1.686**	5	3	2
5	ERM, LTRV	1.068	**1.378**	**1.646**	1.064	1.018	0.817	**1.491**	3	2	1
6	ERM, MOM	0.917	**1.348**	**1.215**	0.922	1.038	0.806	**1.382**	3	2	1
7	ERM, IDSN	0.753	**1.231**	**1.341**	1.060	**1.354**	0.849	**1.680**	4	2	2
8	ERM, VO	0.649	**1.390**	**1.618**	1.058	**1.191**	0.773	**1.656**	4	2	2

Table 3.5

Number of Rejections: Average F-test of Factor Pricing Models with T=60 and K=3

We use all the NYSE, AMEX, and NASDAQ nonfinancial firms which have traded at prices at least $5 listed on the CRSP daily and monthly stock return files and the Compustat annual industrial files from 1972 to 2006. For explanation of the factors, see Table 3.1. For each subsample period, we apply the average F-test proposed by Hwang and Satchell (2007). The third row is the average F-test statistic for the 5% significance level. The bold numbers indicate that they are significantly different from 5% signfiicant level. 'NOR' means number of rejection period.

Models		**Jan 72 - Dec 76**	**Jan 77 - Dec 81**	**Jan 82 - Dec 86**	**Jan 87 - Dec 91**	**Jan 92 - Dec 96**	**Jan 97 - Dec 01**	**Jan 02 - Dec 06**	**Total NOR**	**Pre-92 NOR**	**Post-92 NOR**
	Number of Stocks	1741	2752	2809	3365	3682	4300	3990			
	5% Average F-test	1.097	1.085	1.083	1.079	1.079	1.075	1.076			
Panel A: PCA Factors											
1	PCA1, PCA2, PCA3	0.703	0.831	**1.160**	0.872	**1.583**	0.807	**1.761**	3	1	2
2	PCA1, PCA2, PCA4	0.611	0.768	**1.136**	0.796	**1.263**	0.980	**2.611**	3	1	2
3	PCA1, PCA2, PCA5	0.609	**1.231**	**1.140**	0.878	**1.663**	0.935	**2.813**	4	2	2
4	PCA1, PCA3, PCA4	0.651	0.761	**1.855**	0.954	**1.666**	0.844	**1.749**	3	1	2
5	PCA1, PCA3, PCA5	0.640	1.063	**1.863**	1.030	**2.097**	0.804	**1.915**	3	1	2
6	PCA1, PCA4, PCA5	0.559	0.893	**1.819**	0.966	**1.732**	0.972	**2.814**	3	1	2
7	PCA2, PCA3, PCA4	0.463	**1.100**	**1.769**	**1.086**	**1.185**	0.836	**1.360**	5	3	2
8	PCA2, PCA3, PCA5	0.444	**2.147**	**1.776**	0.969	**1.555**	0.793	**1.456**	4	2	2
9	PCA2, PCA4, PCA5	0.401	**1.869**	**1.721**	1.053	**1.249**	0.981	**2.138**	4	2	2
10	PCA3, PCA4, PCA5	0.434	**1.615**	**2.230**	**1.149**	**1.629**	0.810	**1.460**	5	3	2
Panel B: Risk-Related Factors											
1	ERM, COSK, COKT	0.661	**1.231**	**1.436**	**1.092**	**1.138**	0.765	**1.420**	5	3	2
2	ERM, COSK, DNSD	0.751	**1.529**	**1.371**	1.029	**1.137**	0.740	**1.489**	4	2	2
3	ERM, COSK, LIQ	0.797	1.082	**1.668**	1.030	**1.111**	0.751	1.075	2	1	1
4	ERM, COKT, DNSD	0.717	**1.156**	**1.262**	1.006	**1.102**	0.796	**1.486**	4	2	2
5	ERM, COKT, LIQ	0.750	**1.324**	**1.459**	1.020	1.069	0.788	1.020	2	2	0
6	ERM, DNSD, LIQ	0.831	**1.105**	**1.452**	1.062	0.960	0.732	0.996	2	2	0
Panel C: Firm Characteristics Based Factors											
1	ERM, SMB, HML	0.938	**1.142**	**1.493**	0.981	0.947	0.792	1.032	2	2	0
2	ERM, SMB, ASG	0.722	**1.214**	**1.396**	1.072	1.016	0.758	**1.327**	3	2	1
3	ERM, SMB, ACRU	0.760	**1.154**	**1.495**	1.012	**1.137**	0.767	**1.484**	4	2	2
4	ERM, SMB, LTRV	0.905	**1.131**	**1.710**	1.020	1.048	0.846	**1.416**	3	2	1
5	ERM, SMB, MOM	0.851	0.919	**1.263**	0.931	**1.091**	0.856	**1.330**	3	1	2
6	ERM, SMB, IDSN	0.857	**1.127**	1.045	**1.130**	**1.086**	0.789	**1.420**	4	2	2
7	ERM, SMB, VO	0.820	**1.145**	**1.679**	0.994	**1.236**	0.811	**1.481**	4	2	2
8	ERM, HML, ASG	1.061	**1.334**	**1.428**	0.989	1.006	0.827	1.062	2	2	0
9	ERM, HML, ACRU	1.074	**1.373**	**1.535**	1.060	0.941	0.818	**1.083**	3	2	1
10	ERM, HML, LTRV	1.084	**1.404**	**1.554**	1.041	0.959	0.815	1.074	2	2	0
11	ERM, HML, MOM	0.839	**1.188**	**1.247**	0.929	0.942	0.826	1.043	2	2	0
12	ERM, HML, IDSN	1.073	**1.188**	**1.519**	0.973	**1.104**	0.862	1.073	3	2	1
13	ERM, HML, VO	1.083	**1.401**	**1.527**	1.047	0.972	0.838	**1.082**	3	2	1
14	ERM, ASG, ACRU	0.635	**1.310**	**1.313**	1.036	1.013	0.746	**1.408**	3	2	1
15	ERM, ASG, LTRV	1.016	**1.343**	**1.262**	**1.092**	0.996	0.802	**1.351**	4	3	1
16	ERM, ASG, MOM	0.672	**1.269**	**1.121**	0.991	1.025	0.786	**1.274**	3	2	1
17	ERM, ASG, IDSN	0.696	**1.187**	**1.240**	**1.099**	**1.215**	0.875	**1.417**	5	3	2
18	ERM, ASG, VO	0.646	**1.340**	**1.357**	1.062	**1.099**	0.767	**1.385**	4	2	2
19	ERM, ACRU, LTRV	1.055	**1.381**	**1.370**	**1.081**	1.026	0.827	**1.514**	4	3	1
20	ERM, ACRU, MOM	0.786	**1.348**	**1.184**	0.930	1.055	0.799	**1.326**	3	2	1
21	ERM, ACRU, IDSN	0.751	**1.202**	**1.288**	1.020	**1.458**	0.862	**1.693**	4	2	2
22	ERM, ACRU, VO	0.626	**1.392**	**1.431**	1.073	**1.190**	0.765	**1.668**	4	2	2
23	ERM, MOM, LTRV	0.822	**1.181**	**1.233**	0.923	0.907	0.837	**1.263**	3	2	1
24	ERM, LTRV, IDSN	**1.127**	**1.154**	**1.331**	**1.085**	**1.114**	0.841	**1.508**	6	4	2
25	ERM, LTRV, VO	1.090	**1.411**	**1.637**	1.026	1.011	0.853	**1.480**	3	2	1
26	ERM, MOM, IDSN	0.963	**1.354**	**1.156**	0.984	**1.294**	0.884	**1.400**	4	2	2
27	ERM, MOM, VO	0.928	**1.372**	**1.215**	0.914	1.076	0.838	**1.350**	3	2	1
28	ERM, IDSN, VO	0.777	**1.291**	**1.287**	1.008	**1.408**	0.876	**1.647**	4	2	2

Table 3.6

Number of Rejections: Average F-test of Factor Pricing Models with T=60 and K=4

We use all the NYSE, AMEX, and NASDAQ nonfinancial firms which have traded at prices at least $5 listed on the CRSP daily and monthly stock return files and the Compustat annual industrial files from 1972 to 2006. For explanation of the factors, see Table 3.1. For each subsample period, we apply the average F-test proposed by Hwang and Satchell (2007). The third row is the average F-test statistic for the 5% significance level. The bold numbers indicate that they are significantly different from 5% signfiicant level. 'NOR' means number of rejection period.

Models		**Jan 72 - Dec 76**	**Jan 77 - Dec 81**	**Jan 82 - Dec 86**	**Jan 87 - Dec 91**	**Jan 92 - Dec 96**	**Jan 97 - Dec 01**	**Jan 02 - Dec 06**	**Total NOR**	**Pre-92 NOR**	**Post-92 NOR**
	Number of Stocks	1741	2752	2809	3365	3682	4300	3990			
	5% Average F-test	1.097	1.084	1.083	1.080	1.078	1.075	1.076			
	Panel A: PCA Factors										
1	PCA1, PCA2, PCA3, PCA4	0.670	0.799	**1.174**	0.808	**1.248**	0.870	**1.729**	3	1	2
2	PCA1, PCA2, PCA3, PCA5	0.658	**1.200**	**1.179**	0.885	**1.651**	0.825	**1.896**	4	2	2
3	PCA1, PCA2, PCA4, PCA5	0.574	1.002	**1.152**	0.809	**1.315**	1.016	**2.798**	3	1	2
4	PCA1, PCA3, PCA4, PCA5	0.610	0.872	**1.877**	0.971	**1.728**	0.861	**1.879**	3	1	2
5	PCA2, PCA3, PCA4, PCA5	0.442	**1.822**	**1.793**	**1.098**	**1.232**	0.859	**1.431**	5	3	2
	Panel B: Risk-Related Factors										
1	ERM, COSK, COKT, DNSD	0.759	**1.239**	**1.281**	1.014	**1.143**	0.816	**1.418**	4	2	2
2	ERM, COSK, COKT, LIQ	0.803	**1.086**	**1.467**	1.030	**1.113**	0.810	1.041	3	2	1
3	ERM, COKT, DNSD, LIQ	0.825	**1.100**	**1.300**	1.044	0.962	0.783	1.021	2	2	0
4	ERM, COSK, DNSD, LIQ	0.876	1.082	**1.411**	1.060	1.017	0.738	1.002	1	1	0
	Panel C: Firm Characteristics Based Factors										
1	ERM, SMB, HML, ASG	0.895	**1.110**	**1.401**	0.987	0.958	0.806	1.033	2	2	0
2	ERM, SMB, HML, ACRU	0.950	**1.145**	**1.463**	0.993	0.945	0.799	1.040	2	2	0
3	ERM, SMB, HML, MOM	0.895	0.944	**1.141**	0.934	0.917	0.785	1.032	1	1	0
4	ERM, SMB, HML, LTRV	0.954	**1.136**	**1.359**	0.994	0.964	0.855	1.038	2	2	0
5	ERM, SMB, HML, IDSN	0.926	**1.131**	**1.135**	1.034	1.010	0.818	1.074	2	2	0
6	ERM, SMB, HML, VO	0.970	**1.128**	**1.431**	0.980	0.924	0.813	1.025	2	2	0
7	ERM, SMB, ASG, ACRU	0.729	**1.184**	**1.354**	0.991	1.013	0.761	**1.341**	3	2	1
8	ERM, SMB, ASG, MOM	0.756	0.951	**1.163**	1.001	0.998	0.826	**1.260**	2	1	1
9	ERM, SMB, ASG, LTRV	0.870	**1.172**	**1.303**	1.079	1.009	0.883	**1.317**	3	2	1
10	ERM, SMB, ASG, IDSN	0.769	**1.169**	1.025	**1.169**	1.057	0.790	**1.346**	3	2	1
11	ERM, SMB, ASG, VO	0.730	**1.194**	**1.404**	1.041	1.009	0.780	**1.331**	3	2	1
12	ERM, SMB, ACRU, MOM	0.761	0.919	**1.230**	0.929	1.063	0.851	**1.287**	2	1	1
13	ERM, SMB, ACRU, LTRV	0.918	**1.136**	**1.413**	1.023	1.058	0.892	**1.438**	3	2	1
14	ERM, SMB, ACRU, IDSN	0.836	**1.131**	0.999	**1.087**	**1.153**	0.789	**1.427**	4	2	2
15	ERM, SMB, ACRU, VO	0.775	**1.120**	**1.483**	1.000	**1.149**	0.794	**1.489**	4	2	2
16	ERM, SMB, MOM, LTRV	0.862	0.934	**1.282**	0.943	0.953	0.874	**1.267**	2	1	1
17	ERM, SMB, MOM, IDSN	0.882	0.946	0.970	1.048	1.074	0.778	**1.325**	1	0	1
18	ERM, SMB, MOM, VO	0.836	0.937	**1.262**	0.924	**1.133**	0.889	**1.324**	3	1	2
19	ERM, SMB, LTRV, IDSN	0.913	**1.120**	1.009	**1.151**	1.024	0.852	**1.394**	3	2	1
20	ERM, SMB, LTRV, VO	0.933	**1.107**	**1.698**	0.996	1.040	0.874	**1.420**	3	2	1

Table 3.6-----------*Continued*

Panel C: Firm Characteristics Based Factors											
21	ERM, SMB, IDSN, VO	0.866	**1.100**	1.002	**1.093**	**1.119**	0.798	**1.421**	4	2	2
22	ERM, HML, ASG, ACRU	1.073	**1.338**	**1.410**	0.964	0.937	0.830	1.074	2	2	0
23	ERM, HML, ASG, MOM	0.820	**1.201**	**1.185**	0.975	0.954	0.840	1.043	2	2	0
24	ERM, HML, ASG, LTRV	1.059	**1.356**	**1.368**	0.995	0.980	0.838	1.066	2	2	0
25	ERM, HML, ASG, IDSN	1.025	**1.197**	**1.349**	0.991	**1.107**	0.891	1.052	3	2	1
26	ERM, HML, ASG, VO	1.075	**1.371**	**1.418**	0.984	1.025	0.857	1.070	2	2	0
27	ERM, HML, ACRU, MOM	0.837	**1.151**	**1.248**	0.936	0.899	0.839	1.030	2	2	0
28	ERM, HML, ACRU, LTRV	1.092	**1.410**	**1.485**	1.044	0.948	0.835	**1.093**	3	2	1
29	ERM, HML, ACRU, IDSN	1.074	**1.190**	**1.452**	0.972	**1.143**	0.875	**1.086**	4	2	2
30	ERM, HML, ACRU, VO	1.096	**1.408**	**1.491**	1.051	0.943	0.848	**1.091**	3	2	1
31	ERM, HML, MOM, LTRV	0.881	**1.133**	**1.285**	0.932	0.906	0.815	1.044	2	2	0
32	ERM, HML, MOM, IDSN	0.874	**1.186**	**1.270**	0.952	**1.100**	0.885	1.037	3	2	1
33	ERM, HML, MOM, VO	0.860	**1.204**	**1.254**	0.925	0.944	0.851	1.053	2	2	0
34	ERM, HML, LTRV, IDSN	**1.133**	**1.167**	**1.525**	1.005	**1.100**	0.849	1.076	4	3	1
35	ERM, HML, LTRV, VO	**1.112**	**1.431**	**1.509**	1.022	0.936	0.836	**1.083**	4	3	1
36	ERM, HML, IDSN, VO	1.096	**1.224**	**1.459**	0.964	**1.090**	0.889	1.072	3	2	1
37	ERM, ASG, ACRU, MOM	0.686	**1.301**	**1.125**	0.970	0.988	0.792	**1.253**	3	2	1
38	ERM, ASG, ACRU, LTRV	1.025	**1.343**	**1.204**	1.041	0.983	0.809	**1.374**	3	2	1
39	ERM, ASG, ACRU, IDSN	0.719	**1.191**	**1.232**	1.012	**1.288**	0.877	**1.437**	4	2	2
40	ERM, ASG, ACRU, VO	0.650	**1.358**	**1.319**	1.012	1.034	0.769	**1.403**	3	2	1
41	ERM, ASG, MOM, LTRV	0.806	**1.155**	**1.099**	0.995	0.926	0.817	**1.229**	3	2	1
42	ERM, ASG, MOM, IDSN	0.755	**1.271**	**1.111**	1.027	**1.231**	0.917	**1.296**	4	2	2
43	ERM, ASG, MOM, VO	0.683	**1.298**	**1.116**	0.975	1.063	0.809	**1.258**	3	2	1
44	ERM, ASG, LTRV, IDSN	1.048	**1.145**	**1.191**	**1.122**	**1.121**	0.862	**1.380**	5	3	2
45	ERM, ASG, LTRV, VO	1.033	**1.373**	**1.269**	1.043	0.985	0.825	**1.348**	3	2	1
46	ERM, ASG, IDSN, VO	0.726	**1.239**	**1.228**	1.039	**1.209**	0.900	**1.412**	4	2	2
47	ERM, ACRU, MOM, LTRV	0.815	**1.206**	**1.175**	0.933	0.921	0.848	**1.265**	3	2	1
48	ERM, ACRU, MOM, IDSN	0.905	**1.354**	**1.159**	0.949	**1.401**	0.909	**1.349**	4	2	2
49	ERM, ACRU, MOM, VO	0.813	**1.379**	**1.186**	0.924	**1.103**	0.825	**1.295**	4	2	2
50	ERM, ACRU, LTRV, IDSN	**1.122**	**1.155**	**1.255**	1.050	**1.179**	0.860	**1.532**	5	3	2
51	ERM, ACRU, LTRV, VO	1.086	**1.419**	**1.369**	1.041	1.009	0.856	**1.503**	3	2	1
52	ERM, ACRU, IDSN, VO	0.777	**1.266**	**1.246**	0.976	**1.461**	0.887	**1.662**	4	2	2
53	ERM, LTRV, IDSN, VO	**1.164**	**1.192**	**1.287**	1.029	**1.106**	0.857	**1.489**	5	3	2
54	ERM, MOM, LTRV, IDSN	0.899	**1.159**	**1.158**	1.012	1.068	0.853	**1.284**	3	2	1
55	ERM, MOM, LTRV, VO	0.841	**1.186**	**1.235**	0.909	0.905	0.874	**1.242**	3	2	1
56	ERM, MOM, IDSN, VO	0.986	**1.372**	**1.156**	0.971	**1.344**	0.910	**1.362**	4	2	2

Table 3.7

Average and Conventional F-test of Factor Pricing Models with T=60 and K=4

We use all the NYSE, AMEX, and NASDAQ nonfinancial firms which have traded at prices at least $5 listed on the CRSP daily and monthly stock return files and the Compustat annual industrial files from 1972 to 2006. For explanation of the factors, see Table 3.1. For each subsample period, we apply the average F-test proposed by Hwang and Satchell (2007). The Conventional F-test reports the porportions of reject at the 5% significance level when N=10 with 10,000 times iterations.

		Jan 72 - Dec 76	**Jan 77 - Dec 81**	**Jan 82 - Dec 86**	**Jan 87 - Dec 91**	**Jan 92 - Dec 96**	**Jan 97 - Dec 01**	**Jan 02 - Dec 06**
Panel A: Average F-test								
Number of Stocks		1817	3468	3436	4212	4574	4889	4805
Average F-test	5% Average F-test	1.098	1.080	1.079	1.076	1.075	1.073	1.074
	ERM, COSK, DNSD, LIQ	1.085	1.027	**2.030**	1.021	1.044	1.038	1.078
	ERM, SMB, HML, MOM	1.005	1.031	**1.654**	1.088	1.027	1.120	1.041
Panel B: Conventional F-test								
Conventional F-test (Rejection Rates)	ERM, COSK, DNSD, LIQ	0.013	0.050	**0.102**	0.047	0.030	0.010	0.031
	ERM, SMB, HML, MOM	0.020	0.026	**0.071**	0.039	0.021	0.014	0.046

Figure 4.1

NYSE, AMEX and NASDAQ Share Distribution

At the end of each Month from December 1925 to December 2006, we count the number of stocks traded on NYSE, AMEX and NASDAQ based on firm's price level.

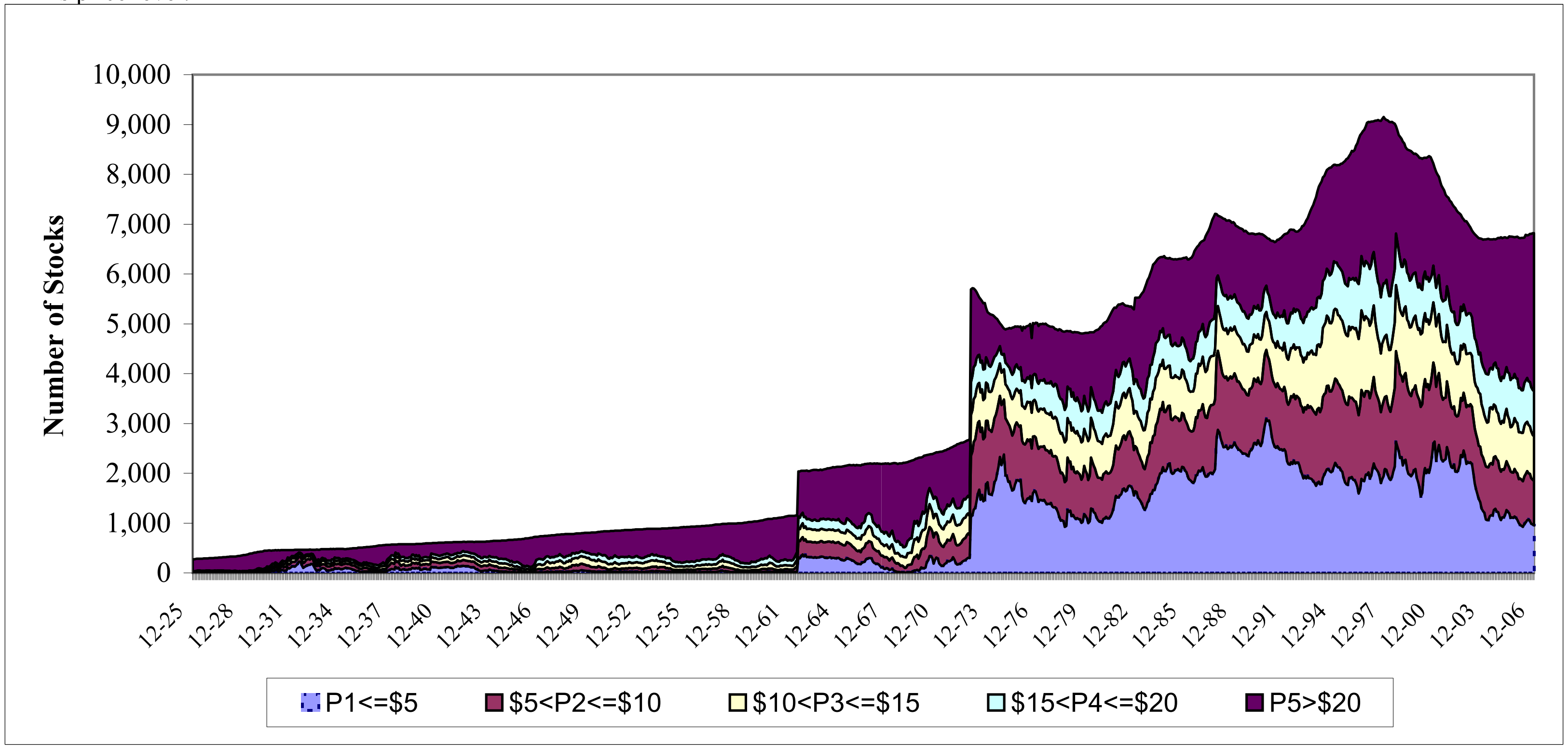

Figure 4.2

Seasonality of the Price Strategies

At the end of each June from 1963 to 2006, we form 5 price range portfolios and 25 portfolios based on firm's price level and size or liquidity. Stocks are firstly sorted into 5 either size or liquidity quintile, then are sub-grouped into 5 price range portfolios. To be included in the 25 Price and Size portfolios, a stock must have shares outstanding and a price level. To be included in the 25 Price and Liquidity portfolios, a stock must have the illiquidity proxy of Amihud (2002). P1 (P5) stands for Penny (share price higher than $5) stock portfolio. S1 (S5) stands for the small (big) portfolio. L1 (L5) stands for the most liquid (illiquid) portfolio. This chart plots the average monthly returns for price strategies of buying penny- and selling high- price stocks (P1-P5), buying small penny- and selling big high-price stocks (S1P1-S5P5), and buying illiquid penny- and selling liquid high- price stocks (L5P1-L1P5).

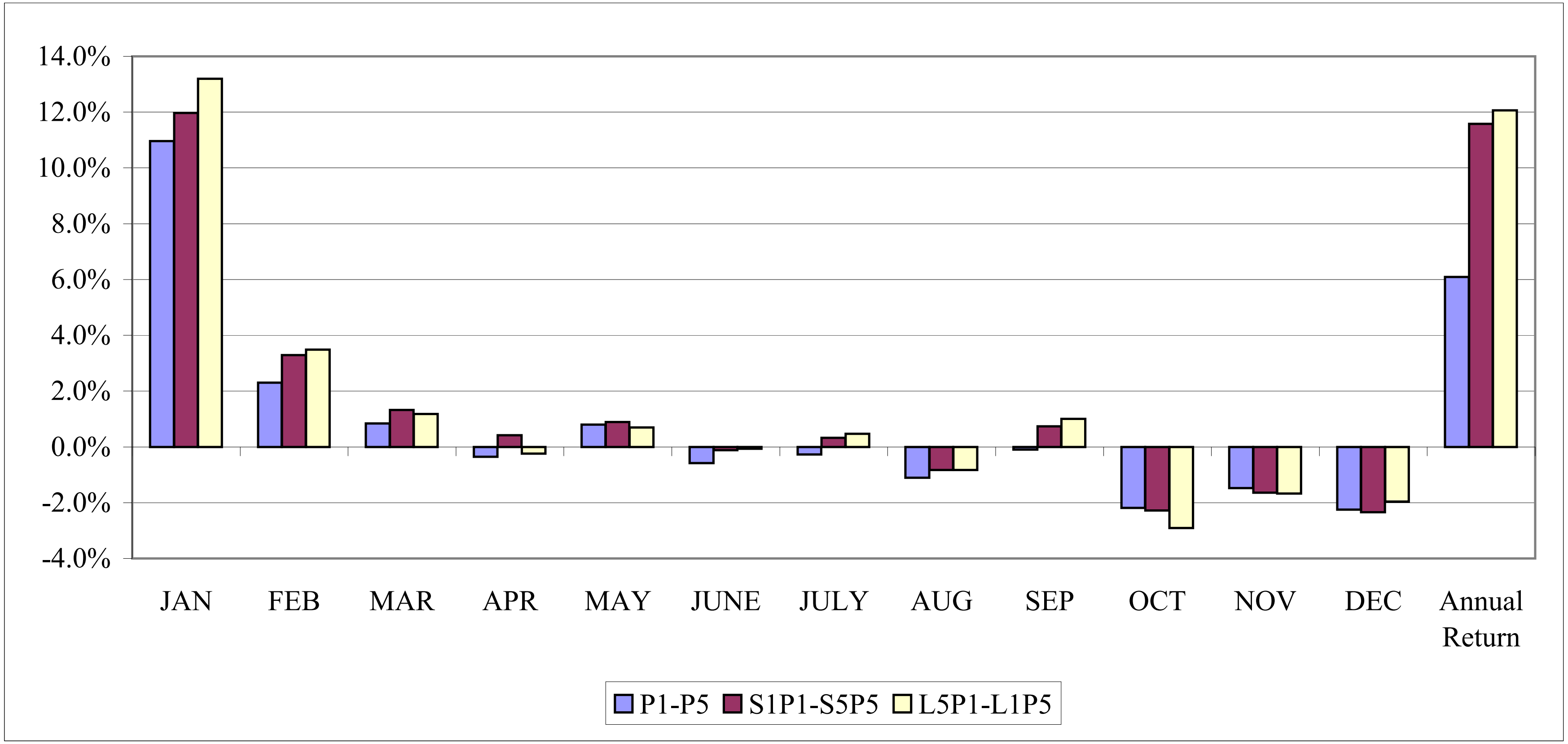

Figure 4.3

Seasonality of The Price Strategies After Adjustment by Fama-French's factors and Momentum

At the end of each June from 1963 to 2006, we form 5 price range portfolios and 25 portfolios based on firm's price level and size or liquidity. Stocks are firstly sorted into 5 either size or liquidity quintile, then are sub-grouped into 5 price range portfolios. To be included in the 25 Price and Size portfolios, a stock must have shares outstanding and a price level. To be included in the 25 Price and Liquidity portfolios, a stock must have the illiquidity proxy of Amihud (2002). P1 (P5) stands for Penny (share price higher than $5) stock portfolio. S1 (S5) stands for the small (big) portfolio. L1 (L5) stands for the most liquid (illiquid) portfolio. This chart plots the average monthly returns after adjustment by Fama-French and Momentum factors for price strategies of buying penny- and selling high- price stocks (P1-P5), buying small penny- and selling big high- price stocks (S1P1-S5P5), and buying illiquid penny- and selling liquid high- price stocks (L5P1-L1P5). ERM, SMB, HML and Momentum factor are Fama and French factors from Kenneth French's data library.

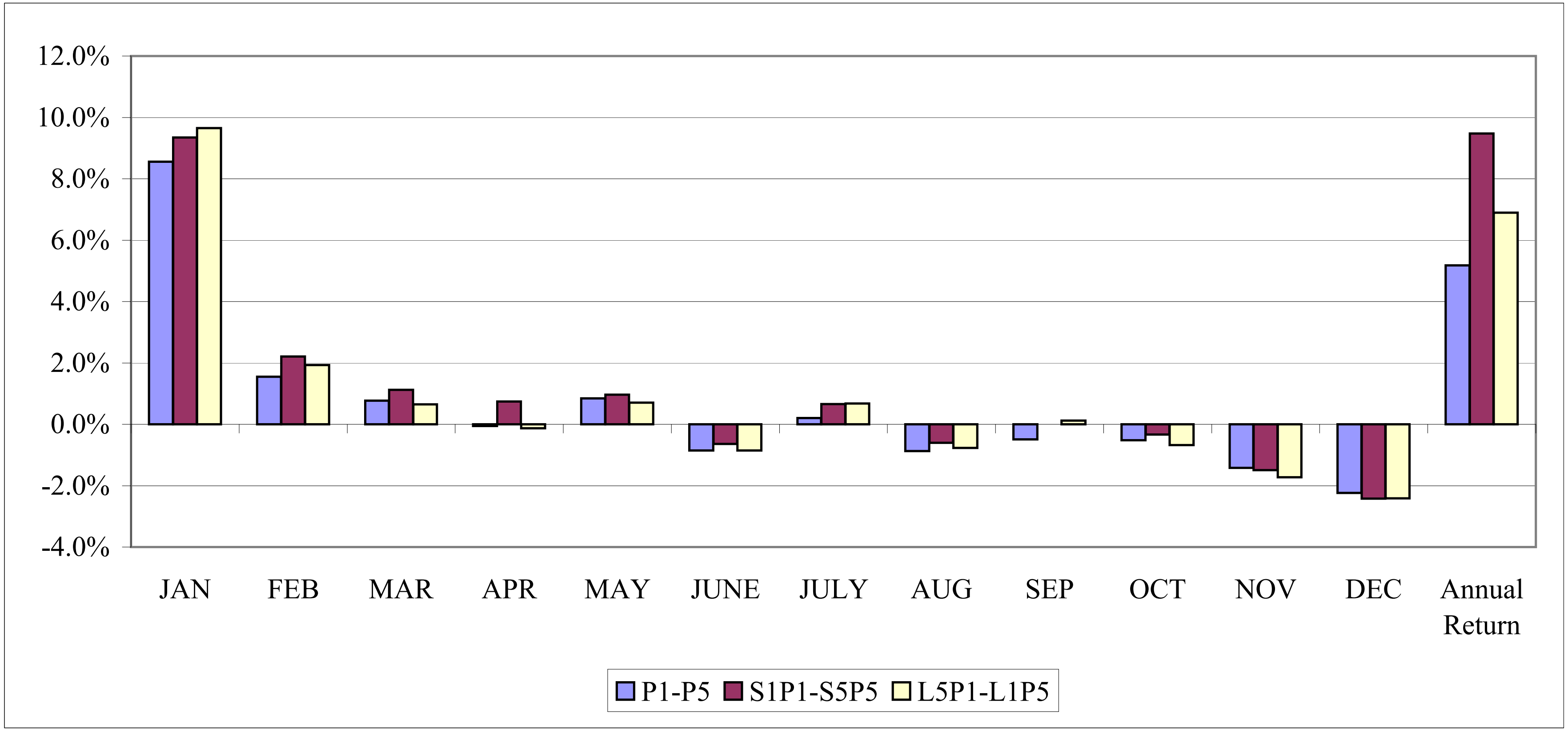

Table 4.1

12 Month Holding Period Returns and Characteristics of 5 Share Price Portfolios

At the end of each June from 1926 to 2006, we form 5 portfolios based on a firm's price level. Each row on the right-hand side of each table shows the average transition vector for a particular portfolio. ln(Size) is the natural logarithm of the product of the number of shares outstanding and share price. No. of stocks is the time-series average of number of stocks within each portfolio.

Panel A: NYSE and AMEX Stocks; July 1926 to Dec 2006

Price Range	Ret	t-stats	Price	ln(Size)	No of Stocks	Transition Vectors P1	P2	P3	P4	P5	Total
P1<=$5	1.836%	5.238	2.803	19.692	206	**69.700%**	19.300%	2.910%	0.680%	0.320%	92.910%
$5<P2<=$10	1.318%	5.020	7.488	20.187	258	18.440%	**51.420%**	19.180%	4.900%	2.780%	96.720%
$10<P3<=$15	1.140%	5.081	12.443	20.653	258	3.580%	21.300%	**40.610%**	20.920%	10.680%	97.090%
$15<P4<=$20	1.136%	5.424	17.288	21.292	219	1.520%	6.890%	21.200%	**33.310%**	34.290%	97.210%
P5>$20	1.004%	5.661	48.086	23.324	795	0.290%	1.180%	3.120%	7.370%	**85.560%**	97.520%
P1-P5	0.831%	3.203									

Panel B: NYSE and AMEX Stocks; July 1926 to June 1963

Price Range	Ret	t-stats	Price	ln(Size)	No of Stocks	Transition Vectors P1	P2	P3	P4	P5	Total
P1<=$5	2.190%	3.542	2.863	17.558	41	**70.360%**	23.240%	4.020%	0.990%	0.370%	98.980%
$5<P2<=$10	1.381%	2.935	7.295	17.820	69	19.250%	**50.970%**	20.020%	5.650%	3.770%	99.660%
$10<P3<=$15	1.091%	2.699	12.178	18.363	76	4.350%	23.390%	**37.690%**	22.220%	12.300%	99.950%
$15<P4<=$20	1.119%	2.968	16.927	18.942	78	2.230%	7.460%	21.500%	**31.650%**	36.610%	99.450%
P5>$20	0.880%	2.896	51.546	21.098	410	0.410%	1.250%	2.850%	6.450%	**88.810%**	99.770%
P1-P5	1.311%	2.919									

Panel C: NYSE and AMEX Stocks; July 1963 to December 2006

Price Range	Ret	t-stats	Price	ln(Size)	No of Stocks	Transition Vectors P1	P2	P3	P4	P5	Total
P1<=$5	1.530%	4.065	2.752	20.257	348	**68.830%**	16.090%	2.010%	0.440%	0.300%	87.670%
$5<P2<=$10	1.263%	4.624	7.655	20.765	421	17.740%	**51.640%**	18.570%	4.330%	1.970%	94.250%
$10<P3<=$15	1.182%	5.124	12.671	21.227	415	2.980%	19.570%	**42.950%**	19.780%	9.390%	94.670%
$15<P4<=$20	1.151%	5.330	17.599	21.868	341	0.950%	6.500%	20.900%	**34.680%**	32.310%	95.340%
P5>$20	1.111%	5.518	45.105	23.895	1127	0.180%	1.140%	3.390%	8.220%	**82.660%**	95.590%
P1-P5	0.418%	1.449									

Panel D: NASDAQ Stocks; July 1973 to December 2006

Price Range	Ret	t-stats	Price	ln(Size)	No of Stocks	Transition Vectors P1	P2	P3	P4	P5	Total
P1<=$5	1.592%	3.978	2.038	20.032	1269	**70.600%**	11.120%	1.600%	0.360%	0.250%	83.930%
$5<P2<=$10	1.160%	3.743	7.383	20.603	751	23.720%	**44.370%**	16.940%	4.630%	2.190%	91.850%
$10<P3<=$15	1.268%	4.621	12.537	22.173	507	4.910%	21.810%	**34.770%**	19.350%	10.630%	91.470%
$15<P4<=$20	1.304%	5.026	17.539	22.769	360	1.980%	7.460%	19.750%	**30.060%**	31.760%	91.010%
P5>$20	1.201%	4.618	37.387	24.036	696	0.750%	2.470%	5.600%	11.110%	**69.720%**	89.650%
P1-P5	0.391%	1.444									

Table 4.2

Performance of Price Portfolios in Longer Holding Period

At the end of each June from 1963 to 2006, we form 5 portfolios based on a firm's price level. ln(Size) is the natural logarithm of the product of the number of shares outstanding and share price. No. of stocks is the time-series average of number of stocks within each portfolio.

Panel A: NYSE, AMEX and NASDAQ Stocks; July 1963 to Dec 2006						Transition Vectors					
Price Range	Ret	t-stats	Price	ln(Size)	No of Stocks	P1	P2	P3	P4	P5	Total
P1<=$5	1.616%	4.414	2.371	20.040	1325	**69.390%**	13.900%	1.900%	0.440%	0.300%	85.930%
$5<P2<=$10	1.216%	4.368	7.532	20.646	999	21.620%	**47.460%**	18.000%	4.730%	2.300%	94.110%
$10<P3<=$15	1.194%	5.043	12.639	21.543	805	4.180%	21.480%	**38.610%**	19.570%	10.520%	94.360%
$15<P4<=$20	1.166%	5.269	17.603	22.201	618	1.500%	7.730%	20.750%	**32.340%**	32.440%	94.760%
P5>$20	1.088%	5.290	44.460	23.907	1663	0.380%	1.710%	4.370%	9.340%	**79.050%**	94.850%
P1-P5	0.528%	1.940									

Panel B: NYSE, AMEX and NASDAQ Stocks; July 1963 to Dec 2006

	Holding Period is 1 Year						Holding Period is 2 Years					
Price Range	Ret	t-stats	Jan Ret	t-stats	Non-Jan Ret	t-stats	Ret	t-stats	Jan Ret	t-stats	Non-Jan Ret	t-stats
P1<=$5	1.616%	4.414	13.386%	8.517	0.559%	1.676	1.655%	4.668	12.863%	8.407	0.649%	2.001
$5<P2<=$10	1.216%	4.368	7.962%	6.757	0.610%	2.278	1.278%	4.574	8.303%	6.857	0.647%	2.428
$10<P3<=$15	1.194%	5.043	5.547%	5.609	0.803%	3.425	1.204%	5.052	5.831%	5.615	0.789%	3.376
$15<P4<=$20	1.166%	5.269	4.218%	4.486	0.892%	4.018	1.188%	5.323	4.620%	4.675	0.879%	3.973
P5>$20	1.088%	5.290	2.425%	2.994	0.968%	4.578	1.071%	5.180	2.645%	3.156	0.930%	4.396
P1-P5	0.528%	1.940	10.961%	9.276	-0.409%	-1.750	0.584%	2.283	10.218%	9.219	-0.281%	-1.270

	Holding Period is 3 Years						Holding Period is 4 Years					
Price Range	Ret	t-stats	Jan Ret	t-stats	Non-Jan Ret	t-stats	Ret	t-stats	Jan Ret	t-stats	Non-Jan Ret	t-stats
P1<=$5	1.645%	4.734	12.426%	8.107	0.677%	2.129	1.636%	4.804	12.024%	7.886	0.703%	2.254
$5<P2<=$10	1.310%	4.668	8.469%	6.775	0.667%	2.509	1.340%	4.769	8.535%	6.760	0.694%	2.612
$10<P3<=$15	1.228%	5.099	6.105%	5.518	0.791%	3.389	1.253%	5.183	6.239%	5.461	0.806%	3.465
$15<P4<=$20	1.210%	5.407	4.876%	4.695	0.881%	4.012	1.217%	5.431	5.002%	4.712	0.877%	4.011
P5>$20	1.100%	5.327	2.872%	3.318	0.941%	4.481	1.119%	5.441	3.037%	3.426	0.947%	4.550
P1-P5	0.545%	2.229	9.554%	9.024	-0.264%	-1.240	0.517%	2.207	8.987%	8.805	-0.244%	-1.187

	Holding Period is 5 Years					
Price Range	Ret	t-stats	Jan Ret	t-stats	Non-Jan Ret	t-stats
P1<=$5	1.633%	4.886	11.691%	7.855	0.730%	2.374
$5<P2<=$10	1.352%	4.829	8.567%	6.708	0.704%	2.670
$10<P3<=$15	1.278%	5.290	6.355%	5.515	0.822%	3.552
$15<P4<=$20	1.235%	5.520	5.081%	4.779	0.889%	4.082
P5>$20	1.134%	5.533	3.132%	3.514	0.955%	4.614
P1-P5	0.499%	2.205	8.560%	8.868	-0.225%	-1.124

Table 4.3

Performance of 25 Price and Size or Liquidity Portfolios

At the end of each June from 1963 to 2006, we form 25 portfolios based on a firm's price level and size or liquidity. Stocks are firstly sorted into 5 either size or liquidity quintile, then are sub-grouped into 5 price range portfolios. To be included in the 25 Price and Size portfolios, a stock must have shares outstanding and a price level. To be included in the 25 Price and Liquidity portfolios, a stock must have the illiquidity proxy of Amihud (2002).

Panel A: 25 Price and Size Portfolios; NYSE, AMEX and NASDAQ Stocks; July 1963 to Dec 2006

	Returns in All Months					Returns in January					Returns in Non-January Months				
Price Range	Small (S1)	S2	S3	S4	Big (S5)	Small (S1)	S2	S3	S4	Big (S5)	Small (S1)	S2	S3	S4	Big (S5)
P1<=$5	1.979%	1.155%	0.897%	0.285%	0.884%	13.908%	12.702%	11.227%	8.930%	8.914%	0.908%	0.119%	-0.030%	-0.491%	0.165%
$5<P2<=$10	1.513%	1.253%	1.029%	0.908%	0.951%	7.586%	8.129%	7.634%	6.769%	5.948%	0.968%	0.636%	0.436%	0.382%	0.503%
$10<P3<=$15	1.533%	1.371%	1.110%	1.091%	1.173%	4.136%	5.293%	5.659%	5.216%	4.182%	1.299%	1.019%	0.701%	0.720%	0.903%
$15<P4<=$20	1.206%	1.279%	1.245%	1.053%	1.093%	3.505%	4.226%	4.666%	3.767%	3.139%	0.999%	1.015%	0.937%	0.810%	0.909%
P5>$20	1.065%	1.230%	1.240%	1.139%	1.022%	2.301%	3.332%	3.206%	2.654%	1.939%	0.954%	1.042%	1.064%	1.003%	0.939%
P1-P5	0.914%	-0.075%	-0.343%	-0.830%	-0.280%	11.607%	9.370%	8.021%	6.358%	6.647%	-0.046%	-0.923%	-1.094%	-1.474%	-0.899%
t-stats	2.815	-0.252	-1.171	-2.554	-0.729	8.313	6.456	5.491	3.832	3.391	-0.157	-3.472	-4.116	-4.856	-2.471
Degree of Freedom	521	521	521	473	413	42	42	42	38	33	478	478	478	434	379

Panel B: Characteristics of 25 Price and Size Portfolios; NYSE, AMEX and NASDAQ Stocks; 1963 to 2006

	Ln(Size)					Price					Number of Stocks				
Price Range	Small (S1)	S2	S3	S4	Big (S5)	Small (S1)	S2	S3	S4	Big (S5)	Small (S1)	S2	S3	S4	Big (S5)
P1<=$5	9.152	10.251	11.177	12.244	14.199	1.600	2.293	2.855	2.731	2.561	739	403	142	33	8
$5<P2<=$10	9.309	10.335	11.250	12.311	14.538	6.800	7.079	7.454	7.747	7.658	167	346	306	144	37
$10<P3<=$15	9.349	10.363	11.295	12.349	15.135	12.006	12.208	12.415	12.595	12.232	62	168	275	222	77
$15<P4<=$20	9.357	10.369	11.333	12.394	15.568	16.712	17.056	17.197	17.443	17.798	29	86	167	220	116
P5>$20	9.329	10.384	11.360	12.487	17.044	28.912	26.798	27.371	29.571	45.960	27	82	204	478	869

Table 4.3-----------*Continued*

Panel C: 25 Price and Liquidity Portfolios; NYSE, AMEX and NASDAQ Stocks; July 1963 to Dec 2006

	Returns in All Months					Returns in January					Returns in Non-January Months				
Price Range	Liquid (L1)	L2	L3	L4	Illiquid (L5)	Liquid (L1)	L2	L3	L4	Illiquid (L5)	Liquid (L1)	L2	L3	L4	Illiquid (L5)
P1<=$5	0.396%	0.873%	1.134%	1.123%	2.008%	18.484%	13.375%	14.779%	14.168%	15.088%	-1.219%	-0.246%	-0.090%	-0.048%	0.834%
$5<P2<=$10	0.891%	0.781%	1.039%	1.335%	1.653%	8.187%	8.932%	7.926%	8.650%	8.321%	0.236%	0.049%	0.420%	0.679%	1.054%
$10<P3<=$15	1.004%	1.005%	1.223%	1.450%	1.478%	5.366%	5.534%	5.924%	5.513%	4.554%	0.613%	0.598%	0.801%	1.085%	1.202%
$15<P4<=$20	1.056%	1.120%	1.207%	1.436%	1.537%	3.515%	3.667%	4.441%	4.599%	3.752%	0.835%	0.891%	0.916%	1.152%	1.338%
P5>$20	1.003%	1.146%	1.279%	1.338%	1.688%	1.894%	2.490%	3.123%	3.402%	3.098%	0.923%	1.025%	1.113%	1.153%	1.562%
P1-P5	-0.699%	-0.427%	-0.288%	-0.215%	0.276%	16.162%	10.816%	11.338%	10.766%	10.378%	-2.205%	-1.434%	-1.331%	-1.201%	-0.630%
t-stats	-0.922	-1.024	-0.798	-0.708	0.785	3.245	4.412	6.880	7.390	8.946	-3.453	-3.999	-4.125	-4.606	-1.872
Degree of Freedom	365	437	497	521	473	29	35	40	42	38	335	401	456	478	434

Panel D: Characteristics of 25 Price and BE/ME Portfolios; NYSE, AMEX and NASDAQ Stocks; 1963 to 2006

	Ln(Size)					ln(Amihud)					Number of Stocks				
Price Range	Liquid (L1)	L2	L3	L4	Illiquid (L5)	Liquid (L1)	L2	L3	L4	Illiquid (L5)	Liquid (L1)	L2	L3	L4	Illiquid (L5)
P1<=$5	13.842	12.356	11.323	10.920	10.232	-3.709	-1.835	-0.412	0.982	3.615	8	46	108	165	375
$5<P2<=$10	14.422	12.519	11.741	11.264	10.894	-3.307	-1.795	-0.485	0.912	2.475	25	90	145	176	157
$10<P3<=$15	15.245	12.911	12.028	11.582	10.957	-3.368	-1.872	-0.529	0.829	2.170	47	108	124	128	60
$15<P4<=$20	15.662	13.132	12.344	11.896	11.336	-3.473	-1.918	-0.539	0.740	2.203	68	110	102	88	27
P5>$20	17.060	13.432	12.767	12.278	11.784	-3.768	-1.996	-0.632	0.655	1.895	556	334	202	111	23

Table 4.4

Performance of 25 Price and Past Return Portfolios

At the end of June each year from 1963 to 2006, we form 25 portfolios based on a firm's price level and the average past 6 months return. Stocks are firstly sorted into 5 return-based quintile, then are sub-grouped into 5 price range portfolios. Loser (Winner) is the portfolio with the lowest (highest) past return stocks. To be included in the portfolio, a stock must have both price and at least past 3 months returns.

Panel A: 25 Price and Liquidity Portfolios; NYSE, AMEX and NASDAQ Stocks; July 1963 to Dec 2006

	Returns in All Months					Returns in January					Returns in Non-January Months				
Price Range	Loser	2	3	4	Winner	Loser	2	3	4	Winner	Loser	2	3	4	Winner
P1<=$5	1.270%	1.592%	1.769%	1.847%	1.789%	15.133%	12.451%	12.467%	12.199%	12.825%	0.025%	0.617%	0.809%	0.918%	0.798%
$5<P2<=$10	0.703%	1.334%	1.362%	1.389%	1.347%	9.033%	8.109%	7.151%	7.393%	7.776%	-0.045%	0.726%	0.842%	0.850%	0.770%
$10<P3<=$15	0.707%	1.176%	1.233%	1.361%	1.384%	5.816%	5.345%	5.501%	5.327%	5.936%	0.248%	0.801%	0.850%	1.005%	0.976%
$15<P4<=$20	0.733%	1.117%	1.175%	1.310%	1.433%	4.630%	3.838%	4.082%	4.171%	4.730%	0.383%	0.873%	0.914%	1.053%	1.137%
P5>$20	0.631%	0.993%	1.081%	1.215%	1.365%	2.616%	2.429%	2.255%	2.471%	3.068%	0.453%	0.864%	0.975%	1.103%	1.212%
P1-P5	0.639%	0.599%	0.689%	0.632%	0.425%	12.517%	10.022%	10.212%	9.728%	9.757%	-0.428%	-0.247%	-0.166%	-0.185%	-0.413%
t-stats	2.112	2.309	2.447	2.466	1.580	9.121	8.707	9.532	9.072	7.583	-1.679	-1.089	-0.644	-0.810	-1.764
Degree of Freedom	521	521	521	521	521	42	42	42	42	42	478	478	478	478	478

Panel B: Characteristics of 25 Price and BE/ME Portfolios; NYSE, AMEX and NASDAQ Stocks; 1963 to 2006

	Ln(Size)					Average Past 6-month Return					Number of Stocks				
Price Range	Loser	2	3	4	Winner	Loser	2	3	4	Winner	Loser	2	3	4	Winner
P1<=$5	12.819	12.608	13.293	13.152	12.828	-6.105%	-0.552%	1.625%	3.983%	12.269%	436	223	164	181	300
$5<P2<=$10	13.975	13.622	13.468	12.963	12.941	-4.797%	-0.470%	1.628%	3.933%	10.576%	214	210	185	176	192
$10<P3<=$15	14.674	14.269	14.503	14.368	13.753	-4.268%	-0.410%	1.610%	3.921%	10.100%	122	189	180	158	137
$15<P4<=$20	15.104	15.122	15.331	14.728	14.359	-3.982%	-0.414%	1.611%	3.914%	9.705%	78	141	148	134	106
P5>$20	16.751	16.974	16.892	17.007	16.315	-3.603%	-0.356%	1.652%	3.911%	9.166%	147	335	422	440	301

Table 4.5

Performance of 25 Price and BE/ME Portfolios

At the end of each June from 1963 to 2006, we form 25 portfolios based on a firm's price level and BE/ME. Stocks are firstly sorted into 5 BE/ME quintile, then are sub-grouped into 5 price range portfolios.To be included in the portfolio, a stock must have both price and non-negative BE/ME ratio.

Panel A: 25 Price and BE/ME Portfolios; NYSE, AMEX and NASDAQ Stocks; July 1963 to Dec 2006

	Returns in All Months				
Price Range	Low	2	3	4	High
P1<=$5	1.091%	1.343%	1.874%	2.030%	2.287%
$5<P2<=$10	0.653%	1.310%	1.385%	1.460%	1.540%
$10<P3<=$15	0.654%	0.936%	1.305%	1.502%	1.410%
$15<P4<=$20	0.673%	1.096%	1.294%	1.294%	1.360%
P5>$20	0.915%	1.010%	1.209%	1.269%	1.291%
P1-P5	0.176%	0.333%	0.665%	0.732%	0.996%
t-stats	0.448	1.038	2.027	2.532	4.064
Degree of Freedom	521	521	521	509	521

	Returns in January				
Price Range	Low	2	3	4	High
P1<=$5	12.927%	12.141%	14.231%	13.858%	12.131%
$5<P2<=$10	7.687%	9.234%	8.215%	8.254%	7.831%
$10<P3<=$15	5.346%	5.623%	5.469%	5.694%	5.601%
$15<P4<=$20	3.207%	4.171%	4.192%	3.933%	4.398%
P5>$20	1.831%	2.072%	2.421%	2.807%	3.154%
P1-P5	11.096%	10.070%	11.809%	10.980%	8.977%
t-stats	6.300	7.970	8.222	9.122	7.457
Degree of Freedom	42	42	42	41	42

	Returns in Non-January Months				
Price Range	Low	2	3	4	High
P1<=$5	0.029%	0.373%	0.765%	0.968%	1.404%
$5<P2<=$10	0.022%	0.598%	0.772%	0.850%	0.976%
$10<P3<=$15	0.233%	0.515%	0.931%	1.126%	1.034%
$15<P4<=$20	0.446%	0.819%	1.034%	1.058%	1.087%
P5>$20	0.833%	0.915%	1.100%	1.131%	1.124%
P1-P5	-0.804%	-0.541%	-0.335%	-0.187%	0.280%
t-stats	-2.191	-1.804	-1.141	-0.730	1.293
Degree of Freedom	478	478	478	467	478

Panel B: Characteristics of 25 Price and BE/ME Portfolios; NYSE, AMEX and NASDAQ Stocks; 1963 to 2006

	Ln(Size)				
Price Range	Low	2	3	4	High
P1<=$5	11.949	13.000	13.423	12.131	11.850
$5<P2<=$10	13.759	13.216	13.342	13.547	13.677
$10<P3<=$15	15.020	14.800	13.897	14.167	14.479
$15<P4<=$20	14.894	15.756	14.815	14.734	15.100
P5>$20	17.297	17.034	16.569	16.288	15.853

	BE/ME				
Price Range	Low	2	3	4	High
P1<=$5	0.128	0.368	0.626	0.981	35.485
$5<P2<=$10	0.136	0.372	0.626	0.960	12.018
$10<P3<=$15	0.142	0.369	0.622	0.951	13.018
$15<P4<=$20	0.145	0.368	0.619	0.945	25.379
P5>$20	0.148	0.364	0.613	0.935	37.305

	Number of Stocks				
Price Range	Low	2	3	4	High
P1<=$5	135	146	154	206	339
$5<P2<=$10	84	119	148	179	167
$10<P3<=$15	60	109	121	120	89
$15<P4<=$20	54	98	101	89	60
P5>$20	229	342	289	221	134

Table 4.6

Performance of 25 Price and E/P Portfolios

At the end of each June from 1963 to 2006, we form 25 portfolios based on a firm's price and E/P ratio. Stocks are firstly sorted into 5 E/P quintile, then are sub-grouped into 5 price range portfolios. To be included in the portfolio, a stock must have both E/P and price level data.

Panel A: 25 Price and Liquidity Portfolios; NYSE, AMEX and NASDAQ Stocks; July 1963 to Dec 2006

	Returns in All Months					Returns in January					Returns in Non-January Months				
Price Range	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
P1<=$5	1.875%	1.741%	1.859%	1.999%	2.072%	16.020%	12.074%	11.312%	11.508%	11.348%	0.606%	0.813%	1.010%	1.147%	1.239%
$5<P2<=$10	1.031%	1.166%	1.352%	1.615%	1.586%	10.047%	8.152%	7.369%	7.897%	8.231%	0.221%	0.540%	0.812%	1.051%	0.990%
$10<P3<=$15	0.801%	1.087%	1.276%	1.479%	1.582%	6.840%	6.172%	4.889%	5.364%	5.830%	0.259%	0.630%	0.952%	1.131%	1.201%
$15<P4<=$20	0.945%	0.896%	1.100%	1.348%	1.539%	5.309%	4.558%	3.652%	3.926%	4.634%	0.553%	0.567%	0.871%	1.117%	1.261%
P5>$20	0.890%	0.828%	1.048%	1.197%	1.381%	3.493%	2.173%	2.256%	2.548%	2.964%	0.657%	0.708%	0.939%	1.076%	1.238%
P1-P5	0.987%	0.908%	0.803%	0.659%	0.637%	12.520%	9.895%	9.026%	8.643%	8.269%	-0.048%	0.102%	0.065%	-0.057%	-0.048%
t-stats	3.031	3.168	3.162	2.608	2.662	8.995	8.663	8.496	7.034	7.842	-0.168	0.384	0.280	-0.254	-0.220
Degree of Freedom	509	509	509	485	497	41	41	41	39	40	467	467	467	445	456

Panel B: Characteristics of 25 Price and BE/ME Portfolios; NYSE, AMEX and NASDAQ Stocks; 1963 to 2006

	Ln(Size)					E/P					Number of Stocks				
Price Range	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
P1<=$5	12.803	13.371	11.614	12.151	12.908	-0.779	0.009	0.062	0.094	0.302	516	234	101	82	177
$5<P2<=$10	12.965	13.781	13.349	14.139	12.872	-0.242	0.013	0.062	0.093	0.182	154	179	125	127	178
$10<P3<=$15	13.494	14.723	15.014	13.617	14.042	-0.182	0.017	0.063	0.093	0.159	62	118	125	135	134
$15<P4<=$20	14.635	14.567	15.809	14.423	14.549	-0.150	0.020	0.063	0.092	0.156	30	88	118	131	111
P5>$20	15.763	16.684	17.107	17.055	16.473	-0.117	0.023	0.063	0.091	0.234	71	258	410	408	285

Table 4.7

Cross-Sectional Regressions for Individual Stocks

For each month t over July 1963 to December 2006, all NYSE, AMEX and NASDAQ stocks are regressed on lagged accounting and return based variables. 'MOM' is the average return in the previous 6 months. BE/ME is defined as in Davis, Fama and French (2000). E/P is the ratio of earning per share to share price. LIQ is liquidity measure of Amihud (2002).

Panel A: Cross-Sectional Regressions of Individual Stocks in All Months

Model		Intercept	ln(Price)	ln(Size)	MOM	BE/ME	E/P	ln(LIQ)	R-Square
1	Coefficient	0.018	-0.003						0.030
	t-stat	(4.232)	-(3.739)						
2	Coefficient	0.027	-0.003	-0.001					0.038
	t-stat	(4.764)	-(2.728)	-(2.439)					
3	Coefficient	0.018	-0.004		0.060				0.042
	t-stat	(4.561)	-(4.394)		(6.220)				
4	Coefficient	0.009	-0.002			0.000			0.012
	t-stat	(3.760)	-(3.101)			-(0.825)			
5	Coefficient	0.009	-0.002				0.006		0.013
	t-stat	(3.675)	-(3.421)				(3.036)		
6	Coefficient	0.014	-0.002					0.001	0.042
	t-stat	(3.117)	-(1.750)					(2.911)	
7	Coefficient	0.011	-0.002	0.000	0.037	0.001	0.000		0.028
	t-stat	(2.099)	-(2.810)	-(0.888)	(5.788)	(4.685)	-(0.586)		

Panel B: Cross-Sectional Regressions of Individual Stocks in January

Model		Intercept	ln(Price)	ln(Size)	MOM	BE/ME	E/P	ln(LIQ)	R-Square
1	Coefficient	0.049	-0.007						0.031
	t-stat	(2.276)	-(1.854)						
2	Coefficient	0.043	-0.008	0.001					0.038
	t-stat	(1.942)	-(1.461)	(0.535)					
3	Coefficient	0.047	-0.008		-0.019				0.044
	t-stat	(2.665)	-(2.176)		-(0.326)				
4	Coefficient	0.003	0.000			-0.001			0.007
	t-stat	(0.575)	-(0.045)			-(1.008)			
5	Coefficient	0.002	0.000				0.000		0.007
	t-stat	(0.491)	(0.110)				-(0.042)		
6	Coefficient	0.054	-0.009					-0.002	0.041
	t-stat	(2.025)	-(1.573)					-(0.931)	
7	Coefficient	-0.008	0.000	0.001	0.007	0.000	0.001		0.013
	t-stat	-(0.831)	-(0.041)	(1.509)	(0.318)	-(0.102)	(1.393)		

Panel C: Cross-Sectional Regressions of Individual Stocks in Other Months

Model		Intercept	ln(Price)	ln(Size)	MOM	BE/ME	E/P	ln(LIQ)	R-Square
1	Coefficient	0.022	-0.004						0.041
	t-stat	(3.190)	-(3.128)						
2	Coefficient	0.025	-0.003	-0.001					0.047
	t-stat	(2.956)	-(1.922)	-(2.490)					
3	Coefficient	0.022	-0.005		0.089				0.058
	t-stat	(3.369)	-(3.493)		(5.462)				
4	Coefficient	0.006	-0.001			0.000			0.006
	t-stat	(3.158)	-(3.053)			-(0.108)			
5	Coefficient	0.006	-0.001				0.010		0.007
	t-stat	(2.879)	-(3.153)				(2.402)		
6	Coefficient	0.018	-0.003					0.001	0.050
	t-stat	(2.498)	-(2.107)					(2.835)	
7	Coefficient	0.011	-0.001	-0.001	0.022	0.000	0.000		0.014
	t-stat	(2.562)	-(3.267)	-(1.799)	(2.802)	(0.537)	-(1.698)		

Table 4.8

Explaining the Price Strategy: Time-Series Regression

At the end of each June from 1963 to 2006, we form 5 price range portfolios and 25 portfolios based on a firm's price level and size or liquidity. Stocks are firstly sorted into 5 either size or liquidity quintile, then are sub-grouped into 5 price range portfolios. To be included in the 25 Price and Size portfolios, a stock must have shares outstanding and a price level. To be included in the 25 Price and Liquidity portfolios, a stock must have the illiquidity proxy of Amihud (2002). P1 (P5) stands for Penny (share price higher than $5) stock portfolio. S1 (S5) stands for the small (big) portfolio. L1 (L5) stands for the most liquid (illiquid) portfolio. The dependent variables are payoffs of three price strategies: buying penny- and selling high- price stocks (P1-P5), buying small penny- and selling big high- price stocks (S1P1-S5P5), and buying illiquid penny- and selling liquid high- price stocks (L5P1-L1P5). Fama and French factors: ERM, SMB, HML, and Momentum factor are from Kenneth French's data library. JANDM, FEBDM,...DECDM are 12 dummy variables which indicate the months of the year.

	P1-P5	S1P1-S5P5	L5P1-L1P5
JANDM	0.086	0.093	0.097
	(12.626)	(12.496)	(12.343)
FEBDM	0.015	0.022	0.019
	(2.398)	(3.103)	(2.597)
MARDM	0.008	0.011	0.006
	(1.199)	(1.585)	(0.874)
APRDM	-0.001	0.007	-0.001
	-(0.089)	(1.049)	-(0.178)
MAYDM	0.008	0.010	0.007
	(1.336)	(1.373)	(0.964)
JUNEDM	-0.009	-0.006	-0.009
	-(1.333)	-(0.901)	-(1.152)
JULYDM	0.002	0.007	0.007
	(0.324)	(0.944)	(0.930)
AUGDM	-0.009	-0.006	-0.008
	-(1.386)	-(0.873)	-(1.055)
SEPDM	-0.005	0.000	0.001
	-(0.783)	-(0.003)	(0.169)
OCTDM	-0.005	-0.003	-0.007
	-(0.820)	-(0.470)	-(0.918)
NOVDM	-0.014	-0.015	-0.017
	-(2.251)	-(2.137)	-(2.367)
DECDM	-0.022	-0.024	-0.024
	-(3.492)	-(3.420)	-(3.259)
ERM	-0.150	-0.291	-0.194
	-(3.146)	-(5.530)	-(3.524)
SMB	1.073	1.229	1.429
	(17.054)	(17.681)	(19.661)
HML	0.004	0.104	0.314
	(0.059)	(1.281)	(3.707)
MOM	-0.141	-0.052	0.010
	-(2.995)	-(1.004)	(0.182)
Adjusted R-squared	0.552	0.549	0.585
Wald F-statistic			
(*JANDM*=*FEBDM*=…=*DECDM*=0)	15.819	15.653	15.005

Table 4.9

Price Strategy for Dual Class Stocks

At end of December 2001, we identify 20 stocks with dual class shares (A and B) in the CRSP database. Then we manually look up the voting rights ratios from companys' annual reports. This table reports the average monthly prices and returns for these 20 stocks from January 2002 to December 2007. There are two price strategies for each firm in the table. Payoff 1 is calculated as follows. At the end of each month, we only invest in the low-price class stock and hold for the next month. Payoff 2 is the average monthly return for a zero cost invesment: at the end of each month, long the low-price class and short the high price class. Portfolios are held for the following month and then rebalanced. For Berkshire Hathaway, the price strategy is based on the difference between A share and 30 times B share. In this table, we normalize "B" share as the share class which has 1 voting right, and "A" as another share class which has all other voting rights.

	Voting Rights	Average Monthly Price				Average Monthly Return				Price Strategies			
NAME	B:A	B	A	B-A	t-stats	B	A	B-A	t-stats	Payoff 1	t-stats	Payoff 2	t-stats
KELLY SERVICES INC	1:0	27.656	26.558	1.098	6.698	0.437%	0.174%	0.263%	0.467	**0.508%**	0.639	0.355%	0.646
CITADEL HOLDING CORP	1:0	6.734	6.817	-0.083	-3.806	2.869%	2.880%	-0.011%	-0.024	**3.446%**	3.820	**1.271%**	**2.788**
GREIF BROTHERS CORP	1:0	49.394	51.203	-1.809	-4.185	2.491%	2.737%	-0.246%	-0.496	2.664%	2.630	0.454%	0.958
BEL FUSE INC	1:0	27.046	30.162	-3.116	-9.543	1.194%	0.810%	0.383%	0.725	0.854%	0.729	0.053%	0.100
ADVANTA CORP	1:0	21.205	22.608	-1.403	-8.570	1.256%	1.618%	-0.361%	-1.381	**1.619%**	1.084	**0.641%**	**2.525**
PLAYBOY ENTERPRISES INC	1:0	11.233	12.167	-0.934	-11.444	0.090%	-0.178%	0.268%	0.944	-0.004%	-0.003	0.523%	1.851
BALDWIN & LYONS INC	1:0	24.676	25.048	-0.372	-2.517	1.112%	1.122%	-0.010%	-0.014	**2.161%**	2.791	**2.041%**	**3.140**
VIACOM INC	1:0	35.814	35.693	0.121	4.888	-0.033%	-0.004%	-0.029%	-0.622	**0.025%**	0.034	**0.119%**	**2.666**
BROWN FORMAN CORP	1:0	67.920	66.228	1.692	12.668	1.506%	1.540%	-0.034%	-0.200	**1.576%**	2.670	0.159%	0.931
MOOG INC	1:10	36.143	36.901	-0.758	-4.154	2.534%	1.968%	0.565%	0.932	**2.951%**	3.257	**1.375%**	**2.347**
BIO RAD LABORATORIES INC	1:10	59.504	59.733	-0.229	-3.023	2.033%	2.013%	0.020%	0.108	**2.360%**	2.267	**0.622%**	**3.608**
FOREST CITY ENTERPRISES INC	1:10	47.922	48.079	-0.158	-2.673	1.531%	1.515%	0.016%	0.132	**1.570%**	2.357	**0.415%**	**3.596**
CONSTELLATION BRANDS INC	1:10	31.366	31.458	-0.092	0.892	1.519%	1.484%	0.035%	0.347	**1.529%**	1.854	**0.356%**	**2.367**
WILEY JOHN & SONS INC	1:10	32.730	32.777	-0.047	-1.865	1.071%	1.075%	-0.003%	-0.031	**1.297%**	1.967	**0.414%**	**4.487**
DONEGAL GROUP INC	1:10	17.389	16.608	0.781	4.470	1.745%	2.114%	-0.370%	-0.376	**2.835%**	3.156	1.693%	1.823
GRAY COMMUNICATIONS SYSTEMS INC	1:10	10.974	11.348	-0.375	-2.416	0.417%	0.154%	0.263%	0.521	**0.497%**	0.419	0.595%	1.199
K V PHARMACEUTICAL CO	1:20	23.265	23.863	-0.598	-4.651	1.293%	1.187%	0.106%	0.355	1.240%	0.968	0.386%	1.289
SENECA FOODS CORP NEW	1:20	19.663	20.035	-0.372	-5.487	0.929%	1.065%	-0.136%	-0.310	**1.564%**	2.674	**1.317%**	**3.182**
HUBBELL INC	1:20	43.591	41.593	1.998	9.221	1.362%	1.490%	-0.128%	-0.821	1.365%	1.821	0.067%	0.425
BERKSHIRE HATHAWAY INC	1:200	2950	88699	-208	-3.537	1.053%	1.047%	0.005%	0.076	**1.055%**	2.294	**0.206%**	**3.047**