ESSAYS IN INTERNATIONAL ASSET PRICING

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The empirical research focuses on the common risk factors in stock returns and trading activities.

The first essay is titled "Asset Pricing with Extreme Liquidity Risk". Defining extreme liquidity as the tails of illiquidity for all stocks, I propose a direct measure of market-wide extreme liquidity risk and find that extreme liquidity risk is priced cross-sectionally in the U.S. equity market. From 1973 through 2011, stocks in the highest quintile of extreme liquidity risk loadings earned value-weighted average returns 6.6% per year higher than stocks in the lowest quintile. The extreme liquidity risk premium is robust to common risk factors related to size, value and momentum. The premium is different from that on aggregate liquidity risk documented in Pástor and Stambaugh (2003) as well as that based on tail risk of Kelly (2011). Extreme liquidity estimates can offer a warning sign of extreme liquidity events. Predictive regressions show that extreme liquidity measure reliably outperforms aggregate liquidity measures in predicting future market returns. Finally, I incorporate the extreme liquidity risk into Acharya and Pedersen's (2005) framework and find new supporting evidence for their liquidity-adjusted capital asset pricing model.

The second essay is co-authored with Prof. Andrew Karolyi. We have developed a multi-factor returns-generating model for an international setting that captures how restrictions on investability or accessibility can matter. The model works reasonably well in a wide variety of

settings. More specifically, using monthly returns for over 37,000 stocks from 46 developed and emerging market countries over a two-decade period, we propose and test a multi-factor model that includes factor portfolios based on firm characteristics and that builds separate factors comprised of globally-accessible stocks, which we call "global factors," and of locally-accessible stocks, which we call "local factors." Our new "hybrid" multi-factor model with both global and local factors not only captures strong common variation in global stock returns, but also achieves low pricing errors and rejection rates using conventional testing procedures for a variety of regional and global test asset portfolios formed on size, value, and momentum.

In the third essay, I examine the implications of the Lo and Wang (2000, 2006) mutual fund separation model in the cross-sectional behavior of global trading activity. It demonstrates that return-based factors work poorly around the world. On average across countries, market-wide turnover captures 37% of all systematic turnover components in individual stock trading, and two additional Fama and French (1993) factor turnovers increase the explanatory power by 23%. Similarly Lo and Wang's (2000) turnovers only capture on average 64% of all systematic turnover components. Using this multi-factor asset pricing-trading framework, a horserace is further performed to explore other factors in return by examining the turnover behavior of different factor mimicking portfolios. All the return-based factors capture at most 67% of the common variation in trading, suggesting that stock pricing and trading volume may not be compatible around the world. In cross-country analysis, the explanatory power of the return-based factor model varies substantially across countries and markets, with better performance for European developed markets and China. Surprisingly, in North America, Japan and most emerging markets there are larger amounts of commonality in trading, mostly higher than 47%, for reasons other than return motive.

BIOGRAPHICAL SKETCH

Ying Wu graduated from Peking University with a bachelor's degree in Economics in 2001. She continued her studies in Academy of Mathematics and Systems Science, Chinese Academy of Science and obtained her master's degree in Management Science and Engineering in 2004. In 2007, she began her doctoral study in Economics at Cornell University.

In loving memory of my grandmother

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CHAPTER 1

INTRODUCTION

One of the central questions in finance is why different assets earn different rates of return. All asset pricing models agree on the central insight that returns are compensation for bearing systematic risk. What they differ on is what constitutes systematic risk. The most celebrated asset pricing model is the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965a), and Mossin (1966) which identify the return on market portfolio as the only common factor, exposures to which determine expected returns. The results in early empirical tests of Fama and Macbeth (1973) seem to reject the prediction that expected returns are related only to market betas. The failure of the CAPM to explain cross-sectionally return difference has prompted researchers to resort to other variables, often based on stock characteristics. The most prominent example is the Fama and French (1993) three-factor model, in which a size factor and a book-to-market-equity factor are added to the market risk factor in the CAPM. In the years since their seminal study, Fama and French (1993) three-factor model has remained extremely influential while, at the same time, debate has emerged over the empirical performance of their three factors.

Three key debates, among many others, have further advanced with new and more broad-based evidence over the past decade:

a) The "liquidity crunch of 2007-2008" (Brunnermeier, 2009) highlights the need to better understand what exactly a liquidity shock is despite that there have been numerous studies

question whether systematic liquidity risk is a priced factor[1]. Pástor and Stambaugh (2003) find that stocks with high loadings on the market liquidity factor outperform stocks with low loadings by 7.5% annually. Acharya and Pedersen (2005) derive an equilibrium model for returns that includes the liquidity level and a stock's liquidity co-variation with market liquidity and the market return. Hasbrouck (2009), however, finds only weak evidence of liquidity risk as a priced factor during a long horizon, 1926–2006. Pástor and Stambaugh (2003) leave the question of "whether expected returns are related to stocks' sensitivities to fluctuations in other aspects of aggregate liquidity" as one direction for future research. Given the most recent financial crisis, Pedersen (2008) emphasizes the importance of investigating extreme liquidity risk, which is the risk that market liquidity worsens to the extent that dealers are shutting down when the trader needs to unwind;

b) Whether securities are priced locally or globally is an enduring question in international asset pricing (Karolyi and Stulz, 2003; Lewis, 2011). Early empirical tests focused on whether market risk is priced locally or globally. In the past decade, however, focus has shifted to the role of firm characteristics, such as size, book-to-market-equity ratios, cash-flow-to-price ratios, and momentum, in pricing securities in global markets. And an important debate has ensured over whether the explanatory power of these characteristics arises locally or globally. Along this line of investigation, two most recent studies provide all-encompassing examinations of the firm-level characteristics that explain the cross-sectional variation in global stock returns. Hou, Karolyi, and Kho (HKK, 2011) examine the relative performance of global, local, and what they call "international" versions of various multifactor models to explain the

[1] Among many others, I include Amihud and Mendelson (1986), Brennan and Subrahmanyan (1996), Brennan, Chordia, and Subrahmanyan (1998), Jacoby, Flower, and Gottesman (2000), Jones (2002), Pástor and Stambaugh (2003), Acharya and Pedersen (2005), Sadka (2006), Chordia, Huh, and Subrahmanyam (2009), and Brennan, Chordia, Subrahmanyam, and Tong (2012).

returns of industry and characteristics-sorted test portfolios in each country. The international versions of their models represent a factor structure that includes separately local, country-specific factors as well as foreign factors built from stocks outside the country of interest. They find that the international versions of these multifactor models have much lower pricing errors than the purely local and global versions. They recommend that the foreign components of these factors are as important as local components for pricing global stocks. Fama and French (2012), however, show that a global multi-factor model performs only passably for average returns on global size/book-to-market ratios ("B/M" hereafter) and size/momentum portfolios, and it works poorly when asked to explain average returns on regional (for North America, Europe, Japan, Asia-Pacific) size/B/M or size/momentum portfolios. They test hybrid models following the methods in Griffin (2002) and HKK (2011) but find little improvement in performance in terms of explanatory power and lower pricing errors over the strictly local versions of the model (for which they deem the performance only passable);

c) If price and quantity are the fundamental building blocks of any theory of market interactions, the importance of trading volume in modeling asset markets is clear. Although there have been many rich explanation for the level of trading volume, such as tax-driven trading, liquidity trading, portfolio rebalancing and speculation, less effort has been devoted to improving our understanding of the commonality in trading activity across different stocks. Decomposing trading activity to measure how much of the trading process is driven by systematic factors and how much is because of firm-specific causes is valuable for modeling asset pricing and trading volume. Understanding commonality of trading around the world is also important for global asset managers concerned with diversifying their investment and trading strategies.

The dissertation contributes to the three debates. More specifically, in CHAPTER 2, I propose a

threshold-based measure of liquidity risk and find that it is priced in the cross section of stock returns. The nature of extreme liquidity risk is that the market experiences infrequent liquidity events of extreme magnitude, although it is in a normal liquidity state most of the time. The arrival of such liquidity crises is often unexpected, so an investor may have little or no clue as to when the market will seize up. The fear that market liquidity could dry up precipitously could have a significant impact on investors' trading behaviors and on equilibrium asset prices, even before the realization of such an event. My findings describe the economic magnitude of extreme liquidity risk for the U.S. equity market.

CHAPTER 3, entitled "The Role of Investability Restrictions on Size, Value, and Momentum in International Stock Returns", is co-authored with Prof. Andrew Karolyi. We propose and test a new multi-factor model based on firm characteristics that builds separate factor portfolios comprised of only globally-accessible stocks, which we call "global factors," and of locally-accessible stocks, which we call "local factors." We define the measure of investability, or accessibility, based on the extent to which stocks are actually listed and actively traded, primarily or secondarily in the cross-listed form, in the markets fully open to global investors. We find that neither a purely global factor model nor a purely local factor model can work as well as the new "hybrid" when asked to explain average returns on global and regional size/value and size/momentum portfolios. The new "hybrid" model does not encounter the problems of the purely global factor models, such as high rates of rejections with GRS tests and large average absolute intercepts. Rather, it improves the regression fit and reduces the pricing errors, with or without microcap stocks. And, at the same time, the new "hybrid" model fares reasonably relative to a purely local factor model, and works even better for emerging markets, in terms of explanatory power, model pricing errors and rejection rates. The robustness of the new "hybrid"

model is confirmed by tests conducted with a variety of definitions of global accessibility, other double-sorted test portfolios, expanded test portfolios, and other asset pricing models. We interpret our findings in this study as a step forward in the international asset pricing literature with important implications for practitioners in guiding cost-of-capital calculations and risk control and performance evaluation analysis of global portfolios.

CHAPTER 4 then examines the implication of the Lo and Wang (2000, 2006) mutual fund separation model in the cross-sectional behavior of global trading activity. Considerable evidence has shown that the systematic variation of stock returns are related with firm-level characteristics such as size, book-to-market equity, cash flow to price, momentum while we know little about the theoretical foundation for the co-movement in stock trading. To fill the gap, Lo and Wang (LW hereafter, 2000 and 2006) have developed a multifactor model for turnover based on mutual fund separation theorem. This model suggests that the number of return factors and the number of turnover factors should be the same. And the turnover factors in turnover model are nothing but the turnover on the *K* return factors. Although their model gives rise to a decomposition of turnover into systematic and idiosyncratic components, difficulties still exist in implementing conventional procedures of multifactor estimation due to severe heteroscedasticity and nonstationarity in turnover data. In order to overcome these problems, Cremers and Mei (CM hereafter, 2007) employ two statistical procedures developed by Bai and Ng (BN hereafter, 2002 and 2004) and document that there are four or five systematic factors driving stock turnover in the NYSE and AMEX for the period of 1962-2001.This chapter is motivated in the same spirit but broadens the investigation to over 30,000 stocks from 48 countries using weekly turnover data over the 1977 to 2010 period. Given the widespread acceptance of the common factors in return, do these fundamental factors, like the market factor, the size factor, the value

factor and the momentum factor, also drive the systematic trading around the world? The purpose of this paper is to answer this important question. The key finding is that on average 33% of the co-movement of trading around the world could not be explained by these common factors in return. The difference between the return-motivated commonality in trading and the true commonality in trading varies substantially across markets, with larger gaps for North America, Japan and emerging markets.

CHAPTER 2

ASSET PRICING WITH EXTREME LIQUIDITY RISK

2.1 Introduction

The "liquidity crunch of 2007-2008" (Brunnermeier, 2009) highlights the need to measure and model liquidity risk, which, in its extreme form, arises from the simultaneous drying up of liquidity across assets and can lead to the freezing up of the markets. Liquidity risk is not continuous, but is subject to abrupt changes. Investors might not worry about liquidity risk in normal market climates, but it can become a concern in the case of liquidity crises. After liquidity risk exceeds a certain threshold, it doesn't follow a mean-reversion pattern; instead, it feeds on itself, gathers momentum, and causes more severe market declines than would occur in normal occurrences (Brunnermeier and Pedersen, 2009). Despite the intuitive appeal of a threshold-based measure of liquidity risk, there has been little empirical research into how liquidity risk in its extreme form is priced in the cross-section of stock returns. Prior research has found that a stock's exposure to systematic liquidity risk and whether its liquidity dries up at inopportune times does matter for investors (e.g., Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006; Korajczyk and Sadka, 2008; Lee, 2011). However, because most studies focus on the aggregate level of market liquidity in which extreme liquidity events are rarely observed, this research could not accurately measure extreme liquidity risk, which is the risk that market liquidity worsens to the extent that dealers are shutting down when the trader needs to unwind (Pedersen, 2008).

In this paper, I propose a direct and viable measure of economy-wide extreme liquidity risk by taking a panel approach. The nature of extreme liquidity risk is that the market experiences infrequent liquidity events of extreme magnitude, although it is in a normal liquidity state most of the time. The arrival of such liquidity crises is often unexpected, so an investor may have little or no clue as to when the market will seize up. The fear that market liquidity could dry up precipitously could have a significant impact on investors' trading behaviors and on equilibrium asset prices, even before the realization of such an event. Rather than waiting to accumulate extreme observations in market-wide liquidity dry-ups, I assume that extreme liquidity risks of individual stocks are driven by a common underlying dynamic.2 Therefore, information about the likelihood of a market-wide extreme liquidity event could be extracted from the cross section of extreme liquidity events occurring for different individual stocks at each point in time. Based on this approach, I build my extreme liquidity estimate from the Amihud (2002) illiquidity measure for individual firms on a daily basis. I find that the cross-section of expected stock returns reflects a premium for extreme liquidity risk. From 1973 through 2011, stocks in the highest quintile of extreme liquidity risk loadings earned value-weighted average returns of 0.55% per month higher than stocks in the lowest quintile. The extreme liquidity risk premium remains robust after controlling for a number of common risk factors, including the Fama and French (1993) three factors, the Carhart (1997) momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor, Kelly's (2011) traded tail risk factor, and Acharya and Pedersen's (2005) liquidity-adjusted capital asset pricing model (CAPM). Extreme liquidity estimates can

[2] One example for this assumption is the limited number of liquidity suppliers (Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes, 2010). Another reason is the correlated trading among institutionals (Koch, Ruenzi, and Starks, 2009).

offer a warning sign of extreme liquidity events3. Predictive regressions also show that my extreme liquidity risk estimates forecast market returns consistently and outperforms aggregate liquidity measures. I incorporate my measured extreme liquidity risk into Acharya and Pedersen's (2005) framework and provide new evidence to support their liquidity-adjusted CAPM. The cross-sectional return premium corresponding to their three liquidity betas, using my measure of extreme liquidity risk, is statistically and economically significant.

My analysis focuses on the tail distribution of liquidity risk. This intuition comes from the recent financial crisis, which has reinforced the importance of the risk of infrequent, but severe, market events, and from a long standing literature on how tail risk plays a special role in determining expected return. Early studies analyzed the behavior of the tails in stock returns, following seminal work by Mandelbrot (1963) and Fama (1965) that documented that stock returns are not Gaussian but have univariate heavy tails. In the past decade, focus has shifted to the role of heavy-tailed shocks to economic fundamentals in pricing securities. Researchers, including Eraker and Shaliastovich (2008), Bansal and Shaliastovich (2011), Drechsler and Yaron (2011), Gabaix (2012), and Wachter (2012), have built asset pricing models in which fat-tailed processes are used to explain the equity premium, excess volatility, and risk free rate puzzles. Empirical studies, such as Ang, Chen and Xing (2006), Kelly (2011), and Ruenzi and Weigert (2011), investigate the impact of downside risk and tail risk on the cross-section of expected stock returns. They find that investors demand additional compensation for stocks that are crash-prone, that is, stocks that have particularly bad returns exactly when the market crashes. None of these papers, however, investigates the implication of extreme liquidity risk for asset pricing. Although

[3] Examples include the Mideast oil embargo in 1973, the stock market crash in 1987, the Long Term Capital Management (LTCM) crisis in 1999, the stock market downturn of 2002, and the "liquidity crunch of 2007–2008" (Brunnermeier, 2009). I later discuss these events in detail.

the study of liquidity considers the factors impacting the cost of trading, rarely are the contagion and correlation of liquidity demands, such as those observed in the most recent global financial crisis, taken into account in security risk measures. In order for a measurement of liquidity to be meaningful to market participants, it needs to include, not just the aggregate level of liquidity, but also the possibility of extreme liquidity event that leads investors to withdraw from markets they would otherwise be prepared to invest in. This serves as the primary motivation for my paper.

My investigation differs from numerous earlier studies that question whether systematic liquidity risk is a priced factor.4 Pástor and Stambaugh (2003) find that stocks with high loadings on the market liquidity factor outperform stocks with low loadings by 7.5% annually. Acharya and Pedersen (2005) derive an equilibrium model for returns that includes the liquidity level and a stock's liquidity co-variation with market liquidity and the market return. Hasbrouck (2009), however, finds only weak evidence of liquidity risk as a priced factor during a long horizon, 1926–2006. Pástor and Stambaugh (2003) leave the question of "whether expected returns are related to stocks' sensitivities to fluctuations in other aspects of aggregate liquidity" as one direction for future research. I seek to answer this question by focusing on a new dimension of liquidity risk: the likelihood of market liquidity at its extremes. My extreme liquidity measures can offer a warning sign of extreme liquidity events. The measured extreme liquidity index has hit its three-year high jump before periods characterized by liquidity crises. High extreme liquidity risk is associated with bad market states. It implies that stocks that hedge extreme liquidity risk are more valuable than those adversely exposed to extreme liquidity risk, and

[4] Among many others, I include Amihud and Mendelson (1986), Brennan and Subrahmanyan (1996), Brennan, Chordia, and Subrahmanyan (1998), Jacoby, Flower, and Gottesman (2000), Jones (2002), Pástor and Stambaugh (2003), Acharya and Pedersen (2005), Sadka (2006), Chordia, Huh, and Subrahmanyam (2009), and Brennan, Chordia, Subrahmanyam, and Tong (2012).

therefore have lower expected returns. I find strong evidence that the market-wide extreme liquidity risk is positively priced in the cross-section. I also implement Acharya and Pedersen's (2005) liquidity-adjusted CAPM using extreme liquidity risk and provide consistent evidence for the return premium related to all three liquidity-related betas in their model.

My inspiration for this particular extreme liquidity risk choice is also drawn from important new literature on how commonality in liquidity – also known as liquidity black holes – intensifies during large market downturns. Brunnermeier and Pedersen (2009) and other models predict that the large market declines affect the funding liquidity of financial intermediaries. As a consequence, these intermediaries reduce the provision of liquidity across many securities. The resulting decrease in market liquidity and the increase in commonality in liquidity lead to further losses and/or margin increase, creating an "illiquidity spiral" that further tightens the funding liquidity and pushes down the price. Empirical studies have found consistent evidence that commonality in liquidity increases during market downturns, such as those of Comerton-Forde et al. (2010), and Hameed, Kang, and Viswanathan (2010), with regard to the U.S., and that of Karolyi, Lee, and van Dijk (2012) regarding global markets. Given the close relation between large market declines and liquidity dry-ups, a logical question is whether extreme liquidity risk is a state variable important for asset pricing. I find that the cross-section of expected stock returns does reflect a premium for extreme liquidity risk, which may shed light on the source of tail risk, specifically during episodes of panic liquidation.

How I measure the level of extreme liquidity risk is critical for my exercise. My empirical estimate is based on the assumption that extreme liquidity risks of individual stocks are driven by a common underlying process. Given this assumption, the rich variation in the cross section of extreme liquidity events occurring for individual stocks could be used to provide accurate

information about the prevailing market-wide level of extreme liquidity risk for each point in time. This avoids having to accumulate years of extreme liquidity events from the aggregate market time series in order to estimate extreme liquidity risk, and therefore avoids using stale observations that carry little information about current extreme liquidity risk. My approach applies Hill's (1975) power law estimator to the cross section of extreme liquidity events across stocks in the market. It is distinct from a large volume of literature that has modeled extreme returns using jump processes (e.g., Duffie, Pan and Singleton, 2000) and copulas (e.g., Ané and Kharoubi, 2003; Ruenzi and Weigert, 2011). Instead, my approach models conditional liquidity tails in discrete time and uses dynamic extreme value theory. This procedure has been adopted as a measure of systemic banking sector risk by Allen, Bali, and Tang (2011), as a measure of return tail risk by Kelly (2011), and as a measure of hedge fund tail risk by Jiang and Kelly (2011).

The remainder of the paper is organized as follows: Section II explains the construction of the extreme liquidity measure, presents the data and summary statistics, and furnishes empirical features of extreme liquidity measure. Section III examines the significance of a cross-sectional relation between extreme liquidity risk and expected stock returns. Section IV lays out several robustness checks, and Section V concludes.

2.2 Measuring Extreme Liquidity Risk

2.2.1 The Tail Distribution of Liquidity

A stock is in a normal liquidity state most days, but can experience liquidity events of extreme magnitude, so the nature of extreme liquidity risk is that it is infrequent, comes suddenly, and is

somewhat unpredictable. Investors might care little about liquidity in normal conditions, but high transaction costs might become a first order concern if the market hits a disaster liquidity state; that is, its illiquidity cost lies at the right tail of the distribution. The arrival of such liquidity crises is often unexpected, so an investor may have little or no clue as to when the market will seize up. The fear that market liquidity could dry up precipitously could have a significant impact on investors' trading behaviors and on equilibrium asset prices, even before the realization of such events.

Extreme value theory provides a statistical framework characterizing the asymptotic extreme characteristics of stationary distributions. The theory allows us to obtain an adequate characterization of the extreme behavior and, to this end, the estimation of the so-called tail index is essential, for which theory offers a variety of different approaches.

Originally Mandelbrot (1963), and later Fama (1965), pointed out that the distribution of the empirical returns is often leptokurtic and frequently positively skewed, which implies that it is peaked and fat-tailed. Since these observations were made, extreme value theory has been increasingly used in the modeling of the tail of stock returns.5 More recent studies (Plerou, Gopikrishnan, Amara, Gabaix, and Stanley, 2000; Gabaix, Gopikrishnan, Plerou, and Stanley, 2006; and Gabaix, 2009) have argued that the power law applies not only to the tail distribution of returns but also to the tail distributions of other critical financial time series, including price impact, trading volume, the number of trades, and the size of large investors. Among them, the unconditional tail distribution of price impact is aptly described by a power law, which yields a concave price impact function (Hasbrouck, 1991; Hasbrouck and Seppi, 2001; and Plerou,

[5] Consider, among many others, studies by Quintos, Fan, and Phillips (2001), Wagner (2003), Galbraith and Zernov (2004), and Werner and Upper (2004).

Gopikrishnan, Gabaix, and Stanley, 2002). The power law parameterization is often used, for example, by Barra (1997); Grinold and Kahn (1999); Hasbrouck and Seppi (2001); and Gabaix, Gopikrishnan, Plerou, and Stanley (2003).

Given the power law of price impact, I use Amihud (2002) illiquidity measure as my measure of price impact6 and therefore propose a novel specification for equity liquidities in which the tail distribution obeys a power law that potentially changes over time,

$$P\left(ILLIQ_{t,d}^{i} > x \middle| ILLIQ_{t,d}^{i} > p_t^*, \mathcal{F}_{\mathrm{t}}\right) \sim (x/p_t^*)^{-a^i \gamma_t}$$

(1)

Equation (1) states that the right tail of stock illiquidity is defined as the set of liquidity events, that is, the observations $\mathrm{ILLIQ}_{\mathrm{t,d}}^{\mathrm{i}}$ in terms of Amihud (2002) illiquidity measure, exceeding some high threshold p^*_t and it follows a power law. The term of $\mathrm{ILLIQ}_{\mathrm{t,d}}^{\mathrm{i}}$ takes the form of stock i available on day d in month t

$$ILLIQ^i_{t,d} = |R^i_{t,d}| / V^i_{t,d}$$

(2)

in which $R^i_{t,d}$ and $V^i_{t,d}$ are, respectively, the return and dollar volume (in millions) on day d in month t. The second term in the exponent, γ_t, varies with the conditioning information set $\mathcal{F}_t$. While different assets have different levels of extreme liquidity risk (determined by the constant a^i), dynamics are the same for all assets because they are driven by a common conditional process. Thus, I refer to - γ_t as economy-wide extreme event risk in liquidity. The focus of this paper is the right tail of the liquidity distribution. The convention in extreme value theory is to

[6] Amihud's (2002) illiquidity measure has been extensively used in the literature on stock market liquidity and asset pricing. As suggested by Goyenko, Holden and Trzcinka (2009), it does well in measuring price impact.

represent a tail distribution as the right tail, and I follow this convention closely.

The threshold parameter p^*_t is set to define where the center of the distribution ends and the tail begins. It is necessary to have enough observations in the tail to make inferences. On the other hand, using data points from the center of the sampling distribution tends to reduce the effectiveness of the tail estimates. Here I follow Gabaix *et al.* (2006) and Kelly (2011) by fixing the threshold at the 95th percentile of the cross section distribution month-by-month.[7] Consequently, the threshold varies as the cross-sectional distribution fans out and compresses over time, which is a convenient way of mitigating undue effects of aggregate market liquidity level on the tail risk estimates.

The Hill (1975) estimator is established as one of the most suitable methods for financial applications: the semi-parametric estimation approach is based on the assumption that the underlying distribution is in the maximum domain of attraction of the Fréchet extreme value distribution. This generally holds for fat-tailed distributions as analyzed in finance. Unlike, for example, the estimation approach based on the generalized extreme value distribution, the assumption for the Hill estimator does not require that exact asymptotic limits be met. I therefore apply the Hill (1975) estimator for the tail exponent of economy-wide liquidity for each month by employing the pooled set of daily Amihud (2002) liquidity observations for all stocks in month t. The extreme liquidity index based on the method of Hill (1975) is defined as

$$1/\gamma_t = (1/N_t)\sum_{k=1}^{N_t} ln\,(ILLIQ^{(k)}_{t,d} / p^*_t)$$

(3)

[7] Similar empirical results are obtained when the thresholds are set to be between the 90th and 99th percentiles. I later discuss the robustness check on the threshold choice.

where N_t is the number of daily illiquidity observations that exceed the threshold p^*_t for month t, and $ILLIQ^{(k)}_{t,d}$ is a daily Amihud (2002) illiquidity measure during that month if it is larger than p^*_t.

Given that for stock i,

$$E_{t-1}[ln(x^i_{k,t} / p^*_t)] = 1 / (a^i \gamma_t)$$

(4)

the expected value of $1/\gamma_t$ is the cross-sectional average tail exponent,

$$E_{t-1}[(1/N_t)\sum^{N_t}_{k=1} ln (x_{k,t} / p^*_t) \mid \gamma_t] = 1 / (\bar{a}\, \gamma_t) ,$$

where $\bar{a} \equiv n/\sum^{n}_{i=1}(1/a^i)$

(5)

Different stocks will experience extreme liquidity events in different periods. The heterogeneity in the set of a^i coefficients entering in the tail calculation over time will affect the estimation of the market-wide extreme liquidity risk. However, the conditional expectation of the Hill (1975) measure is unaffected by this heterogeneity since *ex ante* it is unknown which stocks will be in the tail part. Equation (5) states that the Hill estimator is expected to be equal to the true common tail component $1/\gamma_t$ times a constant multiple; therefore, the expected value of month-by-month Hill estimates is perfectly correlated with the true economy-wide tail process $1/\gamma_t$.

2.2.2 Data and Summary Statistics

I collect daily Center for Research in Security Prices (CRSP) data from July 1967 to December 2011 from NYSE stocks with share codes 10 and 11. To keep the liquidity measure consistent across stocks, I exclude NASDAQ because the NASDAQ returns and volume data are available

from CRSP for only part of this period (beginning in 1972). Also the volume data of NASDAQ includes interdealer trades, unlike those reported on the NYSE and the AMEX. On the other hand, the CRSP sample covers all size groups, and indeed very small, microcap stocks produce challenging results (Fama and French, 2008), especially those with strong idiosyncratic liquidity shocks. Incorporating the observations from these micro-cap stocks would contaminate the estimation of systematic extreme liquidity risk. I therefore control for the potential influence of microcap stocks by excluding stocks on the AMEX[8], although the results are not driven by this exclusion.

On the other hand, because the accuracy of my approach relies on the quantity of observations in the right tail distribution, I require the liquidity observations from a large panel of stocks to gain sufficient information about the tail at each point. Figure 2.1 plots the effective number of stocks in NYSE from CRSP each month. The sample has fewer than 1,000 stocks until 1951 and, in July 1968, the sample size roughly rises to more than 1,200 stocks. I therefore focus my sample on the 1968 to 2011 period to prevent the issue of noisy estimates due to too few data points.

All existing NYSE common stocks are considered for the whole sample period. However, in each month, I eliminate the stocks for which some data are missing.[9] Also removed from a trading day are all the stocks for which the firm experienced a merger, delisting, partial liquidation, or seasoned equity offerings during that month. The stocks with less than one year of trading history on the NYSE at the start of the month are similarly discarded from that month. Finally, I eliminate from a trading day within that month any stock whose trading volume is zero.

[8] Stocks on the NASDAQ and AMEX will be considered in the asset pricing tests of section III.
[9] For example, if a stock's trading volume is missing in CRSP on any day, we simply remove that stock from that day.

I form twenty equal-weighted portfolios based on the cross-section distribution of Amihud (2002) illiquidity measures month-by-month, and Table 2.1 reports the summary statistics on the cross-sectional properties of the whole NYSE sample. Here the sorting is based on the stock-date observations within each month: a stock is included in one particular portfolio as long as it has at least one daily Amihud (2002) illiquidity observation lying in the illiquidity range specified for that portfolio. It is possible for one stock to be included in both the most illiquid portfolio and the most liquid one during the same month. Not surprisingly, we see that illiquid stocks, that is, stocks with high average illiquidity cost, tend to have a lower return, a high volatility of returns, a lower turnover, and a small market capitalization. The most illiquid stocks in the last of twenty portfolios yield a much lower level of simple average monthly return, 0.51%, compared with 1.60% for the most liquid stocks in the first of twenty portfolios. Their simple average monthly volatility is 3.46%, higher than that for the most liquid stocks, 1.89%. At the same time, the simple average monthly turnover is 4.10%, lower than 11.39% for the most liquid stocks. The simple average size for the most illiquid stocks, $0.12 billion, is also smaller than that for most liquid stocks, $11.77 billion.[10]

The tail index measure in (5) only uses the observations that exceed the tail threshold p^*_t, that is, the observations of the most illiquid portfolios. And the extreme liquidity estimate accesses the average distance between the most extreme observations and the benchmark. Therefore, when the index is applied to the cross section of liquidity, it varies monotonically with the average frequency of extreme realizations. For example, when applied to the liquidity of various firms

[10] The summary statistics are similar in terms of value-weighted returns and value-weighted illiquidity for these twenty portfolios. Quite a few studies focus on equal-weighted return and illiquidity measures, such as Chordia *et al.* (2000), Amihud (2002), and Acharya and Pedersen (2005), to name just a few. As suggested in Acharya and Pedersen (2005), computing the return and illiquidity as equal-weighted average can compensate for the over-representation in the sample of large liquid stocks, as compared to the "true" portfolios in the economy.

each month, the index will be larger when more firms experience extremely low liquidity. This monotonic property with the likelihood of extreme liquidity events is what makes the extreme liquidity index an attractive empirical proxy for tail risk in liquidity. The more positive the power law exponent $1/\gamma_t$, the heavier the tails of the particular stock illiquidity costs, the higher extreme liquidity risk. In practice, I follow Kelly (2011) and normalize the extreme liquidity estimates (subtract mean and divide by standard deviation), which is denoted by *ELR* for later analysis[11].

2.2.3 Empirical Features of the Extreme Liquidity Risk Measure

Figure 2.2 plots the estimated extreme liquidity risk series along with the NBER recessions. My sample starts around the late 1960's bull market peak. Estimated extreme liquidity risk is low at the starting point, and continues to fall sharply until the midpoint of 1969, when it reaches its lowest level for the whole period. Extreme liquidity risk starts to rise sharply in the recession of 1969–1970 when the U.S. stock market experienced a severe bear market. The risk index then fluctuates for several years, with obvious jumps during three recessions: from November 1973 through March 1975, from January 1980 through July 1980, and from July 1981 through November 1982. Extreme liquidity risk begins to go up quickly in the months following the 1987 October crash and reaches its highest level in the 1990 liquidity crisis. The technology boom that follows then pushes down the market-wide extreme liquidity risk until the LTCM collapse and the Russian debt crisis. Throughout the last half of the decade, extreme liquid risk rises quickly to another peak, especially during the 2007–2009 financial crisis and recession.

[11] The results for unnormalized estimates are very close and available upon request in an internet appendix.

Although aggregate illiquidity measures[12] also increase during periods characterized by liquidity crises, the extreme liquidity risk index is weakly associated with aggregate liquidity measures. As shown in Appendix I, my extreme liquidity measures have correlations of 0.12, -0.07, 0.15, and 0.01 with Pástor and Stambaugh (2003) aggregate liquidity innovations, Acharya and Pedersen's (2005) aggregate illiquidity innovations, Hu, Pan, and Wang (2012) market-wide liquidity measures, and Sadka (2006) permanent liquidity factor, respectively. This suggests that my extreme liquidity captures a dimension of liquidity risk which is different from the aggregate level. On the other hand, extreme liquidity measure has a relatively high correlation of 0.48 with the average commonality in liquidity. Extreme liquidity risk appears fairly closely associated with credit risk, having the correlations of 0.41 and -0.22 with the term spread (the difference between yields on long- and short-term government bonds) and the default spread (the difference in yields on BAA and AAA corporate bonds). Compared with supply-side sources for commonality in liquidity, extreme liquidity index appears more closely associated with demand-side factors[13]. In particular, it shares a monthly correlation of 0.63 with ETFs volume, as a measure of index-related basket trading in Karolyi, Lee, and van Dijk (2012). It is also closely correlated with NYSE margin debt outstanding (0.50) in which high levels of margin debt shows the effect of over-leveraging and makes the market vulnerable to nasty tumbles.

It is hard to predict liquidity dry-ups in that liquidity risk is often high after a long period of abundant liquidity. But my extreme liquidity measures can offer a warning sign of possible

[12] Consider, for example, the innovation of market liquidity in Pástor and Stambaugh (2003) and the innovation of market illiquidity in Acharya and Pedersen (2005).

[13] Some empirical studies have found support for supply-side sources of commonality in liquidity related to the funding constraints of financial intermediaries (e.g., Coughenour and Saad, 2004; Comerton-Forde *et al.* 2010; Hameed, Kang, and Viswanathan, 2010). Other work has explored demand-side sources, for example those driven by correlated trading activity (e.g., Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001; Koch, Ruenzi, and Starks, 2009).

financial panics in that the sharp increase in extreme liquidity measure gives rise to the financial vulnerability and the likelihood of a liquidity crisis. The measured extreme liquidity index growth has achieved its three-year high before periods that were characterized by liquidity crises, for example, the Mideast oil embargo in November 1973, the stock market crash in October 1987, the 1991 Japanese asset price bubble bursts, the LTCM collapse in 1999, the stock market downturn of 2002, the "liquidity crunch of 2007–2008" (Brunnermeier, 2009), and the European sovereign debt crisis in 2009. Compared with the abrupt changes in aggregate liquidity measures, the relatively persistent movement of extreme liquidity series, with the autocorrelation of 0.98, suggests that extreme liquidity risk has the potential to impact returns. To investigate this hypothesis, I estimate a series of predictive regressions for market returns based on the estimated extreme liquidity series. The dependent variable is the return on the CRSP value-weighted index at frequencies of one month, three months, six months, one year, three years, and five years. I compare the performance of my extreme liquidity risk measure with those of Pástor and Stambaugh (2003) liquidity measure and Acharya and Pedersen's (2005) illiquidity measure. Extreme liquidity risk forecasts returns consistently over all horizons and outperforms the aggregate liquidity measures. For example, in the five-year horizon, extreme liquidity risk yields R^2 value of 7.12%, higher than 0.21% for Pástor and Stambaugh (2003) liquidity level measure and 1.81% for Acharya and Pedersen's (2005) illiquidity level measure.

My measure of extreme liquidity tends to be high when market volatility is high. This positive association between volatility and the extreme liquidity measure, reported in Appendix I, is reasonable, because the compensation required to providers of liquidity for a given level of order flow could well be greater when volatility is higher. A kind of "flight-to-quality" effect appears

in months with exceptionally high extreme liquidity risk[14]. That is, months in which extreme liquidity rises severely tend to be months in which stocks and fixed-income assets move in opposite directions. During the months when extreme liquidity measure is at least two standard deviations above its mean, the correlation between the return on the CRSP value-weighted index and the return on long-term government bonds is -0.16. In addition, extreme liquidity risk shares a monthly correlation of -0.52, -0.14, -0.48 and -0.17 with dividend-price ratio, unemployment, inflation, and the Chicago Fed National Activity Index (CFNAI).

2.3 Extreme Liquidity Risk and the Cross Section of Expected Returns

2.3.1 Is Extreme Liquidity Risk Priced?

My extreme liquidity risk measure relies on a large cross section of stocks and yields a monthly series spanning almost 40 years. As such, the series is well suited for this study's focus on extreme liquidity risk and asset pricing. In this section, I test whether a stock's expected return is related to the sensitivity of its return to extreme liquidity risk. Stocks with high predictive loadings on extreme liquidity risk are discounted more steeply and thus have higher expected returns going forward. On the other hand, stocks with low or negative extreme liquidity risk loadings serve as effective hedges and therefore have comparatively higher prices and lower expected returns. At the end of each year, I estimate extreme liquidity risk sensitivities of individual stocks with respect to extreme liquidity risk by the form

$$E_t\,[r_{i,t+1}] = \mu_i + \beta_i\, ELR_t$$

[14] In crisis periods, the flight-to-quality phenomenon is well documented in the U.S. markets, for example, by Longstaff (2004) and Vayanos (2004), and with the global empirical evidence of Hund and Lesmond (2008) and Goyenko and Sarkissian (2008), among others.

(6)

Here the regression uses only data available at that time. And eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Stocks are then sorted into quintile portfolios based on their estimated extreme liquidity risk loadings. In addition, I follow Pástor and Stambaugh (2003) and construct decile portfolios to assess the robustness. The post-formation returns on these portfolios during the next 12 months are linked across years to form a single return series for each portfolio, which covers the period from July 1973 to December 2011.

Panel A of Table 2.2 reports the preceding loadings, the post-ranking loadings, and additional properties for quintile portfolios formed on an annual basis. The upper part of Panel A presents summary statistics in which stocks are value-weighted, and those for the equal weighting are shown in the lower part. Taking the value-weighted returns as an example, both the preceding extreme liquidity loadings and the post-ranking loadings increase across quintiles.[15] The "5–1" spread is comprised of longing quintile 5 (stocks with the highest preceding extreme liquidity loadings) and shorting quintile 1 (stocks with the lowest preceding extreme liquidity loadings). It has an overall-period post-ranking extreme liquidity loading of 0.58 (t = 2.33), even larger than its preceding loading, 0.22. Additional properties are reported: The lowest quintile portfolio contains stocks of smaller firms, the value-weighted size (averaged over time) is $22.93 billion, as compared to $27.70 billion in quintile 5. Stocks in the lowest loading portfolios tend to be less liquid, as measured by the value-weighted Amihud (2002) illiquidity measure, although this

[15] Here the preceding loadings are the β_i in the regression (6). The post-ranking extreme liquidity loadings are estimated by regressing the portfolio excess returns on the extreme liquidity risk estimate and the market excess return factor over the whole sample period.

pattern is also not monotonic. Table 2.2 also reports the quintile portfolios' betas with respect to the Fama-French (1993) three factors (MKT, SMB, and HML), the Carhart (1997) momentum factor (MOM), the Pástor and Stambaugh (2003) traded liquidity factor (PS-Liquidity), and Kelly's (2011) tail risk factor (K-Tail)[16]. The betas are estimated by regressing the quintile excess returns on all of the six factor portfolio returns. The MKT beta of the "5–1" spread is statistically significant. The SMB beta (-0.26) confirms the pattern in average market capitalizations. The momentum beta for the "5–1" spread is significantly positive (0.22, t = 4.87), suggesting some tilt toward past winners. The liquidity beta (-0.08) is consistent with the pattern in the Amihud (2002) illiquidity measure. The "5–1" spread's tail beta is significantly positive (0.21, with a t-statistic of 4.17), indicating some tilt toward stocks with high loadings on the tail risk in return.

The empirical features of quintile portfolios sorted on extreme liquidity risk are robust to the weighting scheme and rebalancing frequency. Changing from value weighted portfolios to equally weighted portfolios does not qualitatively change these properties except that the average portfolio sizes shrink and the average Amihud (2002) illiquidity cost for quintile 1 becomes much higher than that for quintile 5. Panel B of Table 2.2 reports summary statistics for the one-month post-formation experiments,[17] which are nearly identical to those in Panel A in which the post formation period is one year.

Asparouhova, Bessembinder and Kalcheva (2010) document that noisy prices lead to biases in

[16] The MKT, SMB, HML, and MOM data are obtained from Prof. Kenneth R. French's data library, the PS-Liquidity data is obtained from Prof. Robert F. Stambaugh's website, and the K-Tail data is constructed by Kelly (2011).

[17] Each month, I estimate the extreme liquidity loading for each stock in the regression (6) that uses the most recent 60 months of data. Stocks are then sorted into quintile portfolios and decile portfolios based on their estimated extreme liquidity risk loadings. One month post-formation value-weighted and equal-weighted portfolio returns are tracked. Portfolios are reconstituted each month.

intercept and slope coefficients obtained in any ordinary least squares (OLS) regression using rates of return as the dependent variable.[18] To mitigate such bias, Asparouhova, Bessembinder and Kalcheva (2012), in particular, assess the effects of value-weighted returns, when weights are based on prior-month market values and on prior-December market values. Their analysis provides strong reason to prefer the weighting by the prior-month size to the weighting by prior-December size, since "the latter method does not correct for bias in months other than the first month after portfolio formation" (Asparouhova, Bessembinder and Kalcheva, 2012). Given the possibility of noise existence in portfolios sorted on extreme liquidity risk, I focus on the value-weighted returns in which weights are based on prior-month market values[19].

Table 2.3 illustrates the systematic differences in the average returns of portfolios sorted on the extreme liquidity risk loadings. From 1973 through 2011, stocks in the highest quintile of extreme liquidity risk loadings earned value-weighted average returns 6.6% per year higher than stocks in the lowest quintile, with a *t*-statistic of 2.73. The equal-weighted average return on the high-minus-low extreme liquidity risk portfolio was 5.52% per annum (t = 3.15). Average portfolio returns demonstrate a stable monotonic pattern that increases in tail risk. Table 2.3 also reports the regression alphas for the value-weighted (and equal-weighted) portfolios: 1) alphas with respect to the Fama and French three-factor model; 2) alphas with respect to the Carhart four-factor model; 3) alphas with respect to the Carhart four-factor plus Pástor and Stambaugh (2003) traded liquidity factor as a fifth control; 4) alphas after considering Kelly's (2011) tail risk factor as a sixth control beyond the Carhart four-factor and the Pástor and Stambaugh (2003)

[18] Asparouhova, Bessembinder and Kalcheva (2010) follow Blume and Stambaugh (1983) in referring to the underlying security value as the true price, and interpret noise to mean any temporary deviation of transaction prices from true prices. The sources of noise in price, in their study, include, but are not limited to, microstructure-based frictions, the presence of irrational traders, and the inelasticity of short-run liquidity supply.

[19] The results for the value-weighted returns in which weights are based on prior-December market value, available in an appendix, are similar to those reported in Tables 2-8.

traded liquidity factor. Alphas of the high-minus-low quintile portfolio are large and statistically significant for all of the models: in terms of value-weighted returns, the Fama-French alpha is 8.40%[20] per year (t = 3.56), the four-factor alpha is 6.72% per year (t = 2.84), the five-factor alpha is 7.32% per year (t = 3.05), and the six-factor alpha is 6.60% per year (t = 2.81). When Acharya and Pedersen's (2005) liquidity-adjusted CAPM is used as the benchmark model, the alpha is still significantly positive and economically large, with the value of 7.92% (t = 3.39) per year. Adding more factors, such as SMB, HML, and MOM, to Acharya and Pedersen's (2005) liquidity-adjusted CAPM doesn't change the magnitudes and statistical significances of the alphas, which remain 6.72% (t = 2.84) per year for the "5–1" spread and 9.72% (t = 3.15) per year for the "10–1" spread. The same is true for equal-weighted returns, for example, in which the "5–1" spread alpha is 5.40% (t = 3.28) for the six-factor model. Regression alphas retain the same stable monotonicity that is observed for the raw average portfolio returns.

Panel B of Table 2.3 presents the results under alternative portfolio construction, monthly rebalance. These results show that monthly-rebalancing portfolio returns have the same qualitative behavior with the annual-rebalancing portfolio returns. Value-weighted return for the "5–1" spread portfolio is 0.44% per month (5.28% annualized, t = 2.39), and equal-weighted return yields 0.38% per month (4.56% annualized, t = 2.13). Compared with the results when portfolios are value-weighted, evidence of the extreme liquidity risk premium is slightly stronger for equally-weighted portfolios. When portfolios are monthly rebalanced, the regression alphas of the "5–1" spread portfolio are 0.49% (5.88% annualized, t = 3.01) per month for the Fama and French three-factor model, 0.44% (5.28% annualized, t = 2.66) per month for the Carhart four-factor model, 0.39% (4.68% annualized, t = 2.47) per month for the extended six-factor model,

[20] Annual alphas are computed as 12 times the monthly estimates.

and 0.52% (6.24% annualized, t = 3.00) per month for Acharya and Pedersen's (2005) liquidity-adjusted CAPM, respectively.

Table 2.4 reports Fama-MacBeth regression results of excess (risk-unadjusted) returns on characteristics best known to be associated with expected returns: SIZE, B/M, Mom, Volatility, Turnover, Amihud (2002) liquidity measure, and betas on both normal liquidity risk constructed by Pástor and Stambaugh (2003) and tail risk in return by Kelly (2011). The average slopes on the extreme liquidity risk beta are all economically large (varies from 0.23 to 0.66) and always highly significant (t-statistics all above 2.15). In contrast, the average slopes on normal liquidity risk beta are rather small (around 0.17) and not statistically distinguishable from zero for most of the scenarios listed in Table 2.4, especially when the factor of turnover or the beta on extreme liquidity risk is considered. The coefficients of SIZE, B/M, Mom, and Volatility are, respectively, negative, and positive, positive, and negative, corresponding with similar studies such as Fama and French (1992), Ang *et al*. (2006), Lewellen (2012). Lee and Swaminathan (2000) show that the turnover of the past 3 to 12 months is negatively related to subsequent returns, especially among stocks that performed poorly over the same past 3 to 12 months. The effect persists after controlling for size and B/M factors and the negative coefficients for the lag of turnover confirms their findings. The positive coefficients for the lag of Amihud (2002) liquidity measure confirm Spiegel and Wang (2005).

Results from two-way portfolio sorts are reported in Appendix II. Stocks are independently sorted by size[21] and their preceding extreme liquidity risk loadings. Portfolios are rebalanced at the end of each year. Value-weighted returns for the one month post-formation portfolios are

[21]The size breakpoints come from Prof. Kenneth R. French's data library. The breakpoints use all NYSE stocks with available market equity.

reported in Panel A and equal-weighted returns are presented in Panel B. Within each size quintile I calculate the average returns (value-weighted and equal-weighted) on the high-minus-low portfolio on extreme liquidity risk. Value-weighted "5–1" spreads within size quintiles range from 0.37% to 0.72% per month (*t*-statistics are 2.49 and 3.63, respectively). All of the alphas are significant with respect to a variety of benchmark models. Using the alphas corresponding to the Acharya and Pedersen's (2005) liquidity-adjusted CAPM as an example, the alphas (per month) of the "5–1" spreads are 0.47% for the smallest stocks, 0.72% for the second smallest stocks, 0.69% for the middle size stocks, 0.82% for the second biggest stocks, and 0.57% for the biggest stocks. The extreme liquidity risk premium retains economically large in big stocks and there is only weak evidence of size effect for the premium. In Panel B, equal-weighted returns on high-minus-low extreme liquidity risk loading portfolio are slightly smaller than the value-weighted returns, but still more than 0.30% per month in all cases. Almost all of the alphas are significant, robust to considering alternative priced factors.

Appendix III summarizes the mean returns for the 80 (4×4×5) triple-sorted portfolios. Sorts are performed sequentially, first sorting on size and then again, within each group, on the basis of the Amihud (2002) illiquidity measure. Finally each of the sixteen sub-groups is subdivided into five portfolios according to their preceding extreme liquidity loadings. The average return monotonically increases from the lowest quintile of extreme liquidity loading (0.37% per month) to the highest quintile (0.92% per month), and so does the six-factor alpha (the results for other regression models, not shown, are nearly identical.) Even within each size and liquidity cost category, the patterns of cross-sectional returns related to the extreme liquidity risk loading are discernible. All of the sixteen "5–1" spread portfolios have positive mean returns and regression alphas. On average, the return spread of the hedge portfolio on the extreme liquidity loading is

54 basis points per month across the sixteen size/liquidity-cost portfolios, with its regression alpha for the six-factor model of 0.62% per month (t = 3.09). As shown in Panel B of Appendix III, the results are similar when the portfolios are equally weighted: Almost all of the "5–1" return spreads are beyond 0.23% per month and most of the regression alphas are above 0.21% per month.

Next I test the hypothesis that all of the alphas in each set of test asset portfolios are jointly equal to zero, using the test of Gibbons, Ross, and Shanken (1989). The hypothesis is always rejected at a 1% significant level, for both equally weighted and value-weighted portfolios; for all quintile, decile, double, and triple-sorted portfolios; and for all of the six benchmark models.

The possible presence of industry clustering raises concern about the interpretation of abnormal returns from methods that do not explicitly account for industry effects. I then examine to what extent the industry rotation matters in measuring the long-term abnormal returns for extreme liquidity risk. An industry-neutral strategy is therefore employed: I identify all of the stocks by their Fama-French 30 industries, and within each industry I sort the target stocks in five quintile groups. I then form industry-neutral portfolios by combining the stocks in quintile 1 from all 30 of the Fama-French industries into a single quintile 1 portfolio, and similarly with the remaining four groups to form the five industry-neutral portfolios. Untabulated results (available upon request in an internet appendix) show that the industry-neutral quintile hedge portfolio on extreme liquidity risk has the alpha of 39 basis points (t = 3.12) per month for the Carhart four-factor model, the alpha of 40 basis points (t = 3.07) per month for the Carhart four-factor model plus both the Pástor and Stambaugh (2003) traded liquidity factor and Kelly's (2011) tail risk factor, and the alpha of 41 basis points (t = 3.16) per month for Acharya and Pedersen's (2005) liquidity-adjusted CAPM. The extreme liquidity risk premium is not driven by industry

clustering as industry neutrality is maintained in this strategy[22].

To better understanding the extreme liquidity risk premium, I apply the Hill (1975) estimator for the left tail exponent, that is, the most liquid observations, of the pooled set of daily Amihud (2002) illiquidity observations for all stocks month-by-month. I then test the hypothesis that the extreme liquidity risk measure is merely a manifestation of the fat-tail distribution underlying the price impact measures. If the beta based on the new Hill (1975) estimator also helps explain the cross section of stock returns, it will lead us not to reject the null hypothesis. The portfolios sorted on the betas with respect to the new estimator behaviors differently from the main experiment: Average raw returns neither increase nor decrease with the loadings. Although the "5–1" spread portfolio earns, on average, 0.11% per month throughout the sample period, it is with a *t*-statistic of only 0.59, which indicates that the spread return is statistically indistinguishable from zero. Moreover, the positive average return for the hedge portfolio is not robust to considering alternative priced factors. For example, the alpha for the Fama-French three-factor model is -0.01% (t = -0.05). Such weak evidence on the extreme liquid measure suggests us to reject the hypothesis and validates that extreme liquidity risk premium found in the main experiment indeed captures, to some extent, the market-wide liquidity pressure which is important for asset pricing.

I next investigate whether the empirical validity of extreme liquidity risk premium is influenced by the purely mechanical way in which the tail threshold parameter, p^*_t, is chosen. I gradually adjust the threshold, from the 90th to the 99th percentile, and repeat the main experiment above. When the thresholds are set to be between the 91th and 99th percentiles, the empirical results are

[22] Another experiment I investigated was to exclude financial firms when quintile/decile portfolios are constructed. The results (available upon request) are quantitatively similar to those reported in Table 2 and 3.

very similar with those for the 95th percentile. On the other hand, if the threshold is at the 90th percentile, the average value-weighted return of the "10–1" spread portfolio becomes statistically insignificant at the 95% confidence level although both the average return and regression alphas of the quintile spread are statistically significant. This examination suggests that an inappropriately low threshold is more likely to contaminate the estimation of extreme liquidity risk.

In consideration of the practical use of the Amihud (2002) illiquidity measure on real data, two additional experiments are conducted: 1) I winsorize the effect of outliers by excluding all of the most illiquid observations beyond 99th percentile, reset the 95th-percentile threshold for the new winsorized distribution before constructing the extreme liquidity risk estimate, the results (available upon request) based on the new extreme liquidity risk measure are very close to those reported in Table 2.2 and 2.3; 2) I artificially implement the approach using alternate days in order to evaluate the concern of the independence assumption for the pooled set of stock-day Amihud (2002) illiquidity observations. Extreme liquidity risk premium based on the new treatment is almost identical to that showed in Table 2.3. For example, regression alpha for the value-weighted quintile spread is still 6.60% per year (t = 2.67) when the six-factor model is employed as the benchmark model.

In sum, there is strong evidence supporting the hypothesis that extreme liquidity risk is priced cross-sectionally. The premium for this risk is positive in that stocks highly sensitive to extreme liquidity shocks offer higher expected returns. This positive premium confirms the intuition that a sharp drop in extreme liquidity is undesirable for the representative investor, so that the investor might require compensation for holding such stocks with higher exposure to extreme liquidity risk.

2.3.2 Revisiting Acharya and Pedersen's (2005) Liquidity-adjusted CAPM

In Acharya and Pedersen's (2005) liquidity-adjusted CAPM, the required excess return is the expected relative illiquidity cost plus four betas times the risk premium. As in the standard CAPM, the required return on an asset increases linearly with the market beta. The model yields three additional effects: 1) return increases with the covariance between a security's liquidity and the market liquidity; 2) return decreases with the covariance between a security's return and the market liquidity; 3) return decreases with the covariance between a security's liquidity and the market return.

The previous sections focus on the second effect, and this section first tests the hypothesis that the two other effects also help explain the cross-section of average stock returns. To capture the first liquidity risk effect, at the end of each year, β^2 is estimated for each stock by regressing its Amihud (2002) illiquidity cost on the market illiquidity level, which is the same with Acharya and Pedersen (2005). Similarly, I calculate β^4, corresponding to the third liquidity risk effect, for each stock using the regression in which the independent variable is the return of market portfolio, measured by the return on the CRSP value-weighted index. I find a return premium associated with β^4 but no return premium on β^2. The lack of the return premium with respect to β^2 confirms the small magnitude of the first liquidity risk effect documented in Acharya and Pedersen (2005)[23]. Across quintile portfolios sorted on β^4, the return difference between the

[23] As in Acharya and Pedersen (2005), β^2 is related to the return premium due to commonality in liquidity. I therefore follow Karolyi, Lee, and van Dijk (2011) and use the R^2 of regressions of the liquidity of individual stocks on market liquidity to obtain a measure of commonality in liquidity. Each month, I estimate the R^2 for each stock and then construct quintile portfolios based on the sorting on the level of R^2s. In this experiment, the value-weighted return premium monotonically increases from the lowest R^2 quintile (0.82%) to the highest quintile (1.07%). Both the "5–1" spread and "10–1" spread are robust to considering alternative priced factors. The results are close when the portfolios are equally weighted, but slightly weaker when the portfolios are rebalanced annually.

highest loading quintile and the lowest loading quintile is -19 basis points per month[24], with a *t*-statistic of -1.85. Compared with quintile portfolios, decile portfolios provide stronger evidence: Alphas of the high-minus-low β^4-sorted portfolio, for example, are statistically significant for all of the benchmark models. The risk-adjusted premium for the decile spread remains -15 basis points per month (t = -2.10) for the extended six-factor model. Even in terms of value-weighted returns, the decile spread alpha yields -29 basis points per month (t = -2.24) for the same model.

Table 2.5 presents the testing results for the hypothesis that the overall liquidity-related net beta is correlated with the difference of expected return cross-sectionally. Here I implement Acharya and Pedersen's (2005) liquidity-adjusted CAPM, using the extreme liquidity risk[25], and find consistent evidence for return premium on the liquidity-related net beta. Table 2.5 reports mean returns and regression alphas for the portfolios sorted on the liquidity-related net beta[26], β^{net}, against all of the six benchmark models. For the quintile portfolios, stocks in the highest quintile earn higher returns and have higher Amihud (2002) illiquidity cost than those in the lowest quintile. The mean return of the "5-1"spread is 0.79% per month in terms of value weighting (t = 3.84) and 0.37% per month in terms of equal weighting (t = 3.44). After controlling a variety of common risk factors, risk-adjusted premiums still increase with the liquidity-related net beta. For example, when portfolios are annually rebalanced, stocks in quintile 5 outperform stocks in quintile 1 by earning an additional 0.78% per month (9.36% per year) after benchmarking the raw returns against the Carhart four-factor model plus the Pástor and Stambaugh (2003) traded liquidity factor as the fifth control. Again, both the "5–1" spread and the "10–1" spread are

[24] Note that this effect stems from the willingness of investors to accept a lower expected return on a security that is liquid in a down market.

25 I also estimate the liquidity-related net beta by using the innovation in aggregate market illiquidity as the proxy for market illiquidity, and construct quintile portfolios in a similar way with previous experiments. However it is hard to find clear evidence in the way that Acharya and Pedersen (2005) predicts.

[26] $\beta^{net} = \beta^2 - \beta^3 - \beta^4$

significant at the 10% level.

To conclude, I implement Acharya and Pedersen's (2005) liquidity-adjusted CAPM, using my extreme liquidity risk measures, and find consistent evidence that the liquidity-related net beta helps explain the cross-sectional differences in expected returns across stocks.

2.4 Robustness Check

Appendix IV indicates that extreme liquidity traded factor has low correlations with other common risk factors. The correlations between the extreme liquidity traded factor and the market return, the size factor, the value factor, and the momentum factor are -0.26, -0.20, 0.10, and 0.19, respectively. We can also notice that the extreme liquidity traded factor is weakly correlated with the Pástor and Stambaugh (2003) traded liquidity factor and Kelly's (2011) tail risk factor, which again suggests that extreme liquidity risk is a separate and distinct type of risk compared to the aggregate liquidity risk and the tail risk in return.

2.4.1 Sub-period Analysis

Given the evidence above that market-wide extreme liquidity risk is a state variable important for asset pricing, a logical question is whether the magnitude of extreme liquidity risk premium varies over time. Section II notes extreme liquidity risk measure goes up during recessions. A natural comparative sub-period analysis reveals the difference of extreme liquidity risk premiums between normal times and times of crisis.

I first separate the whole sample period into two sub-periods and Table 2.6 distinguishes the return premiums on extreme liquidity risk during economic recessions and those in the economic

expansions. There is a noticeable decrease in the regression alphas for the recession sub-period. In terms of value-weighted returns and annual rebalance, the risk-adjusted return of the spread falls sharply from 0.61% per month to 0.37% per month when using the extended six-factor model as the benchmark model.

I next look into another set of two sub-periods, one with sudden market downturns and the other without market downturns. The alphas decrease more obviously in this experiment. All of the risk-adjusted returns of the quintile spreads, either value-weighted or equal-weighted, are negative during the times with sudden market downturns, and the magnitudes are large. For instance, the alpha of the "5–1" spread portfolios is -1.12% per month during the downturn period, much lower than the 0.65% per month for the period without downturns, and here the benchmark model includes Acharya and Pedersen's (2005) liquidity-adjusted CAPM and three additional factors (SMB, HML, and MOM).

Another example for the financial crisis is a liquidity dry-up event. I then check the periods with liquidity dry-ups and those without liquidity dry-ups. Here liquidity dry-ups includes months when the average liquidity is at least two standard deviations below its means measured by Pástor and Stambaugh (2003) liquidity innovations or the average illiquidity is at least two standard deviations above its means evaluated by Acharya and Pedersen (2005). The spread portfolio, which longs stocks with higher beta of extreme liquidity risk and shorts stocks with lower beta, performs also worse among the months of liquidity dry-ups.

2.4.2 Out of Sample Test

Given the positive evidence on the pricing of extreme liquidity risk, I try to pin down the positive

risk premium more precisely into two sub-samples traded on different exchanges: NYSE&AMEX, and NASDAQ. After all, my extreme liquidity estimate is based on the information extracted from the NYSE stocks while the portfolios incorporate all NYSE/AMEX/NASDAD stocks. The experiment on the NASDAQ stock serves as an out-of-sample test[27] and Table 2.7 provides another indication of the robustness of my results.

Both the NASDAQ sample and the NYSE/AMEX sample deliver strong results not only for the average returns of spread portfolios but also for the regression alphas estimated under different factor specifications. With annual rebalancing, the "5–1" spread from the sample of NASDAQ stocks earn value-weighted average return 0.71% per month, with a *t*-statistic of 3.15, higher than the 0.52% per month (t = 2.81) for the NYSE/AMEX sample. The equal-weighted "5–1" spread portfolio earns average returns of 0.58% (t = 3.23) per month for the NASDAQ sample and 0.46% (t = 3.59) per month for the NYSE/AMEX sample. Both of the sub-samples have large and statistically significant alphas of the value-weighted "5–1" spread portfolio. When the extended six-factor model is considered, the quintile spread for the NYSE/AMEX stocks earns a risk-adjusted return of 0.55% per month (t = 3.05) while the NASDAQ stocks yield a risk-adjusted return of 0.60% per month (t = 2.69). In terms of equal-weighted returns, the regression alphas are 0.42% per month (t = 3.35) for NYSE/AMEX stocks and 0.46% per month (t = 2.72) for NASDAQ stocks, using the same benchmark model.

2.4.3 Alternative Liquidity Measure

My extreme liquidity risk estimate in the previous analyses is based on the Amihud (2002) illiquidity measure. In this section I try another proxy for the price impact, the Roll Impact,

[27] I also check another set of two sub-samples: NYSE, and NASDAQ/AMEX, and it produces almost identical results.

which is "a close second behind Amihud" suggested by Goyenko, Holden and Trzcinka (2009). The Roll Impact for time interval *t* is defined as follows:

$$Roll\ Impact_t = Roll_t\ /\ Average\ Daily\ Dollar\ Volume_t$$

(7)

where $Roll_t$ takes the form

$$Roll = \begin{cases} 2\sqrt{-cov(\Delta P_t, \Delta P_{t-1})} & when\ cov(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0 & when\ cov(\Delta P_t, \Delta P_{t-1}) \geq 0 \end{cases}$$

(8)

There is one problem with using the Roll Impact as the basis for the estimation of extreme liquidity risk. It is measured over a number of day observations, which are then averaged, while my estimate requires a large panel of day-stock observations within each month. To solve this problem, I make an adjustment on the measure of the Roll Impact: for each stock *i* and each day *d* in month *t*, I select a reference period which consists of the preceding 22 days (*d-22, d-21, ..., d-1*) and the day *d*. The reference period is used to measure the Roll Impact for the stock on that day. On a given trading day *d*, the stock *i*'s daily trading dollar volumes in the reference period are used to measure the average daily dollar volume in the denominator of the Roll Impact. The serial covariance of the trade prices, which appears in the numerator of the Roll Impact, is also based on the trading data during the same reference period. For each stock with valid observations in month *t*, its trailing 23-day measure of the Roll Impact is accordingly estimated for each day in month *t*. Similar to the previous sections, I apply Hill's (1975) estimator to the cross section of illiquidity observations in terms of the Roll Impact for all of the qualified NYSE stocks month-by-month. I acknowledge several limitations in the implementation. It might not be able to incorporate the new information promptly by the trailing method. I also cannot disregard the fact that the Roll Impact is set to be zero whenever the serial covariance of traded price is

larger than or equal to zero. I expect that the noisy estimates built on the Roll Impact most likely will fail to provide supporting evidence for the hypothesis that extreme liquidity risk is priced cross-sectionally in the U.S. stock market, and interpret this experiment as a sensitivity test to gauge the robustness of my results.

When portfolios are annually rebalanced and the stocks within each portfolio are equally-weighted, stocks in the highest decile of extreme liquidity risk loading earn value-weighted average return 0.45% per month higher than stocks in the lowest decile, with the *t*-statistic of 3.31. The equal-weighted "5–1" spread portfolio average return is 0.36% per month (t = 3.23). I next test if the risk premium survives a number of common risk factors. Taking the "5–1" spread as an example, the alphas are 0.30% per month (t = 2.65) for the Fama-French three-factor model, 0.24% per month (t = 2.07) for the Carhart four-factor model, 0.21% per month (t = 1.82) for the Carhart four-factor model plus the Pástor and Stambaugh (2003) traded liquidity risk factor, 0.35% per month (t = 3.08) for the Acharya and Pedersen's (2005) liquidity-adjusted CAPM, and 0.23% per month (t = 1.98) for the Acharya and Pedersen's (2005) liquidity-adjusted CAPM plus three additional common risk factors. The alpha with respect to the most extensive six-factor model, however, is less statistically significant, with the *t*-statistic of just 1.73, despite that it is large, 0.20% per month. When stocks within each portfolio are value-weighted, the high average return for the "10–1" spread is robust to controlling for a variety of risk factors while the performances on the "5–1" spread get less desirable. Compared to extreme liquidity measure based on the Amihud (2002) illiquidity measure, the Roll Impact appears more related to the level of illiquidity cost. The value-weighted Amihud (2002) illiquidity is 0.13% for the highest loading quintile, much higher than 0.06% reported in Table 2.2 for the quintile 5. The same is also true for equal-weighted portfolios. In addition, the high loading portfolios contain stocks of

small size and growth tilt. The complete set of portfolio properties and returns are reported in Table 2.8.

Overall, the experiment on the alternative price impact measure produces the most disappointing results among all of the robustness tests. But, even with this challenge, there is still evidence suggesting that stocks more exposed to extreme liquidity risk tend to be more heavily discounted.

2.5 Conclusions

I propose a direct measure of market-wide extreme liquidity risk and find that the cross-section of expected stock returns reflects a premium for extreme liquidity risk. From 1973 through 2011, stocks in the highest quintile of extreme liquidity risk loadings earned value-weighted average returns 0.55% per month higher than stocks in the lowest quintile. The extreme liquidity risk premium is robust to common risk factors related to size, value and momentum. The premium is different from that on aggregate liquidity risk documented in Pástor and Stambaugh (2003) as well as that based on the extreme market-wide return of Kelly (2011). Predictive regressions show that my extreme liquidity measure reliably outperforms aggregate liquidity measures in predicting future market returns. Finally, I incorporate the extreme liquidity risk into Acharya and Pedersen's (2005) framework and find new supporting evidence for their liquidity-adjusted capital asset pricing model.

My findings underscore the empirical relevance of extreme liquidity risk for the U.S. equity market. One direction for future research is to construct the higher frequency measures of extreme liquidity risk by utilizing high frequency liquidity benchmarks. Future work could

investigate how the pricing of aggregate liquidity risk documented in Pástor and Stambaugh (2003) is related to the pricing of extreme liquidity risk in this study. It would also be useful to explore whether extreme liquidity risk is priced in other financial markets, such as international equity markets or fixed income markets, and whether information on the extreme liquidity risk of other non equity securities is helpful for the study of equity returns.

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Figure 2.1

Number of Stocks for the Estimation of Extreme Liquidity Risk: 1950-2011

This figure plots the number of stocks each month used for the estimation of market-wide extreme liquidity risk from 1950 to 2011. Daily returns and volumes are taken from the CRSP daily stock file. I exclude NASDAQ in constructing the aggregate extreme liquidity measure because NASDAQ return and volume data are available from CRSP for only part of this period (beginning in 1982). Also, reported volume on NASDAQ includes interdealer trades, unlike the volumes reported on the NYSE and the AMEX. To exclude NASDAQ, I omit stocks with exchange codes of 3 or 33 as of the end of the previous year. Also, the CRSP sample covers all size groups, and indeed very small, microcap stocks produce challenging results (Fama and French, 2008), especially those with strong idiosyncratic liquidity shocks. Incorporating them into the estimation of market-wide extreme liquidity risk will make my estimate much noisy. I therefore control for the potential influence of microcap stocks by excluding AMEX stocks. I use only stocks classified as ordinary common shares (CRSP share codes 10 and 11), excluding American depository receipts, shares of beneficial interest, certificates, units, real estate investment trusts, closed-end funds, companies incorporated outside the United States, and Americus trust companies.

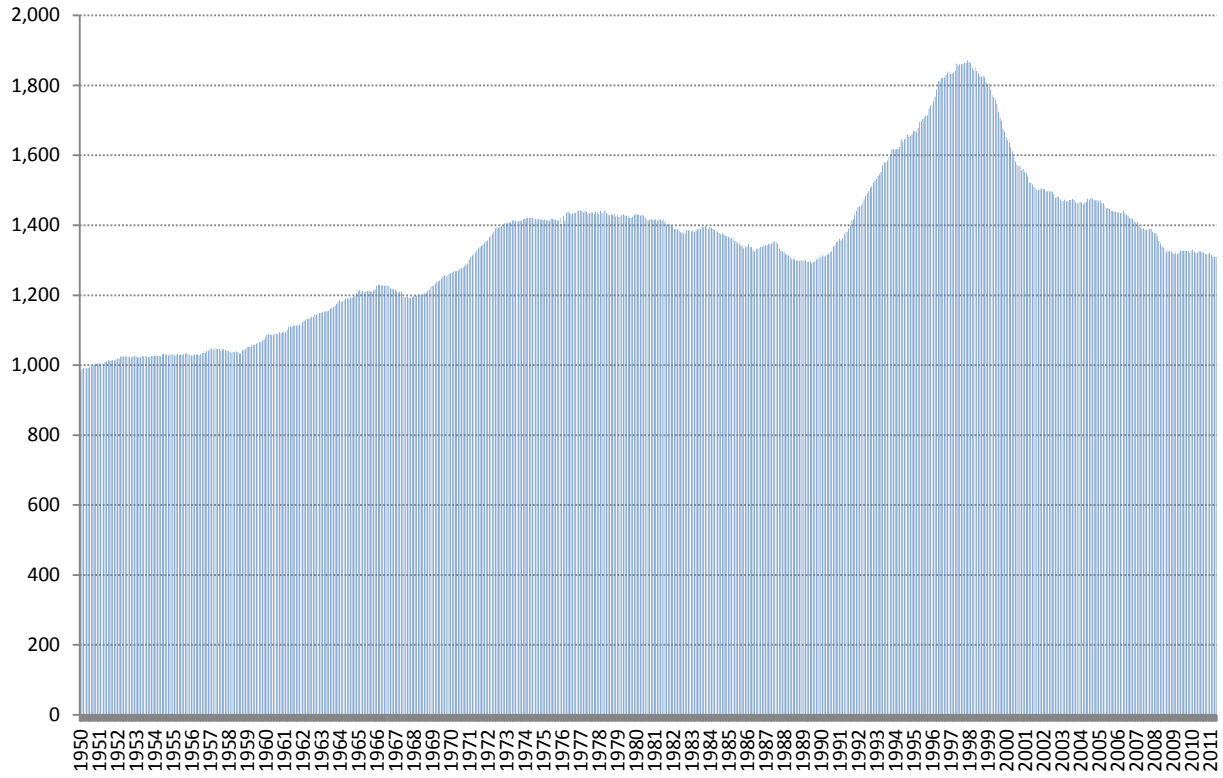


Figure 2.2

Extreme Liquidity Risk Estimates: 1968-2011

This figure plots the monthly estimated extreme liquidity risk time series. The extreme liquidity risk estimates are calculated month-by-month by pooling all daily Amihud (2002) illiquidity observations for the NYSE stocks. The tail series has been scaled to have mean zero and variance one. Shaded areas denote NBER recessions.

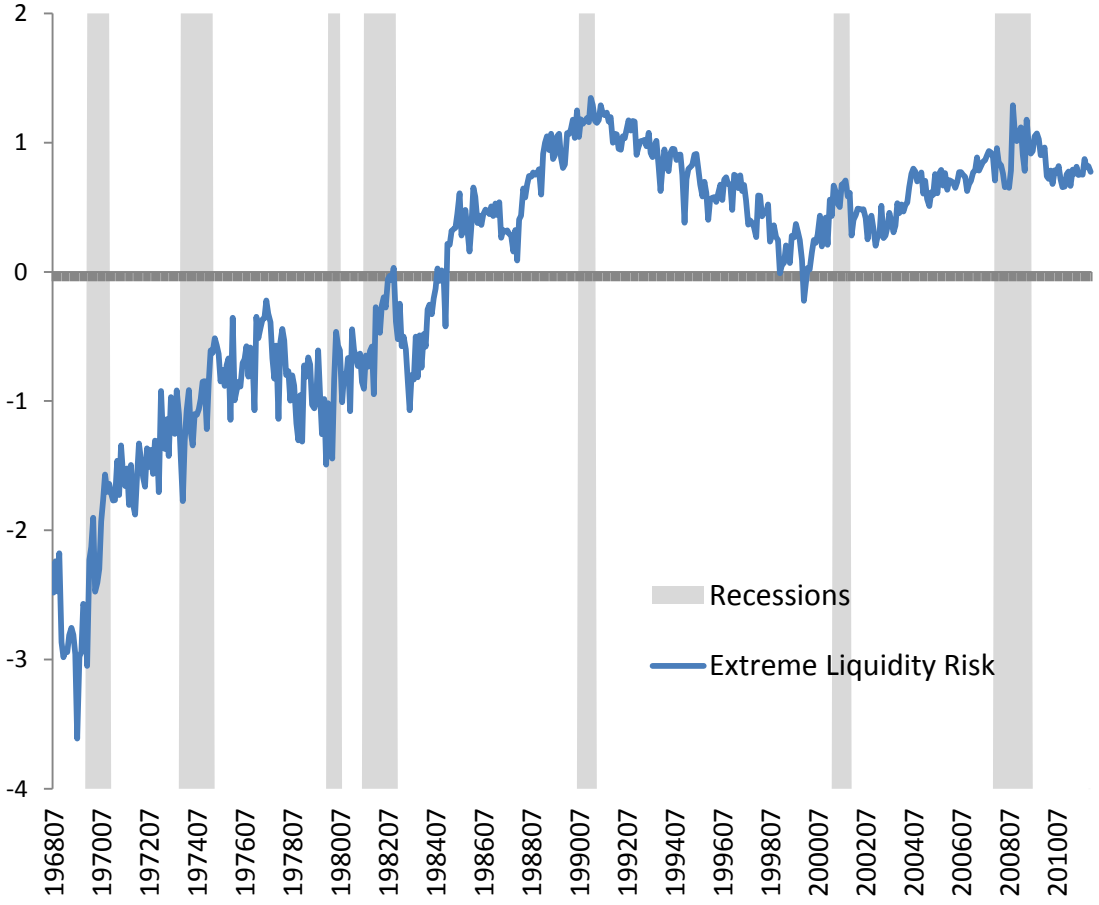


Table 2.1

Summary Statistics: 1973-2011

Group	$E(r^m)$	$E(r^d)$	$\sigma(r)$	$E(c^m)$	$E(c^d)$	$\sigma(c)$	size	trn	price	shares outstanding
	monthly	daily	monthly	monthly	daily	monthly	per stock	monthly	monthly	monthly
	(%)	(%)	(%)	(%)	(%)		($billion)	(%)	($)	(million)
<5th	1.60	0.02	1.89	0.01	0.00	0.01	11.77	11.39	115.58	264.15
5th~10th	1.55	0.04	1.92	0.01	0.00	0.01	8.57	11.19	105.85	206.64
10th~15th	1.54	0.06	1.96	0.01	0.00	0.02	6.10	11.14	101.62	156.64
15th~20th	1.53	0.08	1.99	0.02	0.01	0.02	4.68	11.08	98.21	127.95
20th~25th	1.51	0.09	2.02	0.02	0.01	0.03	3.68	11.02	93.09	106.51
25th~30th	1.54	0.10	2.05	0.03	0.01	0.03	2.94	10.87	89.60	90.10
30th~35th	1.50	0.10	2.08	0.04	0.01	0.04	2.38	10.73	80.67	77.20
35th~40th	1.50	0.11	2.11	0.04	0.02	0.05	1.93	10.56	72.11	66.28
40th~45th	1.50	0.11	2.14	0.06	0.03	0.07	1.57	10.31	57.61	57.20
45th~50th	1.50	0.11	2.18	0.07	0.03	0.08	1.28	10.01	47.22	49.64
50th~55th	1.47	0.10	2.22	0.09	0.05	0.11	1.05	9.67	38.49	43.46
55th~60th	1.46	0.11	2.26	0.11	0.06	0.13	0.87	9.29	31.31	38.32
60th~65th	1.44	0.10	2.30	0.14	0.08	0.17	0.73	8.86	27.13	33.96
65th~70th	1.40	0.10	2.35	0.18	0.11	0.22	0.60	8.40	24.17	30.15
70th~75th	1.35	0.09	2.42	0.22	0.16	0.29	0.49	7.90	21.32	26.82
75th~80th	1.28	0.08	2.51	0.29	0.22	0.39	0.40	7.34	19.64	24.13
80th~85th	1.19	0.06	2.60	0.39	0.33	0.54	0.32	6.74	17.47	21.59
85th~90th	1.05	0.04	2.74	0.56	0.53	0.81	0.25	6.00	15.50	19.36
90th~95th	0.86	-0.01	2.96	0.97	1.03	1.52	0.18	5.17	13.25	17.23
>95th	0.51	-0.05	3.46	6.99	20.43	13.43	0.12	4.10	10.21	15.17

This table reports the properties of twenty equal-weighted portfolios based on the cross-section distribution of extreme liquidity risk involved in each stock on the NYSE each month during 1973-2011. The average monthly return $E(r^m)$, the average daily return $E(r^d)$, the average monthly illiquidity $E(c^m)$, the average daily illiquidity $E(c^d)$, the market capitalization (Size), the turnover (trn), the trading volume (volume), the price (Price), and the shares outstanding (Shares Outstanding) are computed for each group as time-series averages of the respective characteristics. Finally, $\sigma(r)$ is the average of the standard deviation of daily returns for the group's constitute stocks computed each month, and $\sigma(c)$ is the average of the standard deviation of daily illiquidity for the group's constitute stocks computed each month.

Table 2.2

Properties of Extreme Liquidity Loading-sorted Portfolios: 1973-2011

Extreme Liquidity Loading	Low				High				
	1	2	3	4	5	**5–1**	*t-stat.*	**10–1**	*t-stat.*
Panel A: Annual Rebalance									
Value-weighted									
Preceding loadings	-0.12	-0.03	0.00	0.03	0.10	**0.22**	*9.69*	**0.30**	*9.65*
Post-ranking loadings	-0.46	-0.01	0.05	0.11	0.12	**0.58**	*2.33*	**0.61**	*1.90*
Additional Properties									
Market cap	22.93	35.96	34.01	31.83	27.70	**4.77**	*2.37*	**3.57**	*1.85*
(Il)liquidity	0.09	0.05	0.04	0.03	0.06	**-0.04**	*-8.50*	**-0.08**	*-8.71*
MKT beta	1.17	1.06	0.95	0.94	0.94	**-0.24**	*-5.16*	**-0.31**	*-5.36*
SMB beta	0.22	-0.09	-0.12	-0.15	-0.04	**-0.26**	*-4.00*	**-0.43**	*-5.21*
HML beta	-0.09	0.10	0.22	0.12	-0.03	**0.07**	*0.98*	**0.04**	*0.51*
MOM beta	-0.15	-0.05	0.01	0.05	0.06	**0.22**	*4.87*	**0.19**	*3.32*
PS-Liquidity beta	0.03	0.00	0.01	-0.01	-0.05	**-0.08**	*-1.50*	**-0.10**	*-1.53*
K-Tail beta	-0.06	-0.05	0.05	0.06	0.15	**0.21**	*4.17*	**0.37**	*5.80*
Equal-weighted									
Preceding loadings	-0.12	-0.03	0.00	0.03	0.10	**0.22**	*10.06*	**0.30**	*9.91*
Post-ranking loadings	-0.47	-0.07	0.05	0.17	0.08	**0.55**	*3.08*	**0.59**	*2.61*
Additional Properties									
Market cap	1.28	2.22	2.38	2.45	1.85	**0.58**	*5.06*	**0.59**	*5.74*
(Il)liquidity	1.50	1.57	1.13	1.06	0.98	**-0.75**	*-11.81*	**-0.81**	*-12.17*
MKT beta	1.05	0.93	0.87	0.83	0.90	**-0.15**	*-4.62*	**-0.15**	*-3.67*
SMB beta	0.85	0.51	0.39	0.43	0.54	**-0.31**	*-7.07*	**-0.39**	*-6.93*
HML beta	0.09	0.36	0.41	0.33	0.24	**0.14**	*3.10*	**0.22**	*3.71*
MOM beta	-0.17	-0.08	-0.04	-0.02	0.00	**0.17**	*5.44*	**0.18**	*4.73*
PS-Liquidity beta	0.01	-0.01	0.00	0.00	-0.04	**-0.05**	*-1.51*	**-0.09**	*-1.91*
K-Tail beta	0.02	0.00	0.05	0.07	0.16	**0.14**	*4.08*	**0.17**	*3.86*

Table 2.2, continued

Extreme Liquidity Loading	Low				High				
	1	2	3	4	5	**5–1**	*t-stat.*	**10–1**	*t-stat.*
Panel B: Monthly Rebalance									
Value-weighted									
Preceding loadings	-0.13	-0.03	0.00	0.03	0.10	**0.22**	*33.01*	**0.31**	*32.65*
Post-ranking loadings	-0.53	-0.02	0.03	0.13	0.16	**0.68**	*2.45*	**0.71**	*2.13*
Additional Properties									
Market cap	21.75	35.42	34.87	30.69	29.88	**8.13**	*3.94*	**6.38**	*3.21*
(Il)liquidity	0.09	0.04	0.04	0.04	0.06	**-0.03**	*-6.43*	**-0.06**	*-7.28*
MKT beta	1.25	1.05	0.96	0.89	0.90	**-0.35**	*-7.20*	**-0.40**	*-6.82*
SMB beta	0.37	-0.03	-0.16	-0.17	-0.09	**-0.46**	*-6.71*	**-0.56**	*-6.86*
HML beta	-0.16	0.04	0.25	0.13	0.01	**0.17**	*2.37*	**0.18**	*2.09*
MOM beta	-0.15	-0.07	-0.01	0.03	0.08	**0.22**	*4.64*	**0.20**	*3.55*
PS-Liquidity beta	0.00	0.02	0.01	-0.01	-0.06	**-0.05**	*-0.97*	**-0.05**	*-0.80*
K-Tail beta	-0.18	-0.06	0.05	0.09	0.23	**0.41**	*7.58*	**0.56**	*8.81*
Equal-weighted									
Preceding loadings	-0.13	-0.03	0.00	0.03	0.10	**0.22**	*34.15*	**0.30**	*33.68*
Post-ranking loadings	-0.46	-0.02	0.08	0.09	0.11	**0.57**	*2.57*	**0.63**	*2.28*
Additional Properties									
Market cap	1.25	2.25	2.48	2.37	1.90	**0.64**	*5.46*	**0.63**	*5.83*
(Il)liquidity	1.41	1.27	1.15	1.08	1.00	**-0.41**	*-8.44*	**-0.49**	*-8.36*
MKT beta	1.11	0.94	0.88	0.85	0.92	**-0.19**	*-5.13*	**-0.21**	*-4.53*
SMB beta	1.02	0.55	0.41	0.40	0.50	**-0.52**	*-10.06*	**-0.64**	*-9.91*
HML beta	0.03	0.34	0.39	0.36	0.28	**0.25**	*4.61*	**0.33**	*4.87*
MOM beta	-0.11	-0.05	-0.02	0.02	0.03	**0.14**	*3.78*	**0.14**	*3.20*
PS-Liquidity beta	0.00	0.00	0.00	0.00	-0.04	**-0.04**	*-1.05*	**-0.06**	*-1.15*
K-Tail beta	-0.07	0.01	0.03	0.09	0.21	**0.28**	*6.90*	**0.35**	*6.85*

Table 2.2, continued

The table shows the properties for the extreme liquidity risk beta-sorted portfolios. At each year end between 1972 and 2010, I estimate extreme liquidity risk sensitivities of individual stocks with respect to extreme liquidity risk by the form

$$E_t\,[r_{i,t+1}\,]=\mu_i + \beta_i\,ELR_t$$

Here the regression uses only data available at that time. And eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Stocks are then sorted into quintile portfolios and decile portfolios based on their estimated extreme liquidity risk loadings. The post-formation returns on these portfolios during the next 12 months are linked across years to form a single return series for each quintile portfolio and decile portfolio covering the period from July 1973 to December 2011. Panel A reports the quintile portfolios' preceding extreme liquidity loadings ("preceding loadings" in the table) and post-ranking extreme liquidity loadings ("post-ranking loadings" in the table). The post-ranking extreme liquidity loadings are estimated by regressing the portfolio excess returns on the extreme liquidity risk estimate and the market excess return factor over the sample period. Panel B reports the time-series averages of the quintile portfolios' market capitalization and liquidity, obtained as the average of the corresponding Amihud (2002) illiquidity measures across the stocks within each quintile. Market capitalization is reported in billions of U.S. dollars. A stock's liquidity in any given month is the Amihud (2002) illiquidity measure. Also reported are post-ranking betas with respect to the three Fama-French factors, the momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table) and Kelly's (2011) tail risk factor ("K-Tail" in the table). The four right-most columns report results for two high-minus-low zero net investment portfolio, one that longs quintile portfolio 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' corresponding measures.

Table 2.3

Extreme Liquidity Loading-sorted Portfolio Returns: 1973-2011

Extreme Liquidity Loading	Low				High				
	1	2	3	4	5	**5–1**	*t-stat.*	**10–1**	*t-stat.*
Panel A: Annual Rebalance									
Value-weighted									
Mean	0.74	0.84	0.94	1.12	1.29	**0.55**	*2.73*	**0.68**	*2.64*
Alpha: FF	-0.32	-0.13	-0.02	0.22	0.39	**0.70**	*3.56*	**0.89**	*3.49*
Alpha: FF + Mom	-0.19	-0.10	-0.01	0.19	0.37	**0.56**	*2.84*	**0.81**	*3.14*
Alpha: FF + Mom + PS-Liquidity	-0.21	-0.10	-0.02	0.19	0.40	**0.61**	*3.05*	**0.87**	*3.35*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.20	-0.08	-0.03	0.18	0.36	**0.55**	*2.81*	**0.77**	*3.06*
Alpha: AP-CAPM	-0.29	-0.09	0.07	0.25	0.37	**0.66**	*3.39*	**0.82**	*3.23*
Alpha: AP-CAPM + FF + Mom	-0.19	-0.09	-0.01	0.19	0.37	**0.56**	*2.84*	**0.81**	*3.15*
Equal-weighted									
Mean	0.97	1.13	1.24	1.33	1.43	**0.46**	*3.15*	**0.58**	*3.19*
Alpha: FF	-0.30	-0.06	0.09	0.22	0.26	**0.56**	*4.13*	**0.68**	*3.94*
Alpha: FF + Mom	-0.14	0.01	0.14	0.25	0.31	**0.45**	*3.31*	**0.56**	*3.22*
Alpha: FF + Mom + PS-Liquidity	-0.15	0.01	0.14	0.25	0.33	**0.48**	*3.51*	**0.61**	*3.48*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.16	0.01	0.12	0.24	0.29	**0.45**	*3.28*	**0.56**	*3.26*
Alpha: AP-CAPM	-0.15	0.13	0.29	0.39	0.42	**0.58**	*4.12*	**0.71**	*4.01*
Alpha: AP-CAPM + FF + Mom	-0.24	-0.09	0.05	0.17	0.24	**0.48**	*3.49*	**0.58**	*3.38*
Panel B: Monthly Rebalance									
Value-weighted									
Mean	0.75	0.91	0.91	1.08	1.19	**0.44**	*2.39*	**0.42**	*2.02*
Alpha: FF	-0.33	-0.05	-0.06	0.18	0.29	**0.62**	*2.84*	**0.6**	*2.27*
Alpha: FF + Mom	-0.25	0.00	-0.04	0.18	0.28	**0.53**	*2.38*	**0.56**	*2.10*
Alpha: FF + Mom + PS-Liquidity	-0.25	-0.02	-0.05	0.18	0.31	**0.57**	*2.53*	**0.6**	*2.23*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.20	0.00	-0.06	0.16	0.25	**0.46**	*2.15*	**0.45**	*1.80*
Alpha: AP-CAPM	-0.32	-0.03	0.03	0.21	0.28	**0.60**	*2.73*	**0.58**	*2.18*
Alpha: AP-CAPM + FF + Mom	-0.25	0.00	-0.04	0.18	0.28	**0.53**	*2.38*	**0.56**	*2.10*
Equal-weighted									
Mean	1.04	1.24	1.26	1.35	1.43	**0.38**	*2.13*	**0.46**	*2.05*
Alpha: FF	-0.24	0.04	0.11	0.22	0.24	**0.49**	*3.01*	**0.56**	*2.77*
Alpha: FF + Mom	-0.17	0.09	0.13	0.23	0.27	**0.44**	*2.66*	**0.52**	*2.53*
Alpha: FF + Mom + PS-Liquidity	-0.17	0.09	0.14	0.23	0.30	**0.47**	*2.81*	**0.56**	*2.70*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.15	0.09	0.13	0.21	0.24	**0.39**	*2.47*	**0.47**	*2.35*
Alpha: AP-CAPM	-0.11	0.23	0.30	0.39	0.41	**0.52**	*3.00*	**0.62**	*2.83*
Alpha: AP-CAPM + FF + Mom	-0.26	0.00	0.05	0.15	0.20	**0.46**	*2.80*	**0.55**	*2.67*

Table 2.3, continued

The table shows the statistics for the extreme liquidity risk beta-sorted portfolios. At each year end between 1972 and 2010, I estimate extreme liquidity risk sensitivities of individual stocks with respect to extreme liquidity risk by the form

$$E_t\,[r_{i,t+1}] = \mu_i + \beta_i ELR_t$$

Here the regression uses only data available at that time. And eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Stocks are then sorted into quintile portfolios and decile portfolios based on their estimated extreme liquidity risk loadings. The post-formation returns on these portfolios during the next 12 months are linked across years to form a single return series for each quintile portfolio and decile portfolio covering the period from July 1973 to December 2011. Panel A reports monthly portfolio returns when portfolios are rebalanced annually and Panel B reports monthly returns when portfolios are rebalanced monthly. The table also reports portfolio regression alphas from regressions of portfolio returns using the Fama-French three-factor model as well as its extended four-, five- and six-factor models considering the momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table), and Kelly's (2011) tail risk factor ("K-Tail" in the table) as additional controls. In addition, the table shows regression alphas from regressions of portfolio returns using Acharya and Pedersen's (2005) liquidity-adjusted CAPM ("AP-CAPM" in the table) as well as extended model controlling size, value and momentum factors. The four right-most columns report results for two high-minus-low zero net investment portfolios, one that longs quintile 5 and short quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' average returns and factor model alphas.

Table 2.4
Fama-Macbeth Regression Estimates Using Individual Security Data: 1973-2011

Panel A: Models with Extreme Liquidity Risk Betas

Model	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI
Beta_Extreme Liquidity Risk	0.66 **	0.57 **	0.51 **	0.47 **	0.59 **	0.63 **	0.30 **	0.45 **	0.47 **	0.24 **	0.42 **	0.49 **	0.42 **	0.23 **	0.23 **	0.23 **
	(2.61)	*(2.39)*	*(2.17)*	*(2.78)*	*(2.23)*	*(2.42)*	*(2.15)*	*(2.22)*	*(2.41)*	*(2.15)*	*(2.48)*	*(2.62)*	*(2.55)*	*(2.22)*	*(2.28)*	*(2.25)*
SIZE	-0.16 *						-0.30 **	-0.10	-0.14	-0.26 **	-0.14	0.14	-0.15	-0.24 **	-0.08	-0.15
	(-1.93)						*(-4.44)*	*(-1.30)*	*(-1.64)*	*(-4.02)*	*(-1.63)*	*(0.79)*	*(-1.14)*	*(-3.74)*	*(-0.68)*	*(-1.26)*
B/M		0.62 **					0.29 **	0.48 **	0.47 **	0.30 **	0.41 **	0.50 **	0.43 **	0.30 **	0.32 **	0.32 **
		(3.81)					*(2.19)*	*(3.04)*	*(2.88)*	*(2.28)*	*(2.90)*	*(3.29)*	*(3.09)*	*(2.44)*	*(2.57)*	*(2.62)*
Mom			0.78 **				0.71 **	0.66 **	0.66 **	0.70 **	0.67 **	0.64 **	0.70 **	0.70 **	0.70 **	0.72 **
			(4.01)				*(4.25)*	*(3.56)*	*(3.57)*	*(4.31)*	*(3.64)*	*(3.41)*	*(3.85)*	*(4.29)*	*(4.33)*	*(4.48)*
Volatility				-0.14			-0.26 **			-0.27 **				-0.23 **	-0.27 **	-0.25 **
				(1.37)			(-2.90)			(-3.08)				(-2.89)	(-3.18)	(-2.99)
Beta_ K-Tail Risk					0.44 **			0.28 **		0.36 **				0.35 **	0.34 **	0.33 **
					(2.61)			*(2.25)*		*(3.42)*				*(3.38)*	*(3.27)*	*(3.18)*
Beta_PS-Liquidity Risk						0.32 **			0.23	0.12				0.10	0.13	0.12
						(2.20)			*(1.61)*	*(0.89)*				*(0.74)*	*(0.94)*	*(0.90)*
Turnover _NYSE/AMEX											-0.35 **		-0.26 *	-0.22 **		-0.08
											(-2.83)		*(-1.71)*	*(-2.37)*		*(-0.75)*
Turnover _NASDAQ											-1.07		-0.20 **	-0.97		-1.15
											(-1.50)		*(-2.73)*	*(-1.36)*		*(-1.62)*
Amihud_ NYSE/AMEX												0.24 **	0.01		0.16 *	0.10
												(2.31)	*(0.09)*		*(1.82)*	*(1.06)*
Amihud _ NASDAQ												0.42	0.26		0.38	-0.07
												(0.73)	*(0.45)*		*(0.68)*	*(-0.88)*
Intercept	1.09 **	0.79 **	0.58 **	1.02 **	0.71 **	0.75 **	1.86 **	0.84 **	0.94 **	1.77 **	1.08 **	0.54	1.08 **	1.72 **	1.52 **	1.59 **
	(2.72)	*(2.93)*	*(2.25)*	*(5.23)*	*(2.76)*	*(2.78)*	*(6.77)*	*(2.29)*	*(2.43)*	*(6.62)*	*(2.96)*	*(1.05)*	*(2.78)*	*(6.50)*	*(5.13)*	*(5.68)*
Months	468															
Observations	1,003,683															

Table 2.4, continued

Panel B: Models without Extreme Liquidity Risk Betas

Model	I'	II'	III'	IV'	V'	VI'	VII'	VIII'	IX'	X'	XI'	XII'	XIII'	XIV'	XV'	XVI'
SIZE	-0.15 *						-0.30 **	-0.08	-0.12	-0.26 **	-0.12	0.18	-0.12	-0.23 **	-0.07	-0.13
	(-1.76)						*(-4.38)*	*(-0.95)*	*(-1.36)*	*(-3.93)*	*(-1.39)*	*(1.01)*	*(-0.91)*	*(-3.65)*	*(-0.58)*	*(-1.10)*
B/M		0.67 **					0.30 **	0.53 **	0.52 **	0.30 **	0.44 **	0.54 **	0.46 **	0.30 **	0.33 **	0.33 **
		(3.84)					*(2.23)*	*(3.11)*	*(2.98)*	*(2.29)*	*(2.99)*	*(3.40)*	*(3.20)*	*(2.45)*	*(2.58)*	*(2.63)*
Mom			0.79 **				0.71 **	0.67 **	0.67 **	0.70 **	0.67 **	0.64 **	0.70 **	0.70 **	0.70 **	0.71 **
			(3.95)				*(4.21)*	*(3.51)*	*(3.45)*	*(4.26)*	*(3.61)*	*(3.38)*	*(3.82)*	*(4.24)*	*(4.28)*	*(4.42)*
Volatility				-0.17			-0.28 **			-0.28 **				-0.24 **	-0.28 **	-0.26 **
				(-1.61)			(-2.97)			(-3.09)				(-2.91)	(-3.19)	(-3.02)
Beta_ K-Tail Risk					0.53 **			0.34 **		0.38 **				0.37 **	0.37 **	0.35 **
					(2.97)			*(2.67)*		*(3.55)*				*(3.53)*	*(3.43)*	*(3.34)*
Beta_PS-Liquidity Risk						0.44 **			0.30 **	0.17				0.14	0.17	0.16
						(2.83)			*(2.06)*	*(1.17)*				*(1.01)*	*(1.21)*	*(1.17)*
Turnover _NYSE/AMEX											-0.36 **		-0.25 *	-0.22 **		-0.07
											(-2.91)		*(-1.66)*	*(-2.35)*		*(-0.61)*
Turnover _NASDAQ											-1.05		-0.20 **	-0.94		-1.12
											(-1.47)		*(-2.73)*	*(-1.32)*		*(-1.58)*
Amihud_ NYSE/AMEX												0.26 **	0.02		0.17 *	0.11
												(2.42)	*(0.20)*		*(1.86)*	*(1.17)*
Amihud _ NASDAQ												0.44	0.26		0.38	-0.07
												(0.77)	*(0.45)*		*(0.68)*	*(-0.88)*
Intercept	1.03 **	0.79 **	0.55 **	1.08 **	0.67 **	0.72 **	1.88 **	0.76 **	0.89 **	1.77 **	1.04 **	0.45	1.01 **	1.72 **	1.51 **	1.57 **
	(2.51)	*(2.86)*	*(2.13)*	*(5.31)*	*(2.54)*	*(2.65)*	*(6.66)*	*(1.99)*	*(2.22)*	*(6.51)*	*(2.78)*	*(0.85)*	*(2.56)*	*(6.40)*	*(5.08)*	*(5.58)*
Months	468															
Observations	1,003,683															

Table 2.4, continued

This table summarizes Fama-MacBeth (1973) monthly cross-section regressions. Coefficient estimates are time-series averages of cross-sectional OLS regressions. And the *t*-statistics (in parenthesis) are computed for the Fama-MacBeth (1973) regressions using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation. In the Newey-West procedure, I use a lag of three. In all regressions, the dependent variable is the monthly individual stock return in excess of the risk-free rate. Eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Then, at each year end between 1972 and 2010, I estimate extreme liquidity risk sensitivities of individual stocks with respect to extreme liquidity risk (*ELR*) by the form

$$E_t\,[r_{i,t+1}] = \mu_i + \beta_i ELR_t$$

Stocks are then sorted into decile value-weighted portfolios based on their preceding extreme liquidity risk loadings. Beta is estimated for each of the ten portfolios over the sample period (post-ranking loading). The post-ranking beta of portfolio *p* is assigned to an individual stock *i*, which belongs to portfolio *p* in the given year. Betas for the Pástor and Stambaugh (2003) aggregate liquidity risk ("Beta PS-Liqidity Risk" in the table) and those for Kelly's (2011) tail risk ("Beta K-Tail Risk" in the table) are constructed in a similar way. The independent variables also include: SIZE represents logarithm of the market capitalization of firms as defined in Fama and French (1992); B/M is the logarithm of the ratio of book value of equity plus deferred taxes to market capitalization as defined in Fama and French (1992); Mom is the stock return from month -12 to month -2; Volatility is the monthly standard deviation that is estimated from daily returns from month -12 to month -1; Turnover_NYSE/AMEX is the average monthly turnover from month -12 to month -1 at each year end if stocks trade on NYSE/AMEX, and zero otherwise; Turnover_NASDAQ is the average monthly turnover from month -12 to month -1 at each year end if stocks trade on NASDAQ, and zero otherwise. Amihud_NYSE/AMEX is the liquidity measure in Amihud (2002) based upon the prior calendar year's data at each year end if stocks trade on NYSE/AMEX, and zero otherwise; Amihud_NASDAQ is the liquidity measure in Amihud (2002) based upon the prior calendar year's data at each year end if stocks trade on NASDAQ, and zero otherwise. * and ** denote significance at the 10% and 5% levels, respectively.

Table 2.5

Liquidity-related Net Beta-Sorted Portfolio Returns: 1973-2011

Extreme Liquidity Loading	Low				High				
	1	2	3	4	5	**5–1**	*t-stat.*	**10–1**	*t-stat.*
Panel A: Properties									
Value-weighted									
Preceding loadings	-3.65	-0.13	0.11	0.37	2.72	**6.37**	*4.61*	**12.51**	*4.15*
Post-ranking loadings	-0.43	-0.08	-0.01	0.03	0.26	**0.70**	*2.66*	**0.63**	*2.00*
Market cap	20.74	35.51	34.12	30.18	17.67	**-3.07**	*-1.56*	**-4.91**	*-7.35*
(Il)liquidity	0.11	0.02	0.06	0.05	0.35	**0.24**	*11.20*	**0.57**	*12.19*
MKT beta	1.14	1.05	0.95	0.93	0.93	**-0.21**	*-4.32*	**-0.32**	*-5.40*
SMB beta	0.29	-0.12	-0.12	-0.07	0.24	**-0.05**	*-0.79*	**-0.04**	*-0.49*
HML beta	-0.13	0.08	0.19	0.08	-0.04	**0.10**	*1.40*	**0.16**	*1.88*
MOM beta	-0.17	-0.04	0.06	0.06	0.03	**0.20**	*4.24*	**0.16**	*2.75*
PS-Liquidity beta	0.05	-0.02	-0.03	-0.05	-0.03	**-0.08**	*-1.46*	**0.07**	*1.10*
K-Tail beta	-0.10	-0.01	0.12	0.11	0.18	**0.28**	*5.36*	**0.36**	*5.56*
Equal-weighted									
Preceding loadings	-4.31	-0.12	0.11	0.37	4.51	**8.82**	*7.00*	**16.29**	*6.57*
Post-ranking loadings	-0.30	-0.09	0.04	0.08	0.04	**0.00**	*2.66*	**0.00**	*1.94*
Market cap	1.00	2.80	3.06	2.55	0.76	**-0.24**	*-3.71*	**-0.27**	*-18.07*
(Il)liquidity	2.28	0.37	0.44	0.52	2.63	**0.35**	*2.92*	**0.35**	*1.52*
MKT beta	0.97	0.98	0.92	0.88	0.82	**-0.15**	*-6.40*	**-0.15**	*-5.91*
SMB beta	0.75	0.47	0.37	0.48	0.64	**-0.10**	*-3.10*	**-0.16**	*-4.63*
HML beta	0.13	0.32	0.38	0.34	0.26	**0.13**	*3.82*	**0.16**	*4.56*
MOM beta	-0.15	-0.10	-0.02	-0.03	-0.01	**0.14**	*6.05*	**0.13**	*5.48*
PS-Liquidity beta	0.00	0.00	0.00	-0.01	-0.02	**-0.03**	*-1.07*	**-0.02**	*-0.88*
K-Tail beta	0.01	-0.01	0.09	0.10	0.11	**0.10**	*3.84*	**0.06**	*2.18*
Panel B: Returns									
Value-weighted									
Mean	0.68	0.87	1.11	1.12	1.47	**0.79**	*3.84*	**0.58**	*2.31*
Alpha: FF	-0.36	-0.08	0.15	0.20	0.48	**0.84**	*4.02*	**0.63**	*2.49*
Alpha: FF + Mom	-0.24	-0.06	0.12	0.17	0.50	**0.74**	*3.48*	**0.58**	*2.27*
Alpha: FF + Mom + PS-Liquidity	-0.26	-0.05	0.14	0.19	0.52	**0.78**	*3.68*	**0.55**	*2.11*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.24	-0.04	0.11	0.16	0.47	**0.71**	*3.41*	**0.45**	*1.80*
Alpha: AP-CAPM	-0.35	-0.06	0.22	0.22	0.49	**0.84**	4.11	**0.65**	2.62
Alpha: AP-CAPM + FF + Mom	-0.24	-0.05	0.13	0.17	0.48	**0.71**	3.38	**0.54**	2.08
Equal-weighted									
Mean	0.98	1.11	1.32	1.35	1.35	**0.37**	*3.44*	**0.30**	*2.61*
Alpha: FF	-0.23	-0.09	0.15	0.18	0.19	**0.43**	*4.19*	**0.37**	*3.48*
Alpha: FF + Mom	-0.10	0.00	0.19	0.23	0.23	**0.33**	*3.25*	**0.27**	*2.53*
Alpha: FF + Mom + PS-Liquidity	-0.10	0.00	0.20	0.24	0.25	**0.35**	*3.39*	**0.28**	*2.64*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.10	0.00	0.17	0.21	0.22	**0.32**	*3.17*	**0.27**	*2.50*
Alpha: AP-CAPM	-0.14	0.14	0.39	0.41	0.28	**0.42**	4.15	**0.36**	3.32
Alpha: AP-CAPM + FF + Mom	-0.24	-0.03	0.17	0.19	0.05	**0.30**	2.92	**0.23**	2.13

Table 2.5, continued

The table shows the statistics for the liquidity-related net beta-sorted portfolios. At each year end between 1972 and 2010, I estimate the three liquidity betas in Acharya and Pedersen's (2005) liquididity-adjusted CAPM using extreme liquidity risk. Here the regressions use only data available at that time. And eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Stocks are then sorted into quintile portfolios and decile portfolios based on their estimated liquidity-related net betas.The post-formation returns on these portfolios during the next 12 months are linked across years to form a single return series for each quintile portfolio and decile portfolio covering the period from July 1973 to December 2011. Panel A reports the preceding liquidity-related net loadings ("preceding loadings" in the table) and post-ranking liquidity-related net loadings ("post-ranking loadings" in the table) of the quintile portfolios and spread portfolios. The post-ranking liquidity-related net loadings are estimated by regressing the portfolio excess returns on the extreme liquidity risk estimate and the market excess return factor over the sample period. In addition, Panel A reports the time-series averages of the quintile portfolios' market capitalization and (il)liquidity, obtained as the average of the corresponding measures across the stocks within each quintile. Market capitalization is reported in billions of dollars. A stock's liquidity in any given month is the Amihud (2002) illiquidity measure. Also reported are post-ranking betas with respect to the three Fama-French factors, the momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table) and Kelly's (2011) tail risk factor ("K-Tail" in the table). The four right-most columns report results for two high-minus-low zero net investment portfolio, one that longs quintile 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' corresponding measures. Panel B shows the monthly mean returns for the liquidity-related net beta-sorted portfolios that are rebalanced annually. The panel also reports portfolio alphas from regressions of portfolio returns using the Fama-French three-factor model as well as its extended four-, five- and six-factor models considering the momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table), and Kelly's (2011) tail risk factor ("K-Tail" in the table) as additional controls. In addition, the table shows portfolio alphas from regressions of portfolio returns using Acharya and Pedersen's (2005) liquidity-adjusted CAPM ("AP-CAPM" in the table) as well as its extended model controlling the size, value and momentum factors. The four right-most columns report results for two high-minus-low zero net investment portfolios, one that longs quintile 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' average returns and factor model alphas.

Table 2.6

Extreme Liquidity Loading-sorted Portfolio Returns: Normal Times and Times of Crisis

	CASE I					CASE II					CASE III				
	Expansion Period (32 Years)		Contraction Period (6.5 Years)		**Diff. in**	Period w/o Market Downturn (29.5 Years)		Sudden Market Downturn (9 Years)		**Diff. in**	Period w/o Liquidity Dry-ups (35.5 Years)		Liquidity Dry-ups (3 Years)		**Diff. in**
	5–1	*t-stat.*	5–1	*t-stat.*	**5–1**	5–1	*t-stat.*	5–1	*t-stat.*	**5–1**	5–1	*t-stat.*	5–1	*t-stat.*	**5–1**
Panel A: Value-weighted															
Mean	0.54	*2.63*	0.60	*0.94*	**0.07**	0.49	*2.08*	0.75	*1.95*	**0.26**	0.51	*2.61*	0.97	*0.85*	**0.46**
Alpha: FF	0.68	*3.25*	0.64	*1.10*	**-0.04**	0.87	*3.64*	-1.59	*-2.75*	**-2.46**	0.89	*4.43*	-0.25	*-0.20*	**-1.13**
Alpha: FF + Mom	0.62	*2.95*	0.54	*0.97*	**-0.09**	0.74	*3.07*	-1.64	*-2.98*	**-2.38**	0.70	*3.42*	-0.26	*-0.21*	**-0.96**
Alpha: FF + Mom + PS-Liquidity	0.65	*3.03*	0.63	*1.13*	**-0.02**	0.80	*3.32*	-1.66	*-3.01*	**-2.46**	0.71	*3.46*	-0.25	*-0.20*	**-0.96**
Alpha: FF + Mom + PS-Liquidity + K-Tail	0.61	*2.91*	0.37	*0.68*	**-0.24**	0.73	*3.07*	-1.62	*-2.99*	**-2.36**	0.66	*3.27*	-0.02	*-0.01*	**-0.68**
Alpha: AP-CAPM	0.69	3.38	0.34	0.55	**-0.35**	0.85	3.57	-1.51	-2.65	**-2.36**	0.73	3.72	-0.72	-0.56	**-1.45**
Alpha: AP-CAPM + FF + Mom	0.62	2.95	0.54	0.97	**-0.08**	0.74	3.07	-1.64	-2.97	**-2.38**	0.70	3.41	-0.26	-0.21	**-0.96**
Panel B: Equal-weighted															
Mean	0.44	*2.88*	0.55	*1.31*	**0.11**	0.38	*2.24*	0.74	*2.54*	**0.36**	0.41	*2.88*	1.13	*1.29*	**0.72**
Alpha: FF	0.54	*3.65*	0.57	*1.50*	**0.03**	0.67	*4.13*	-0.80	*-1.84*	**-1.47**	0.70	*5.08*	0.43	*0.52*	**-0.27**
Alpha: FF + Mom	0.47	*3.14*	0.49	*1.38*	**0.02**	0.56	*3.44*	-0.83	*-2.01*	**-1.39**	0.55	*3.91*	0.43	*0.51*	**-0.12**
Alpha: FF + Mom + PS-Liquidity	0.49	*3.27*	0.54	*1.53*	**0.05**	0.61	*3.73*	-0.86	*-2.10*	**-1.47**	0.56	*4.00*	0.42	*0.49*	**-0.14**
Alpha: FF + Mom + PS-Liquidity + K-Tail	0.47	*3.15*	0.43	*1.18*	**-0.04**	0.56	*3.48*	-0.84	*-2.06*	**-1.40**	0.53	*3.82*	0.55	*0.68*	**0.02**
Alpha: AP-CAPM	0.61	4.05	0.39	0.98	**-0.22**	0.70	4.16	-0.62	-1.40	**-1.32**	0.61	4.41	0.01	0.01	**-0.60**
Alpha: AP-CAPM + FF + Mom	0.50	3.33	0.50	1.42	**0.00**	0.58	3.58	-0.79	-1.91	**-1.37**	0.57	4.10	0.43	0.52	**-0.14**

Table 2.6, continued

The table shows the statistics for extreme liquidity beta-sorted portfolios during normal times and times of crisis. At each year end between 1972 and 2010, I estimate extreme liquidity risk sensitivities of individual stocks with respect to extreme liquidity risk by the form

$$E_t\,[r_{i,t+1}] = \mu_i + \beta_i ELR_t$$

Here the regression uses only data available at that time. And eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Stocks are then sorted into quintile portfolios and decile portfolios based on their extreme liquidity risk loadings. Panel A reports monthly value-weighted portfolio returns and Panel B reports monthly equally weighted portfolio returns. The panels also reports portfolio alphas from regressions of portfolio returns using the Fama-French three-factor (FF) model as well as its extended four-, five- and six-factor models considering the momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table), and Kelly's (2011) tail risk factor ("K-Tail" in the table) as additional controls. In addition, the table shows portfolio alphas from regressions of portfolio returns using Acharya and Pedersen (2005)'s liquidity-adjusted CAPM ("AP-CAPM" in the table) as well as its extended model controlling the size, value and momentum factors. The left-most five columns of the table report the results for quintile extreme liquidity beta-sorted portfolios during the NBER recession periods and during the NBER expansion periods, respectively, which is denoted as CASE I. The statistics include the average returns of the "5–1" spread portfolio that longs quintile 5 and shorts quintile 1, as well as the *t*-statistic for the hedge portfolios' average returns. The factor model alphas and their *t*-statistics are also reported. The last column for CASE I reports results for differences between the two "5–1" spread portfolios, including the differences in mean returns and regression alphas. Similarly, CASE II, which is shown in the next five columns in the table, reports the results for quintile extreme liquidity beta-sorted portfolios during periods without market downturns and those with sudden market downturns. Here sudden market downturn refers to the case when the market return suddenly turns to be negative. Case III, which is reported in the right-most five column in the tables, shows the results for quintile extreme liquidity beta-sorted portfolios during periods without liquidity dry-ups and those with liquidity dry-ups. Here liquidity dry-ups includes months when the average liquidity is at least two standard deviations below its means measured by Pástor and Stambaugh (2003) liquidity innovations or the average illiquidity is at least two standard deviations above its means evaluated by Acharya and Pedersen (2005).

Table 2.7

Extreme Liquidity Loading-sorted Portfolio Returns: NYSE&AMEX only and NASDAQ only

	NYSE &AMEX Only				NASDAQ Only			
Extreme Liquidity Loading	5–1	*t-stat.*	10–1	*t-stat.*	5–1	*t-stat.*	10–1	*t-stat.*
Panel A: Annual Rebalance								
Value-weighted								
Mean	0.52	*2.81*	0.58	*2.50*	0.71	*3.15*	1.07	*3.66*
Alpha: FF	0.50	*2.65*	0.53	*2.26*	0.78	*3.42*	1.17	*3.97*
Alpha: FF + Mom	0.41	*2.17*	0.46	*1.92*	0.72	*3.13*	1.17	*3.88*
Alpha: FF + Mom + PS-Liquidity	0.43	*2.25*	0.47	*1.92*	0.72	*3.1*	1.19	*3.91*
Alpha: FF + Mom + PS-Liquidity + K-Tail	0.47	*2.43*	0.52	*2.15*	0.60	*2.69*	1.09	*3.62*
Alpha: AP-CAPM	0.67	*3.65*	0.75	*3.28*	0.83	*3.65*	1.19	*4.08*
Alpha: AP-CAPM + FF + Mom	0.59	*3.18*	0.7	*2.96*	0.71	*3.04*	1.16	*3.84*
Equal-weighted								
Mean	0.46	*3.59*	0.52	*3.17*	0.58	*3.23*	0.78	*3.52*
Alpha: FF	0.56	*4.42*	0.63	*3.87*	0.61	*3.62*	0.77	*3.65*
Alpha: FF + Mom	0.47	*3.73*	0.51	*3.13*	0.48	*2.83*	0.65	*3.04*
Alpha: FF + Mom + PS-Liquidity	0.47	*3.63*	0.50	*3.06*	0.52	*3.02*	0.69	*3.19*
Alpha: FF + Mom + PS-Liquidity + K-Tail	0.42	*3.35*	0.45	*2.78*	0.46	*2.72*	0.62	*2.91*
Alpha: AP-CAPM	0.54	*4.35*	0.62	*3.89*	0.76	*4.30*	0.96	*4.38*
Alpha: AP-CAPM + FF + Mom	0.49	*3.85*	0.52	*3.21*	0.48	*2.81*	0.65	*3.04*
Panel B: Monthly Rebalance								
Value-weighted								
Mean	0.45	*2.15*	0.38	*1.49*	0.52	*1.98*	0.83	*2.39*
Alpha: FF	0.64	*3.15*	0.61	*2.47*	0.58	*2.23*	0.93	*2.69*
Alpha: FF + Mom	0.58	*2.81*	0.57	*2.26*	0.60	*2.25*	1.07	*3.04*
Alpha: FF + Mom + PS-Liquidity	0.59	*2.82*	0.57	*2.26*	0.60	*2.23*	1.08	*3.04*
Alpha: FF + Mom + PS-Liquidity + K-Tail	0.51	*2.47*	0.45	*1.84*	0.44	*1.75*	0.89	*2.62*
Alpha: AP-CAPM	0.61	*3.01*	0.54	*2.21*	0.67	*2.55*	0.98	*2.80*
Alpha: AP-CAPM + FF + Mom	0.58	*2.79*	0.56	*2.25*	0.56	*2.08*	1.02	*2.89*
Equal-weighted								
Mean	0.44	*2.91*	0.53	*2.75*	0.45	*2.01*	0.66	*2.45*
Alpha: FF	0.57	*3.93*	0.68	*3.64*	0.46	*2.30*	0.64	*2.61*
Alpha: FF + Mom	0.51	*3.45*	0.61	*3.21*	0.45	*2.17*	0.64	*2.58*
Alpha: FF + Mom + PS-Liquidity	0.50	*3.35*	0.60	*3.12*	0.48	*2.31*	0.67	*2.66*
Alpha: FF + Mom + PS-Liquidity + K-Tail	0.44	*3.01*	0.51	*2.76*	0.38	*1.91*	0.55	*2.26*
Alpha: AP-CAPM	0.54	*3.74*	0.65	*3.48*	0.65	*2.95*	0.87	*3.28*
Alpha: AP-CAPM + FF + Mom	0.52	*3.52*	0.62	*3.27*	0.42	*2.05*	0.62	*2.50*

Table 2.7, continued

The table shows the statistics for two groups of the extreme liquidity beta-sorted portfolios, in which one is based on NYSE&AMEX stocks only and the other is based on NASDAQ stocks only. At each year end between 1972 and 2010, I estimate extreme liquidity risk sensitivities of individual stocks with respect to extreme liquidity risk by the form

$$E_t\,[r_{i,t+1}\,] = \mu_i + \beta_i\,ELR_t$$

Here the regression uses only data available at that time. And eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Stocks are then sorted into quintile portfolios and decile portfolios based on their extreme liquidity risk loadings. Panel A reports monthly portfolio returns when portfolios are rebalanced annually and Panel B reports monthly returns when portfolios are rebalanced monthly. The table also reports portfolio alphas from regressions of portfolio returns using the Fama-French three-factor model as well as its extended four-, five- and six-factor models considering the momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table), and Kelly's (2011) tail risk factor ("K-Tail" in the table) as additional controls. In addition, the table shows portfolio alphas from regressions of portfolio returns using Acharya and Pedersen's (2005) liquidity-adjusted CAPM ("AP-CAPM" in the table) as well as its extended model controlling the size, value and momentum factors. The first four columns report results on the group of NYSE&AMEX stocks for two high-minus-low zero net investment portfolios, one that longs quintile 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' average returns and factor model alphas. The next four columns report results on the group of NASDAQ stocks for two high-minus-low zero net investment portfolios, one that longs quintile 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' average returns and factor model alphas.

Table 2.8

Properties and Returns of Extreme Liquidity Loading-sorted Portfolios Based on Roll Impact: 1973-2011

Extreme Liquidity Loading	Low				High				
	1	2	3	4	5	**5–1**	*t-stat.*	**10–1**	*t-stat.*
Panel A: Properties									
Value-weighted									
Market cap	26.82	39.92	36.07	29.64	20.42	**-6.40**	*-3.53*	**-7.53**	*-4.08*
(Il)liquidity	0.05	0.04	0.04	0.06	0.13	**0.08**	*5.67*	**0.13**	*4.94*
MKT beta	0.98	0.97	0.96	1.03	1.05	**0.07**	*1.63*	**0.09**	*1.80*
SMB beta	-0.02	-0.12	-0.13	-0.02	0.27	**0.29**	*5.09*	**0.33**	*4.77*
HML beta	0.10	0.14	0.06	-0.01	-0.16	**-0.26**	*-4.18*	**-0.03**	*-0.42*
MOM beta	0.02	-0.03	-0.01	-0.04	0.03	**0.01**	*0.33*	**0.12**	*2.48*
PS-Liquidity beta	-0.04	-0.06	0.04	0.01	0.07	**0.11**	*2.38*	**0.08**	*1.36*
K-Tail beta	0.11	0.03	-0.03	-0.03	0.08	**-0.03**	*-0.63*	**0.00**	*0.09*
Equal-weighted									
Market cap	1.57	2.72	2.44	2.11	1.34	**-0.23**	*-2.78*	**-0.07**	*-1.54*
(Il)liquidity	1.05	1.22	1.37	1.24	1.35	**0.30**	*4.72*	**0.37**	*4.39*
MKT beta	0.96	0.89	0.87	0.89	0.97	**0.01**	*0.36*	**0.02**	*0.57*
SMB beta	0.64	0.45	0.44	0.51	0.74	**0.10**	*2.70*	**0.11**	*2.40*
HML beta	0.15	0.34	0.35	0.36	0.26	**0.10**	*2.61*	**0.20**	*4.20*
MOM beta	-0.11	-0.08	-0.07	-0.05	-0.03	**0.08**	*3.04*	**0.10**	*3.30*
PS-Liquidity beta	-0.04	-0.03	-0.01	0.00	0.01	**0.05**	*1.59*	**0.06**	*1.56*
K-Tail beta	0.05	0.03	0.01	0.03	0.08	**0.02**	*0.88*	**0.06**	*1.96*
Panel B: Returns									
Value-weighted									
Mean	0.97	0.88	0.90	0.99	1.22	**0.25**	*1.36*	**0.64**	*2.92*
Alpha: FF	0.00	-0.06	0.01	0.06	0.24	**0.24**	*1.36*	**0.53**	*2.47*
Alpha: FF + Mom	0.01	-0.03	0.02	0.08	0.23	**0.22**	*1.24*	**0.43**	*1.96*
Alpha: FF + Mom + PS-Liquidity	0.03	0.01	-0.01	0.08	0.19	**0.16**	*0.90*	**0.38**	*1.74*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.02	-0.01	0.01	0.09	0.15	**0.17**	*0.96*	**0.38**	*1.73*
Alpha: AP-CAPM	0.05	0.00	0.03	0.07	0.22	**0.17**	*0.95*	**0.56**	*2.59*
Alpha: AP-CAPM + FF + Mom	0.02	-0.01	0.03	0.10	0.24	**0.22**	*1.23*	**0.42**	*1.94*
Equal-weighted									
Mean	1.00	1.18	1.26	1.30	1.36	**0.36**	*3.23*	**0.45**	*3.31*
Alpha: FF	-0.19	0.03	0.12	0.13	0.11	**0.30**	*2.65*	**0.34**	*2.51*
Alpha: FF + Mom	-0.08	0.10	0.18	0.18	0.16	**0.24**	*2.07*	**0.27**	*1.94*
Alpha: FF + Mom + PS-Liquidity	-0.06	0.12	0.19	0.18	0.16	**0.21**	*1.82*	**0.24**	*1.69*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.08	0.11	0.18	0.17	0.12	**0.20**	*1.73*	**0.21**	*1.50*
Alpha: AP-CAPM	0.00	0.26	0.35	0.38	0.35	**0.35**	*3.08*	**0.43**	*3.13*
Alpha: AP-CAPM + FF + Mom	-0.10	0.07	0.15	0.15	0.13	**0.23**	*1.98*	**0.26**	*1.84*

Table 2.8, continued

The table shows the properties and returns for the extreme liquidity beta-sorted portfolios, in which the measure of extreme liquidity index is based on alternative proxy of the price impact, Roll Impact (Goyenko, Holden and Trzcinka, 2009). At each year end between 1972 and 2010, I estimate extreme liquidity risk sensitivities of individual stocks with respect to extreme liquidity risk by the form

$$E_t\,[r_{i,t+1}] = \mu_i + \beta_i ELR_t$$

Here the regression uses only data available at that time. And eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Stocks are then sorted into quintile portfolios and decile portfolios based on their extreme liquidity risk loadings. The post-formation returns on these portfolios during the next 12 months are linked across years to form a single return series for each quintile portfolio and decile portfolio covering the period from July 1973 to December 2011. Panel A reports the time-series averages of the quintile portfolios' market capitalization and liquidity, obtained as the average of the corresponding measures across the stocks within each quintile. Market capitalization is reported in billions of dollars. A stock's liquidity in any given month is the Amihud (2002) illiquidity measure. Also reported are post-ranking betas with respect to the three Fama-French factors, a momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table) and Kelly's (2011) tail risk factor ("K-Tail" in the table). The four right-most columns report results for two high-minus-low zero net investment portfolio, one that longs quintile 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' corresponding measures. Panel B shows the monthly mean return for the extreme liquidity beta-sorted portfolios. The panel also reports portfolio alphas from regressions of portfolio returns using the Fama-French three-factor model as well as its extended four-, five- and six-factor models considering the momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table), and Kelly's (2011) tail risk factor ("K-Tail" in the table) as additional controls. In addition, the table shows portfolio alphas from regressions of portfolio returns using the Acharya and Pedersen (2005)'s liquidity-adjusted CAPM ("AP-CAPM" in the table) as well as its extended model controlling the size, value and momentum factors. The four right-most columns report results for two high-minus-low zero net investment portfolios, one that longs quintile 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' average returns and factor model alphas.

APPENDIX

Appendix I

Correlations of Extreme Liquidity Index with Other Related Variables: 1973 – 2011

		I	II	III	IV	V	VI	VII
Panel A: Liquidity Variables								
I	Extreme Liquidity	1						
II	PS-Liquidity Innovation	0.12	1					
III	AP-Illiquidity Innovation	-0.07	-0.23	1				
IV	HPW-Noise Measure	0.15	-0.17	0.05	1			
V	S-Transitory Factor	0.03	0.08	-0.17	-0.10	1		
VI	S-Permanent Factor	0.01	0.21	-0.28	-0.15	0.16	1	
VII	Commonality in Liquidity	0.48	-0.15	-0.06	0.48	-0.11	-0.19	1
Panel B: Demand-side Factors								
I	Extreme Liquidity	1						
II	Commonality in Turnover	0.40	1					
III	Sentiment Index	0.20	-0.03	1				
IV	ETFs Volume	0.63	0.60	-0.15	1			
V	Global Country Fund Discount	-0.43	-0.01	0.44	-0.11	1		
VI	U.S. Local Country Fund Discount	-0.20	-0.20	-0.12	-0.06	0.21	1	
Panel C: Supply-side Factors								
I	Extreme Liquidity	1						
II	Term Spread	0.41	1					
III	Default Spread	-0.22	0.11	1				
IV	Commercial Paper Spread	0.03	-0.39	0.06	1			
V	TED Spread	-0.01	-0.16	0.36	0.76	1		
VI	Margin Debt Outstanding	0.50	0.12	-0.17	0.35	-0.03	1	
VII	Local Bank Returns	-0.05	-0.04	-0.18	-0.11	-0.15	-0.18	1
Panel D: Other Macro Variables								
I	Extreme Liquidity	1						
II	Dividend-Price Ratio	-0.52	1					
III	Unemployment	-0.14	0.52	1				
IV	Inflation	-0.48	0.39	-0.02	1			
V	CFNAI	-0.17	-0.05	-0.10	0.05	1		
VI	Market Volatility	0.06	-0.17	-0.01	-0.21	-0.38	1	

Appendix I, continued

Panel A of this table reports correlations between extreme liquidity risk estimates and a variety of aggregate (il)liquidity measures. They are considered as follow; Pástor and Stambaugh (2003) monthly aggregate liquidity measure ("PS-Liquidity Innovation" in the table) captures a dimension of liquidity associated with the strength of volume-related return reversals. It is an average of individual-stock measures estimated with daily data and relies on the principle that order flow induces greater return reversals when liquidity is lower. Acharya and Pedersen (2005) monthly liquidity measure ("AP-Illiquidity Innovation" in the table) captures the innovation in equally-weighted illiquidity cost for the market portfolio. As suggested in Acharya and Pedersen (2005), I form market portfolio for each month based on NYSE/AMEX stocks with beginning-of-month price between $5 and $1,000, and with at least 15 days of return and volume data in that month. For each stock in the market portfolio, I estimate its Amihud (2002) illiquidity cost for each month and normalize it to make it stationary and to put it on a scale corresponding to the cost of a single trade. Then I run a regression using equation (22) in Acharya and Pedersen (2005), to predict market illiquidity, and the residual of the regression is interpreted as the market illiquidity innovation. Hu, Pan, and Wang (2012) propose a market-wide liquidity measure ("HPW-Noise Measure" in the table) by exploiting the connection between the amount of arbitrage capital in the market and observed price deviations in U.S. treasury bonds. Data is from Prof. Jun Pan's website. Sadka's (2006) liquidity factors are based on the transitory-fixed ("S-Transitory Factor" in the table) and permanent-variable components ("S-Permanent Factor" in the table) of price impact, as measured from intraday data. The data is from CRSP database. Karolyi, Lee, and van Dijk (2012) construct monthly measures of commonality in liquidity ("Commonality in Liquidity" in the table) and the data is from Journal of Financial Economics website. Panels B and C of the table consider a set of both supply-side and demand-side sources of the commonality in liquidity. Proxies of demand-side forces include the average commonality in turnover, a comprehensive measure of the degree of correlated trading, which is denoted as "Commonality in Turnover" in the table, the U.S. investor sentiment index of Baker and Wurgler (2006) ("Sentiment Index" in the table), ETF volume in Karolyi, Lee, and van Dijk (2012), which is defined as dollar trading volume in exchange traded country funds for 28 countries traded on U.S. markets, Global country fund discount in Karolyi, Lee, and van Dijk (2012) and U.S. local country fund discount in Karolyi, Lee, and van Dijk (2012). Proxies of supply-side forces include term spread (the difference between yields on long and short term government bonds), default spread (the difference in yields on BAA and AAA corporate bonds), commercial paper spread (difference between the percentage 90-Day AA nonfinancial commercial paper interest rate and the three-month T-bill rate), TED spread (difference between the three-month EuroDollar LIBOR rate on the three-month U.S. Treasuries rate, the data is from Bloomberg), the amount of NYSE margin debt outstanding ("Margin Debt Outstanding" in the table), local bank returns in Karolyi, Lee, and van Dijk (2012). Panel D of the table reports correlations between extreme liquidity risk estimates and other macroeconomic variables. Macroeconomic variables include the S&P 500 log dividend-price ratio, the unemployment rate, inflation rate, the Chicago Fed National Activity Index (CFNAI), and market volatility. Sample horizon depends on availability of each variable.

Appendix II

Double-Sorted Portfolio Returns on Size and Extreme Liquidity Loading: 1973-2011

Extreme Liquidity Loading		Low				High		
		1	2	3	4	5	**5–1**	*t-stat.*
Panel A: Value-Weighted								
Mean								
All		0.74	0.84	0.94	1.12	1.29	**0.55**	*2.73*
Small	1	1.18	1.27	1.34	1.38	1.55	**0.37**	*2.49*
	2	0.94	1.19	1.40	1.46	1.57	**0.62**	*3.53*
	3	0.82	1.06	1.30	1.42	1.44	**0.61**	*3.43*
	4	0.77	1.12	1.14	1.30	1.48	**0.72**	*3.63*
Big	5	0.70	0.76	0.88	1.06	1.16	**0.46**	*2.00*
Alpha: FF + Mom								
All		-0.19	-0.10	-0.01	0.19	0.37	**0.56**	*2.84*
Small	1	-0.12	-0.02	0.11	0.14	0.28	**0.41**	*2.81*
	2	-0.28	-0.04	0.19	0.22	0.30	**0.58**	*3.52*
	3	-0.35	-0.13	0.13	0.28	0.28	**0.62**	*3.52*
	4	-0.30	0.02	0.03	0.26	0.41	**0.71**	*3.71*
Big	5	-0.14	-0.13	-0.03	0.18	0.35	**0.50**	*2.16*
Alpha: FF + Mom + PS-Liquidity + K-Tail								
All		-0.20	-0.08	-0.03	0.18	0.36	**0.55**	*2.81*
Small	1	-0.14	-0.01	0.11	0.13	0.27	**0.41**	*2.87*
	2	-0.28	-0.05	0.19	0.22	0.29	**0.58**	*3.50*
	3	-0.34	-0.14	0.10	0.26	0.25	**0.58**	*3.32*
	4	-0.26	0.03	0.02	0.22	0.36	**0.63**	*3.38*
Big	5	-0.14	-0.10	-0.05	0.17	0.34	**0.49**	*2.10*
Alpha: AP-CAPM								
All		-0.29	-0.09	0.07	0.25	0.37	**0.66**	3.39
Small	1	0.05	0.24	0.34	0.40	0.52	**0.47**	3.28
	2	-0.14	0.23	0.48	0.55	0.58	**0.72**	4.24
	3	-0.24	0.11	0.40	0.52	0.46	**0.69**	3.94
	4	-0.30	0.18	0.24	0.39	0.52	**0.82**	4.23
Big	5	-0.30	-0.16	0.01	0.19	0.27	**0.57**	2.52

Appendix II, continue

Extreme Liquidity Loading		Low				High		
		1	2	3	4	5	**5–1**	*t-stat.*
Panel B: Equal-Weighted								
Mean								
All		0.97	1.13	1.24	1.33	1.43	**0.46**	*3.15*
Small	1	1.10	1.20	1.29	1.38	1.44	**0.34**	*2.53*
	2	0.91	1.22	1.40	1.43	1.49	**0.58**	*3.49*
	3	0.82	1.11	1.28	1.39	1.42	**0.59**	*3.29*
	4	0.82	1.12	1.14	1.24	1.46	**0.64**	*3.15*
Big	5	0.91	0.90	0.99	1.11	1.21	**0.30**	*1.41*
Alpha: FF + Mom								
All		-0.14	0.01	0.14	0.25	0.31	**0.45**	*3.31*
Small	1	-0.09	0.03	0.16	0.25	0.25	**0.34**	*2.74*
	2	-0.23	0.02	0.21	0.23	0.29	**0.52**	*3.33*
	3	-0.29	-0.04	0.14	0.29	0.32	**0.61**	*3.41*
	4	-0.18	0.05	0.08	0.22	0.42	**0.60**	*3.01*
Big	5	0.00	-0.01	0.02	0.20	0.35	**0.35**	*1.66*
Alpha: FF + Mom + PS-Liquidity + K-Tail								
All		-0.16	0.01	0.12	0.24	0.29	**0.45**	*3.28*
Small	1	-0.12	0.04	0.14	0.23	0.22	**0.35**	*2.75*
	2	-0.25	0.01	0.20	0.22	0.28	**0.53**	*3.36*
	3	-0.27	-0.05	0.12	0.27	0.29	**0.57**	*3.20*
	4	-0.14	0.04	0.07	0.19	0.37	**0.52**	*2.68*
Big	5	0.00	0.01	-0.01	0.18	0.33	**0.33**	*1.58*
Alpha: AP-CAPM								
All		-0.15	0.13	0.29	0.39	0.42	**0.58**	*4.12*
Small	1	-0.07	0.13	0.25	0.35	0.38	**0.45**	3.50
	2	-0.17	0.26	0.48	0.53	0.52	**0.68**	4.22
	3	-0.25	0.17	0.38	0.49	0.44	**0.68**	3.86
	4	-0.24	0.19	0.25	0.33	0.49	**0.74**	3.70
Big	5	-0.14	-0.01	0.11	0.23	0.29	**0.43**	2.06

Appendix II, continued

This table reports average returns for double-sorted portfolios that are formed on the basis of extreme liquidity risk loading and size. At the end of each year, stocks are independently sorted by size and the preceding extreme liquidity loading. Portfolios are rebalanced annually. The size breakpoints come from Prof. Kenneth R. French data library. The breakpoints use all NYSE stocks with available market equity. Here eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Panel A reports value-weighted portfolio returns and Panel B reports equal-weighted returns. In each panel, it also reports alphas from regressions of portfolio returns using the Carhart (1997)'s four-factor model, the extended six-factor model controlling the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table) and Kelly's (2011) tail risk factor ("K-Tail" in the table), and Acharya and Pedersen's (2005) liquidity-adjusted CAPM ("AP-CAPM" in the table). The four right-most columns report results for two high-minus-low zero net investment portfolios, one that longs quintile 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' average returns and factor model alphas.

Appendix III

Triple-Sorted Portfolio Returns on Size, liquidity and Extreme Liquidity Loading, 1973-2011

Extreme Liquidity Loading		Low				High		
Size	Amihud Illiquidity	1	2	3	4	5	**5–1**	*t-stat.*
Panel A: Value-Weighted								
Mean								
Small	Low	0.11	0.41	0.39	0.53	0.81	**0.70**	*3.03*
Small	2	0.33	0.47	0.43	0.74	0.90	**0.57**	*2.24*
Small	3	0.22	0.44	0.56	0.67	0.87	**0.65**	*2.65*
Small	High	0.32	0.59	0.57	0.69	0.88	**0.56**	*2.12*
2	Low	0.44	0.56	0.52	0.93	0.92	**0.48**	*1.57*
2	2	0.34	0.32	0.52	0.75	0.61	**0.27**	*0.87*
2	3	0.53	0.51	0.47	0.50	0.55	**0.03**	*0.09*
2	High	0.27	0.36	0.45	1.07	1.05	**0.79**	*2.46*
3	Low	0.43	0.67	0.51	0.73	1.05	**0.63**	*1.80*
3	2	0.34	0.51	0.68	1.18	1.13	**0.79**	*2.46*
3	3	0.66	0.61	0.50	0.71	0.98	**0.32**	*0.96*
3	High	0.32	0.64	0.11	1.39	0.75	**0.43**	*1.42*
Large	Low	0.46	0.57	0.67	0.70	0.94	**0.48**	*1.44*
Large	2	0.62	0.33	0.72	0.76	1.17	**0.55**	*1.62*
Large	3	0.35	0.57	0.34	0.92	0.82	**0.46**	*1.49*
Large	High	0.25	0.69	0.51	0.85	1.20	**0.95**	*2.38*
AVERAGE		0.37	0.52	0.50	0.82	0.92	**0.54**	*2.63*
Alpha								
Small	Low	-0.57	-0.06	-0.15	0.01	0.35	**0.92**	*3.93*
Small	2	-0.23	0.01	-0.12	0.35	0.46	**0.70**	*2.74*
Small	3	-0.17	-0.05	0.04	0.18	0.40	**0.57**	*2.33*
Small	High	-0.23	0.08	0.04	0.24	0.42	**0.65**	*2.41*
2	Low	-0.20	0.14	0.01	0.51	0.47	**0.67**	*2.14*
2	2	-0.15	-0.20	0.03	0.21	0.20	**0.34**	*1.08*
2	3	-0.14	0.05	-0.01	0.00	0.06	**0.19**	*0.63*
2	High	-0.23	-0.08	-0.03	0.71	0.72	**0.94**	*2.91*
3	Low	0.02	0.08	-0.09	0.27	0.46	**0.44**	*1.27*
3	2	-0.12	-0.03	0.26	0.84	0.68	**0.79**	*2.43*
3	3	0.11	0.09	-0.05	0.24	0.53	**0.41**	*1.21*
3	High	-0.33	0.23	-0.33	0.90	0.24	**0.57**	*1.84*
Large	Low	-0.10	0.12	0.22	0.17	0.36	**0.46**	*1.37*
Large	2	0.02	-0.14	0.34	0.25	0.68	**0.66**	*1.89*
Large	3	-0.16	0.07	-0.04	0.50	0.40	**0.56**	*1.82*
Large	High	-0.14	0.30	-0.04	0.40	0.89	**1.02**	*2.50*
AVERAGE		-0.16	0.04	0.01	0.36	0.46	**0.62**	*3.09*

Appendix III, continued

Extreme Liquidity Loading		Low				High		
Size	Amihud Illiquidity	1	2	3	4	5	**5–1**	*t-stat.*
Panel B: Equal-Weighted								
Mean								
Small	Low	0.65	0.74	0.85	0.92	0.90	**0.25**	*1.53*
Small	2	0.52	0.74	0.66	0.85	0.92	**0.40**	*2.49*
Small	3	0.56	0.76	0.86	0.81	1.09	**0.52**	*3.15*
Small	High	0.74	0.67	0.73	0.92	0.99	**0.25**	*1.54*
2	Low	0.67	0.85	0.82	0.93	0.94	**0.27**	*1.25*
2	2	0.41	0.61	0.74	0.92	0.86	**0.45**	*2.56*
2	3	0.54	0.84	0.85	0.84	1.07	**0.52**	*2.77*
2	High	0.72	0.78	0.74	1.00	0.95	**0.23**	*1.15*
3	Low	0.66	0.88	0.76	0.90	1.02	**0.36**	*1.77*
3	2	0.59	0.63	0.69	0.93	1.07	**0.48**	*2.27*
3	3	0.45	0.76	0.85	1.04	0.89	**0.44**	*1.78*
3	High	0.57	0.87	0.72	0.97	0.96	**0.39**	*1.92*
Large	Low	0.57	0.93	0.81	0.87	1.03	**0.46**	*2.02*
Large	2	0.53	0.78	0.80	0.84	0.93	**0.40**	*1.77*
Large	3	0.58	0.65	0.69	0.95	0.90	**0.32**	*1.46*
Large	High	0.62	0.75	0.91	1.04	0.95	**0.33**	*1.47*
AVERAGE		0.59	0.77	0.78	0.92	0.97	**0.38**	*2.57*
Alpha								
Small	Low	-0.05	0.05	0.15	0.24	0.25	**0.30**	*1.91*
Small	2	-0.18	0.05	0.01	0.26	0.25	**0.42**	*2.60*
Small	3	-0.13	0.11	0.19	0.21	0.43	**0.56**	*3.43*
Small	High	0.01	0.01	0.08	0.27	0.30	**0.30**	*1.83*
2	Low	0.02	0.20	0.22	0.31	0.31	**0.30**	*1.38*
2	2	-0.23	-0.06	0.12	0.33	0.20	**0.42**	*2.34*
2	3	-0.17	0.22	0.29	0.19	0.40	**0.57**	*2.98*
2	High	0.09	0.14	0.12	0.43	0.31	**0.22**	*1.12*
3	Low	0.07	0.24	0.13	0.32	0.39	**0.32**	*1.52*
3	2	-0.04	0.01	0.08	0.34	0.51	**0.56**	*2.64*
3	3	-0.28	0.09	0.24	0.45	0.25	**0.53**	*2.16*
3	High	-0.08	0.25	0.14	0.37	0.29	**0.37**	*1.83*
Large	Low	-0.12	0.31	0.25	0.31	0.36	**0.47**	*2.10*
Large	2	-0.13	0.13	0.22	0.26	0.40	**0.53**	*2.33*
Large	3	0.00	0.04	0.09	0.34	0.21	**0.21**	*0.93*
Large	High	-0.03	0.11	0.29	0.44	0.30	**0.33**	*1.45*
AVERAGE		-0.08	0.12	0.16	0.32	0.32	**0.40**	*2.82*

Appendix III, continued

This table reports average returns for the 80 (4×4×5) triple-sorted portfolios. Sorts are performed sequentially, first sorting on size and then again, within each group, on the basis of the Amihud (2002) illiquidity cost. Finally each of sixteen sub-groups is subdivided into five portfolios according to their estimated extreme liquidity loadings. Portfolios are rebalanced annually. The size breakpoints come from Prof. Kenneth R. French data library. The breakpoints use all NYSE stocks with available market equity. Here eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Panel A reports value-weighted portfolio returns and Panel B reports equal-weighted returns. In each panel, it also reports portfolio alphas from regressions of portfolio returns using the extended six-factor model, which considers Kelly's (2011) tail risk factor as a sixth control beyond the Carhart (1997) four factors and the Pástor and Stambaugh (2003) traded liquidity factor. The two right-most columns report results for the high-minus-low zero net investment portfolio that longs quintile 5 and shorts quintile 1, as well as *t*-statistics for the hedge portfolios' average returns and factor model alphas.

Appendix IV

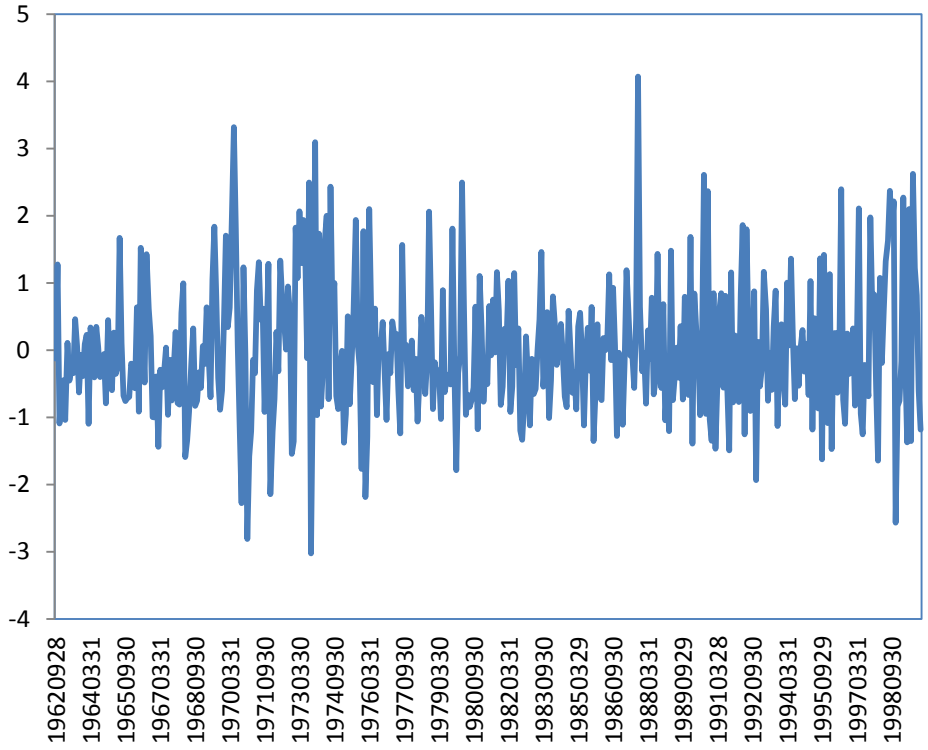
Correlation of Extreme Liquidity Traded Factor with Other Priced Factors: 1973-2011

	MKT	SMB	HML	MOM	PS-Liquidity	K-Tail	**Extreme Liquidity**
MKT	1	0.28	-0.32	-0.13	-0.03	0.42	**-0.26**
SMB		1	-0.23	0.01	-0.03	0.31	**-0.20**
HML			1	-0.16	0.05	-0.16	**0.10**
MOM				1	-0.03	-0.33	**0.19**
PS-Liquidity					1	-0.04	**-0.07**
K-Tail						1	**-0.03**
Extreme Liquidity							**1**

This table reports the monthly correlations between extreme liquidity traded factor and other priced factors, including the Fama and French three factors ("MKT", "SMB", "HML" in the table), the momentum factor ("MOM" in the table), the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table), and Kelly's (2011) tail risk factor ("K-Tail" in the table).

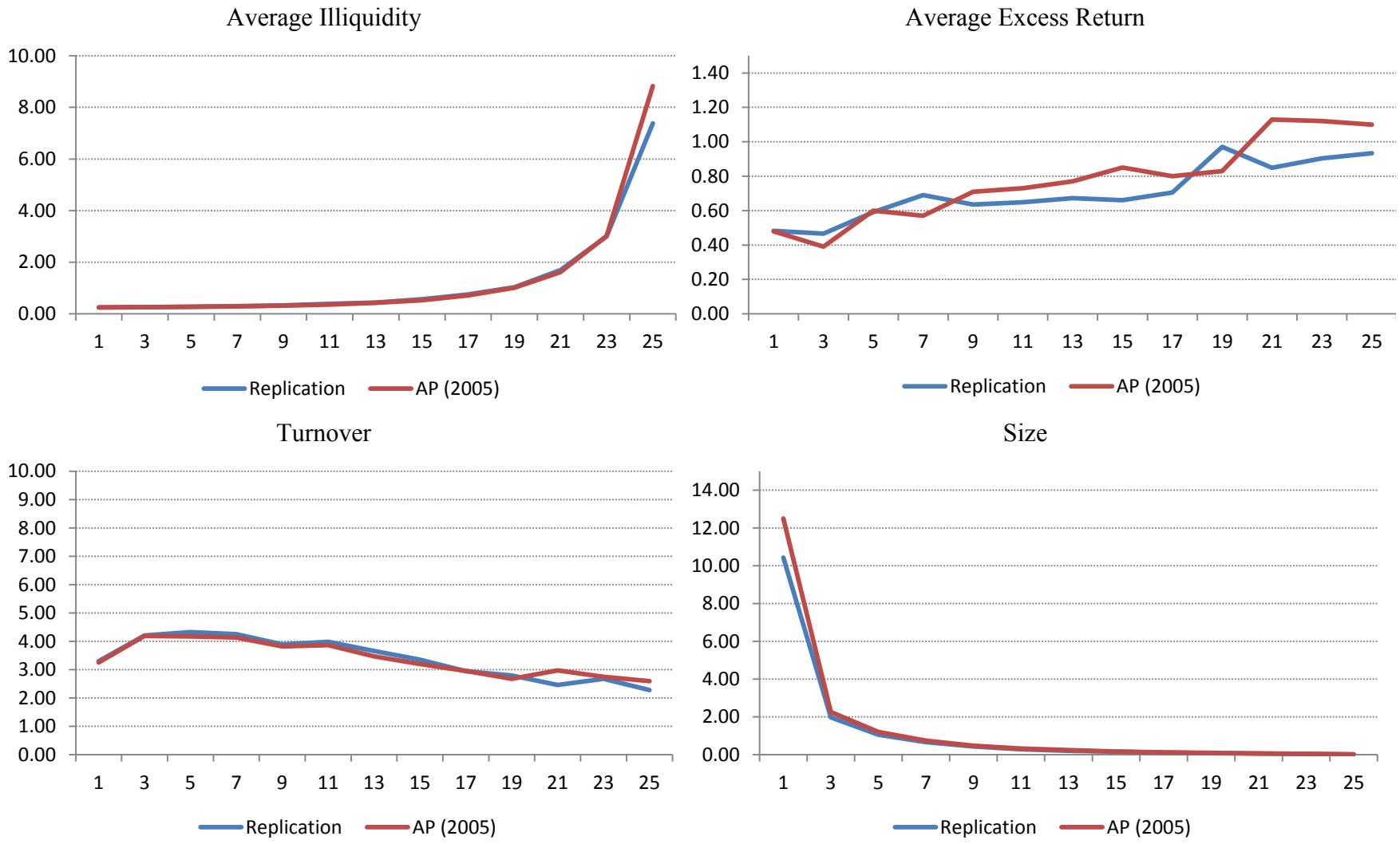
Appendix V

Replication Report for Acharya and Pedersen (2005, Journal of Financial Economics)



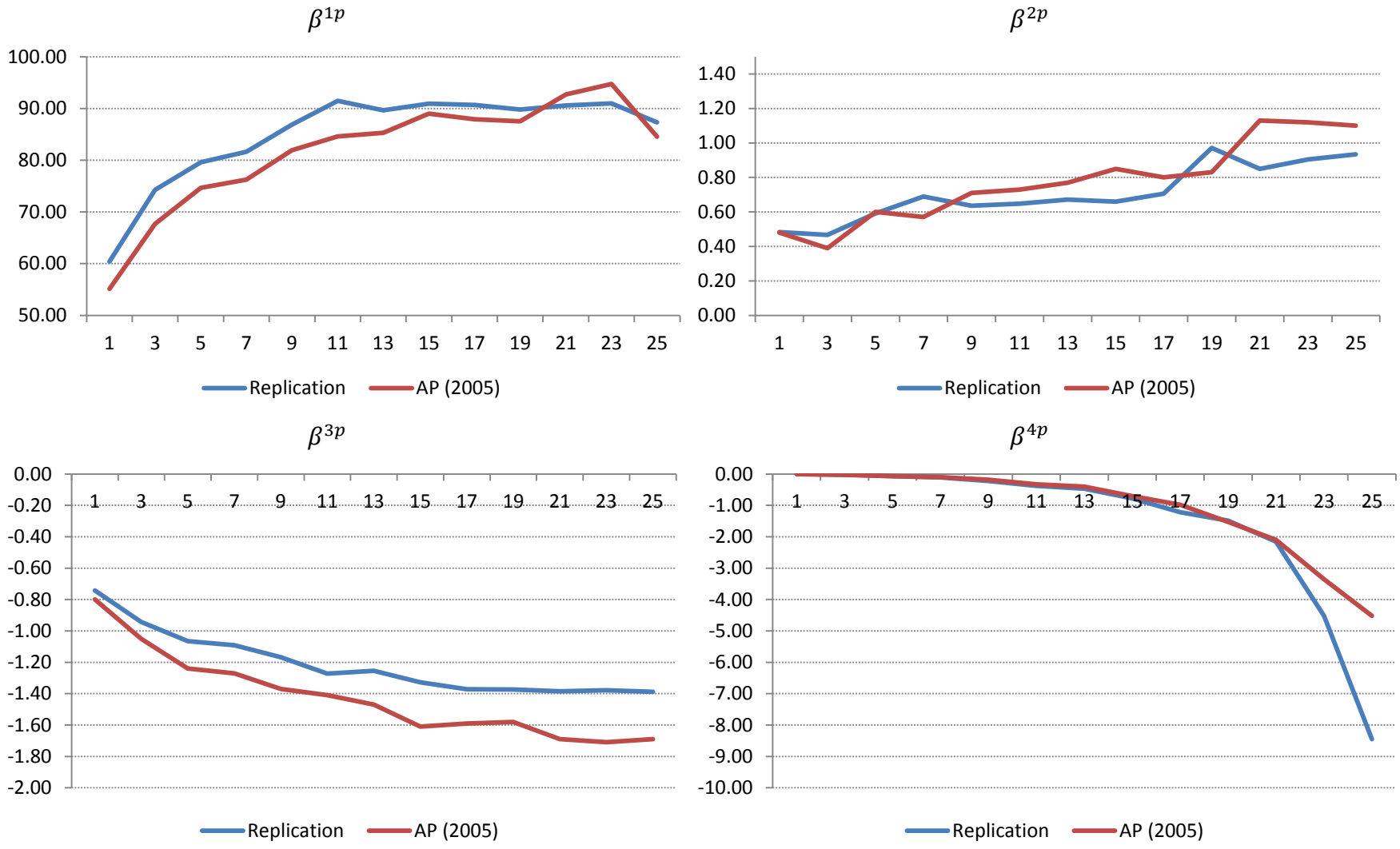
Appendix V Figure 1 Standardized innovations in market illiquidity (similar to Figure 1 in AP, 2005)

Appendix V, continued



Appendix V Figure 2 Properties of illiquidity portfolios (similar to Table 1 in AP, 2005)

Appendix V, continued



Appendix V Figure 2 (continued) Properties of illiquidity portfolios (similar to Table 1 in AP, 2005)

Appendix V, continued

Appendix V Table 1 Summary statistics of the innovations in market illiquidity

	R^2	Standard Deviation	Autocorrelation
AP (2005)	78%	0.17%	-0.03
Replication	77%	0.13%	-0.00

Appendix V Table 2 Properties of illiquidity portfolios (similar to Table 1 in AP, 2005)

Portfolio	β^{1p} (*100)	β^{2p} (*100)	β^{3p} (*100)	β^{4p} (*100)	$E(c^p)$ (%)	$\sigma(\Delta c^p)$ (%)	$E(r^{e,p})$ (%)	trn (%)	Size (bl$)
AP (2005)									
1	55.10	0.00	-0.80	0.00	0.25	0.00	0.48	3.25	12.50
3	67.70	0.00	-1.05	-0.03	0.26	0.00	0.39	4.19	2.26
5	74.67	0.00	-1.24	-0.07	0.27	0.01	0.6	4.17	1.20
7	76.25	0.00	-1.27	-0.10	0.29	0.01	0.57	4.14	0.74
9	81.93	0.01	-1.37	-0.18	0.32	0.02	0.71	3.82	0.48
11	84.59	0.01	-1.41	-0.33	0.36	0.04	0.73	3.87	0.33
13	85.29	0.01	-1.47	-0.40	0.43	0.05	0.77	3.47	0.24
15	88.99	0.02	-1.61	-0.70	0.53	0.08	0.85	3.20	0.17
17	87.89	0.04	-1.59	-0.98	0.71	0.13	0.8	2.96	0.13
19	87.50	0.05	-1.58	-1.53	1.01	0.21	0.83	2.68	0.09
21	92.73	0.09	-1.69	-2.10	1.61	0.34	1.13	2.97	0.06
23	94.76	0.19	-1.71	-3.35	3.02	0.62	1.12	2.75	0.04
25	84.54	0.42	-1.69	-4.52	8.83	1.46	1.1	2.60	0.02
Replication									
1	60.41	0.00	-0.74	0.00	0.25	0.00	0.48	3.30	10.44
3	74.24	0.00	-0.94	-0.02	0.26	0.01	0.47	4.21	1.98
5	79.62	0.00	-1.06	-0.07	0.27	0.01	0.59	4.33	1.06
7	81.65	0.00	-1.09	-0.10	0.29	0.01	0.69	4.25	0.66
9	86.85	0.01	-1.17	-0.22	0.33	0.02	0.64	3.89	0.43
11	91.47	0.01	-1.27	-0.37	0.39	0.10	0.65	3.98	0.29
13	89.67	0.01	-1.26	-0.47	0.44	0.05	0.67	3.66	0.20
15	90.94	0.02	-1.33	-0.78	0.56	0.10	0.66	3.35	0.16
17	90.70	0.04	-1.37	-1.22	0.76	0.14	0.70	2.95	0.11
19	89.77	0.05	-1.37	-1.49	1.03	0.18	0.97	2.80	0.08
21	90.59	0.08	-1.39	-2.16	1.69	0.35	0.85	2.46	0.06
23	90.99	0.14	-1.38	-4.52	3.00	0.70	0.90	2.67	0.04
25	87.31	0.32	-1.39	-8.45	7.38	1.54	0.93	2.28	0.02

Appendix V, continued

This table reports the replication results for Acharya and Pedersen (AP, 2005) and the comparison between my replication results and major empirical results in AP (2005). Appendix Figure 1 corresponds to Figure 1 in AP (2005), and Appendix Figure 2 compares key variables in Table 1 of AP (2005), including the average illiquidity, the average excess return, the turnover and the market capitalization, together with the market beta(β^{1p})and the liquidity beta ($\beta^{2p}, \beta^{3p}, and\ \beta^{4p}$). Appendix Table 1 shows the summary statistics of the innovation in market illiquidity, which is employed in this study. And Appendix Table 2 reports the properties of illiquidity portfolios, corresponding to Table 1 in AP (2005).

CHAPTER 3

THE ROLE OF INVESTABILITY RESTRICTIONS ON SIZE, VALUE, AND MOMENTUM IN INTERNATIONAL STOCK RETURNS

3.1 Introduction

Whether securities are priced locally in segmented markets or globally in a single integrated market is an enduring question in international asset pricing, and one that has been reviewed by Karolyi and Stulz (2003). The liberalization of financial markets around the world has increased market accessibility for global investors, but many indirect barriers, such as political risk, differences in information quality, legal protections for private investors and market regulations, can still inhibit full market integration.

Early empirical tests focused on whether market or consumption risks are priced locally or globally, following predictions made by the seminal international asset pricing models of Solnik (1974), Grauer, Litzenberger and Stehle (1976), Sercu (1980), Stulz (1981), and Errunza and Losq (1985). In the past decade, however, focus has shifted to the role of firm characteristics, such as size, book-to-market-equity ratios, cash-flow-to-price ratios, and momentum, in pricing securities in global markets. And an important debate has emerged over whether the explanatory power of these characteristics arises locally or globally. Griffin (2002) studies a global variant of the three-factor model similar to that of Fama and French (1993, 1998), which includes a market factor, a size factor and a book-to-market-equity factor for four countries (U.S., U.K., Canada, and Japan). He finds that only the local, country-specific components of the global factors are

able to explain the time-series variations in the stock returns and multi-factor models built from local factors only outperform those built from global factors with lower pricing errors. These findings are important because studies advocate for models that incorporate both local and foreign components of factors based on firm characteristics (Bekaert, Hodrick, and Zhang, 2009).

The debate has further advanced with newer, more broad-based evidence in two recent studies. Hou, Karolyi, and Kho (HKK, 2011) examine the relative performance of global, local, and what they call "international" versions of various multifactor models to explain the returns of industry and characteristics-sorted test portfolios in each country. The international versions of their models represent a "hybrid" factor structure that includes separately local, country-specific factors as well as foreign factors built from stocks outside the country of interest. They find that the international versions of these multifactor models have much lower pricing errors than the purely local and global versions.[28] They recommend that the foreign components of these factors are as important as local components for pricing global stocks. Fama and French (2012), however, show that a global multi-factor model performs only passably for average returns on global size/book-to-market ratios ("B/M" hereafter) and size/momentum portfolios, and it works poorly when asked to explain average returns on regional (for North America, Europe, Japan, Asia-Pacific) size/B/M or size/momentum portfolios. They test hybrid models following the methods in Griffin (2002) and HKK (2011) but find that the improved performance in terms of explanatory power and lower pricing errors over the strictly local versions of the model (for which they deem the performance only passable) is negligible.

[28] HKK (2011) also show that the international version of their proposed multifactor model with the market factor, a value factor constructed from cash-flow-to-price ratios, and a momentum factor (following Jegadeesh and Titman, 1993; Rouwenhorst, 1998; Griffin, Ji, and Martin, 2003; and Asness, Moskowitz, and Pedersen, 2009) provides the lowest average pricing error and rejection rates among various versions of competing multifactor models.

In this chapter, we make an important contribution to this debate. We propose and test a new multi-factor model based on firm characteristics that builds *separate* factor portfolios comprised of only globally-accessible stocks, which we call "global factors," and of locally-accessible stocks, which we call "local factors." Our new "hybrid" multi-factor model with both global and local factors not only captures strong common variation in global stock returns, but also achieves low pricing errors and rejection rates using conventional testing procedures for a variety of regional and global test asset portfolios formed on size, value, and momentum. Relative to a purely global factor model for global test asset portfolios, the increase in explanatory power is substantial and the reduction in average absolute pricing errors can be large; these gains are even larger for tests that include microcap stocks, that focus on global test asset portfolios that exclude North America and that include a momentum factor in the model. Relative to purely local factor models for regional test asset portfolios, the pricing errors and model rejection rates for the hybrid model are similar, except for emerging market test asset portfolios for which the hybrid model's pricing errors and rejection rates are much lower.

Our experiment examines monthly returns for over 37,000 stocks from 46 countries over a two-decade period. The intuition for this novel multi-factor structure comes from international asset pricing models that account for barriers to international investment and from the empirical studies that validate them.[29] In particular, Errunza and Losq (1985) define a two-country world with two sets of securities: all securities traded in the "foreign" market are eligible for investment by all investors ("globally accessible"), but those traded in the "domestic" market are ineligible and can only be held by domestic investors ("locally accessible"). These restrictions

[29] Among many others, we include Stulz (1981), Adler and Dumas (1983), Errunza and Losq (1985), Eun and Janakiramanan (1986), Bodurtha (1999), Chaieb and Errunza (2007), and Errunza and Ta (2011), and extensive empirical evidence in Harvey (1991), Bekaert and Harvey (1995), Errunza, Hogan, and Hung (1999), de Jong and de Roon (2005), Carrieri, Errunza, and Hogan (2007), Pukthuanthong and Roll (2009), Eun, Lai, de Roon, and Zhang (2010), and Bekaert, Harvey, Lundblad, and Siegel (2011).

define the expected return on one of the ineligible securities as a function of a global market risk premium (i.e., a global CAPM) plus a "super risk premium" which is proportional to the conditional local market risk. The condition under which local market risk is priced depends on the availability of substitute assets that may offer the same diversification opportunities as with the ineligible securities. The model can reduce to the two polar cases of full integration or full segmentation and, most importantly, allows for intermediate cases in between so that both global and local risks can be priced. Though this model is derived in the context of the CAPM, we seek to extend the same intuition (without formal theoretical justification) to extra-market factors based on firm-specific attributes like size, value and momentum.

How we define the set of globally-accessible ("eligible") and locally-accessible ("ineligible") stocks is critical for our exercise. Accessibility, or investability, refers to the ability of global investors to access certain markets and securities in those markets, so any definition should include consideration of openness (limits on foreign equity holdings), as well as liquidity, size, and float at the market and individual security level. We choose to define globally-accessible stocks in our equity universe as those for which shares are actively traded in the markets fully open to global investors, whether they are listed in their domestic exchange or secondarily cross-listed on exchanges outside of their main listing in their country of domicile. Locally-accessible stocks are, therefore, those that are only traded in their respective home markets. Again, our inspiration for this particular experimental choice comes from extensive research on risk and return attributes and institutional features of internationally cross-listed stocks.[30] Some studies (Foerster and Karolyi, 1993, 1999; Errunza and Miller, 2000) show that the systematic risk

[30] Consider, among many others, studies by Foerster and Karolyi (1993, 1999), Bodurtha (1994), Errunza, Hogan, and Hung (1999), Errunza and Miller (2000), Bekaert, Harvey, and Lumsdaine (2002), Doidge, Karolyi, and Stulz (2004), Carrieri, Errunza, and Hogan (2007), and Carrieri, Chaieb, and Errunza (2011). Karolyi (2006) provides a survey of the cross-listing literature.

exposures of these stocks change dramatically and permanently around their secondary listings: local market betas (measured relative to local market proxies) decline and foreign market betas (measured relative to global market proxies) rise. Newly globally accessible, these cross-listed stocks are much more likely to be held and traded by institutional investors around the world (Ferreira and Matos, 2008).

In our hybrid multi-factor model, global factor portfolios for the market, size, value and momentum are constructed from globally-accessible stocks, while local factor portfolios for the market, size, value and momentum are constructed from locally-accessible stocks that are listed and traded only in their home markets.[31] The locally-accessible stocks are constructed from among the stocks that are not globally accessible *in the region* in which our model is seeking to explain the cross-section of average returns. That is, they include only those that are listed and traded in their home markets. This is different from the construction of factors for the international models in Griffin (2002), HKK (2011), as we reassign what would be local stocks in their local factors to the global factors if those stocks are deemed globally accessible by our definition.

There are, of course, other ways in which stocks can become globally accessible, such as being included in a closed-end country fund, or in one of Morgan Stanley Capital International (MSCI) or Standard & Poor's (S&P) global indexes (especially, in their investable indexes for emerging markets). Indeed, if they do not face insurmountable or costly foreign investment restrictions that preclude them from doing so, many institutions do hold shares of foreign stocks in their home

[31] We will define the globally accessible set to include stocks that secondarily cross-list their shares on one of seven different target markets: the U.S. on one of the major exchanges, New York Stock Exchange (NYSE), American Stock Exchange (AMEX) or Nasdaq, or on the over-the-counter (OTC) markets, the U.K. on the London Stock Exchange, London OTC, or SEAQ International, Euronext Europe, Germany, Luxembourg, Singapore, or Hong Kong. We later discuss the rationale behind this set of target markets.

markets even if they are not secondarily cross-listed elsewhere. Though narrow in its definition, we prefer to consider only those stocks in fully-open markets and among secondary cross-listings for our globally-accessible set because of clear identification as well as the timing of the listing event. We also explore the robustness of our findings to several alternative definitions of global accessibility, such as additional restrictions that account for how actively the cross-listed shares are traded.

Our study differs from that of Fama and French (2012) in that we incorporate into our analysis more than 11,000 stocks from 23 emerging markets. In fact, we include the emerging markets as one of the regions in which we evaluate how well our hybrid multi-factor model performs for size, value, and momentum test asset portfolios. Expanding our analysis into emerging markets is important because it is there that investability restrictions are most likely to bind. We expect that this is where a global or hybrid model is likely to face the greater challenge relative to a purely-local factor model. It turns out that this is the case, but our hybrid model also performs well in developed markets. Like Fama and French (2012), we provide evidence for size groups. Our sample, like theirs, covers all size groups, and indeed very small, microcap stocks produce challenging results (Fama and French, 2008). We control for the potential influence of microcap stocks globally and in each region by performing our tests with and without the extremely-small test asset portfolios and also by building the factor portfolios using value and momentum breakpoints using the top 90% of market capitalization in each region to limit their influence.

3.2 The Design of the Experiment

Fama and French (1993) propose a three-factor model to capture the patterns in U.S. average returns associated with size and value versus growth,

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + s_i F_{Size,t} + h_i F_{B/M,t} + \varepsilon_{i,t} \quad (1)$$

In this regression, R_{it} is the return on asset i in month t, R_f is the risk free rate, R_{mt} is the market return, $F_{Size,t}$ is the difference between the returns of diversified portfolios of small stocks and big stocks (F denotes a factor portfolio), and $F_{B/M,t}$ is the difference between the returns on diversified portfolios of high B/M (value) stocks and low B/M (growth) stocks. Model (1) is motivated by observed patterns in returns and the authors (Fama and French), as well as those of us who follow their lead, readily acknowledge that they try to capture the cross-section of expected returns without specifying the underlying economic model that governs asset pricing. The null hypothesis is that the slope coefficients (β_i, s_i, h_i) and the associated factor portfolio returns capture the cross-section of returns, so we test whether the intercepts equal zero for all test assets. This test is akin to the mean-variance spanning tests of Huberman and Kandel (1987). For a given set of test asset portfolios, we judge each model based on its explanatory power, the magnitude of model pricing errors (the absolute magnitude of the intercepts), and the Gibbons, Ross, and Shanken (GRS, 1989) F-test statistic for the hypothesis that the intercepts are jointly equal to zero across the test assets of interest. We also follow Lewellen, Nagel, and Shanken (2010) by computing the Generalized Least Squares (GLS) cross-sectional regression (CSR) R^2 and a core component of the GRS statistic, denoted $SR(\alpha)$,

$$SR(\alpha) = [\alpha' S^{-1} \alpha]^{1/2} \quad (2)$$

where α is the vector of regression intercepts produced by Model (1) across a set of test asset portfolios. S is the covariance matrix of regression residuals.[32]

Fama and French (2012) build the global and local versions of model (1) for global and local

[32] Gibbons, Ross, and Shanken (1989) relate $SR(\alpha)^2$ to the difference between the square of the maximum Sharpe ratio for the portfolios constructed from the test asset portfolios and factor portfolios and that constructed from the factor portfolios alone. As Fama and French (2011) argue, the advantage of this statistic is that it combines the regression intercepts with a measure of their precision captured by the covariance matrix of the regression residuals.

stock returns, respectively:

$$R_{it} - R_{ft} = \alpha^G{}_i + \beta^G{}_i\,(R^G{}_{mt} - R_{ft}) + s^G{}_i\,F^G{}_{Size,t} + h^G{}_i\,F^G{}_{B/M,t} + \varepsilon_{i,t} \qquad (3a)$$

$$R_{it} - R_{ft} = \alpha^L{}_i + \beta^L{}_i\,(R^L{}_{mt} - R_{ft}) + s^L{}_i\,F^L{}_{Size,t} + h^L{}_i\,F^L{}_{B/M,t} + \varepsilon_{i,t}. \qquad (3b)$$

The superscript "G" on the market and factor portfolios implies that they are constructed from all stocks around the world and the superscript designation of "L" on the market and factor portfolios implies that they are constructed only from local - or regional, in our experiments - stocks. Extending the experiment in this way is naturally complicated by the fact that asset pricing globally or even in a particular region may not be fully integrated.

To capture the impact of investability restrictions on global investing, we propose a new hybrid model based on the Fama-French three-factor model,

$$R_{it} - R_{ft} = \alpha^H{}_i + \beta^A{}_i\,(R^A{}_{mt} - R_{ft}) + s^A{}_i\,F^A{}_{Size,t} + h^A{}_i\,F^A{}_{B/M,t}$$
$$+ \beta^{\bar{A}\text{-}A}{}_i\,R^{\bar{A}\text{-}A}{}_{mt} + s^{\bar{A}\text{-}A}{}_i\,F^{\bar{A}\text{-}A}{}_{Size,t} + h^{\bar{A}\text{-}A}{}_i\,F^{\bar{A}\text{-}A}{}_{B/M,t} + \varepsilon_{i,t},$$

(4)

where the superscript "H" denotes the intercept for the hybrid model, the superscript "A" denotes a market or factor portfolio comprised of stocks only in the globally-accessible sample, and the superscript "Ā-A" denotes a spread factor portfolio that consists of a long position in purely-local stocks in a given region (represented by "Ā") and a short position in the globally-accessible sample ("A"). The spread factor portfolio is built in the spirit of a "*hedged portfolio*" in Errunza and Losq (1985). For example, $F^{\bar{A}\text{-}A}{}_{Size,t}$ is the difference between the size-based factor portfolio of purely-local stocks in a region and that of the globally-accessible stocks. Each of the size-based factor portfolios are constructed as returns of diversified portfolios of small stocks and big stocks among the respective samples of stocks. The spread portfolios for the market factor ($R^{\bar{A}\text{-}A}{}_{mt}$) and the value-based factor ($F^{\bar{A}\text{-}A}{}_{B/M,t}$) are built in a similar fashion.

Our second experiment examines whether the empirical validity of the hybrid model is influenced by the purely mechanical way in which we construct the globally-accessible and purely-local subsamples. We adjust the investment opportunity set by gradually imposing a variety of "viability constraints" on the globally accessible sample. That is, we require that the stocks in the globally accessible sample qualify by meeting certain minimum thresholds of trading volume in the target markets for the secondary cross-listing. In comparing the performance of the hybrid model in which the global factors are built in different ways, we still find reliable evidence about the explanatory power of the hybrid model in explaining returns in both global and regional test asset portfolios.

In our third and final experiment, we investigate whether the cross-sectional explanatory power of the hybrid model is specific to the Fama-French three-factor model in explaining the portfolios sorts on size and B/M. Carhart (1997) proposes a four-factor model for U.S. return in order to capture momentum,

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + s_i F_{Size,t} + h_i F_{B/M,t} + m_i F_{Mom,t} + \varepsilon_{i,t}, \qquad (5)$$

which is Model (1) enhanced with a momentum return, $F_{Mom,t}$ is the difference between the month t returns on a diversified portfolios of the winners and losers of the past year. Similarly, we test a hybrid model based on the Carhart's four-factor model,

$$R_{it} - R_{ft} = \alpha^H_i + \beta^A_i (R^A_{mt} - R_{ft}) + s^A_i F^A_{Size,t} + h^A_i F^A_{B/M,t} + m^A_i F^A_{Mom,t} + \beta^{\bar{A}-A}_i R^{\bar{A}-A}_{mt} + s^{\bar{A}-A}_i F^{\bar{A}-A}_{Size,t} + h^{\bar{A}-A}_i F^{\bar{A}-A}_{B/M,t} + m^{\bar{A}-A}_i F^{\bar{A}-A}_{Mom,t} + \varepsilon_{i,t} \qquad (6)$$

which is Model (4) extended by two momentum factor portfolio returns, $F^A_{Mom,t}$ for the globally-accessible stocks and $F^{\bar{A}-A}_{Mom,t}$, for the spread portfolio of locally-accessible stocks net of those for the globally-accessible stocks.

3.3 Data and Summary Statistics

3.3.1 The Global Equity Universe

We obtain U.S. dollar-denominated stock returns and accounting data from Datastream and Worldscope. To ensure that we have a reasonable number of firm-level observations in each country, the sample period begins in November 1989 and ends in December 2010, which encompasses the widest coverage in the Worldscope database. Our final sample of the global equity universe includes 37,399 stocks from 46 countries. To ensure that there are sufficient numbers of stocks in each test asset portfolio, as in Fama and French (2012), 23 developed markets are combined into four regions: (i) *North America (NA)*, including the U.S. and Canada; (ii) *Japan*; (iii) *Asia Pacific*, including Australia, New Zealand, Hong Kong, and Singapore (but not Japan); and (iv) *Europe*, including Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the U.K. And the remaining 23 countries are combined into *Emerging Markets*, the fifth region in our tests; it includes Israel, Turkey, Pakistan, South Africa, Czech Republic, Poland, Hungary, Russia, China, India, Indonesia, Malaysia, Philippines, South Korea, Taiwan, Thailand, Argentina, Brazil, Chile, Colombia, Mexico, Peru, and Venezuela. We construct test asset portfolios for each of these five regions and for four global experiments: all global markets, developed markets, global markets excluding North America, and developed markets excluding North America.

We require each firm's home country to be clearly identified in the database. Financial firms are excluded from the study due to their different characteristics. We also exclude depositary receipts (DRs), real estate investment trusts (REITs), preferred stocks, and other stocks with

special features.[33] For most countries, we restrict the sample to stocks from major exchanges, which we define as the exchanges on which the majority of stocks in that country are listed. However, multiple exchanges are included in samples for China (Shanghai Stock Exchange and Shenzhen Stock Exchange), Japan (Osaka Stock Exchange, Tokyo Stock Exchange, and JASDAQ), Russia (MICEX and Russian Trading System), South Korea (Korea Stock Exchange and KOSDAQ), Canada (Toronto Stock Exchange and TSX Ventures Exchange), and U.S.(NYSE, AMEX and NASDAQ). To limit the effect of survivorship bias, we include dead stocks in the sample.

To reduce errors in Datastream, we follow several screening procedures for monthly returns as suggested by Ince and Porter (2003) and HKK (2011). First, any return above 300% that is reversed within one month is set to missing. Specifically, if R_t or R_{t-1} is greater than 300%, and if $(1+R_t) \times (1+R_{t-1}) - 1 \leq 50\%$, then both R_t and R_{t-1} are set to missing. Second, in order to exclude remaining outliers in returns that cannot be identified as stock splits or mergers, we treat as missing the monthly returns that fall out of the 0.1% and 99.9% percentile ranges in each country. Third, included firms are required to have at least 12 monthly returns during the sample period.

Additionally, we require the availability of the following financial variables for at least one firm-year observation: market value of equity ("Size" hereafter), B/M, and cash flow to price ("C/P" hereafter). To make sure that the accounting ratios are known before the returns, we match the financial statement data for fiscal year-end in year *t-1* with monthly returns from July of year *t* to

[33] We drop stocks with name including "REIT", "REAL EST", "GDR", "PF", "PREF", or "PRF" as these terms may represent REITs, GDRs, or preferred stocks. We drop stocks with name including "ADS", "CERTIFICATES", "RESPT", "Rights", "Paid in", "UNIT", and a host of others due to various special features. A number of additional country-specific screening rules are applied, a list of which can be obtained from the authors.

June of year *t+1*. We take the inverse of the price-to-book ratio (WC09304) and the price-to-cash flow ratio (WC09604) to calculate the ratios of B/M and C/P, respectively. We do not use negative B/M (or C/P) stocks when calculating the breakpoints for B/M (or C/P) or when forming the size/B/M (or size/C/P) portfolios.

Figure 3.1 exhibits the distribution of our global equity universe across regions over the period from 1990 to 2010, reported by total market capitalization. On average, North America, Europe, Japan, Asia Pacific, and the Emerging Markets account for 43.13%, 25.50%, 13.44%, 4.45%, and 13.49% of global market capitalization. Figure 3.2 offers a slightly different picture based on the total number of stocks. North America constitutes one-quarter of the sample population, higher than Europe (23.08%), Japan (11.50%), and Asia Pacific (10.47%) but lower than the Emerging Markets (29.72%). Proportionally more large-cap stocks are concentrated in North America, especially the U.S. In contrast, proportionally more of the stocks from Asia Pacific and Emerging Markets are small cap stocks. In addition, Figures 1 and 2 show the distribution of our global equity universe across countries within each region. Among the countries in Europe, the average size of stocks in the Netherlands, Spain, and Switzerland are larger than those in Greece, Sweden, and the U.K. Hong Kong accounts for 40.62% of all market capitalization in Asia Pacific but only constitutes 24.96% of the sample population in the region. Most of the stocks in Emerging Markets are from Asia, either by count or by total market capitalization. The average size of stocks varies substantially across emerging market countries, with greater values for Mexico, Brazil, Russia, and China.

Figure 3.3 shows the sample over time and breaks it down by regions. There are some differences in the evolution of counts and total market capitalization. The counts steadily increase from around 10,000 in 1990 to a peak of almost 28,000 in 2008. Especially, the count in

Emerging Markets has jumped from less than 2,000 in 1990 to nearly 9,500 in 2009. In contrast to these counts, global market capitalization has less steady growth. It rises from US$7 trillion in 1990 to a peak of US$26 trillion in 2000. It falls after 2000 before reaching another peak of almost US$40 trillion in 2007. In the most recent two years, it rises again to reach US$34 trillion in 2010.

Table 3.1 presents summary statistics of total counts and other firm-level characteristics for each country. We report the time-series averages of median size, B/M, C/P, and momentum ("Mom" hereafter). There is considerable cross-country variation in the average median B/M, but much less for C/P. Mom for month *t* is the cumulative return for *t-11* to *t-1*, skipping the sort month *t*. The first momentum sort absorbs one year of data, so the sample period for Mom is November 1990 through December 2010. Among all the countries in our sample, Mom ranges from a low of -2.19% (Japan) to highs of 40.97% (Poland), 37.17% (Russia), and 26.48% (China).

3.3.2 The Globally-Accessible and Purely-Local Samples

We categorize stocks into two subsets based on accessibility or investability constraints as defined by whether or not the stock is actively traded in the markets fully open to global investors. Ultimately, we identify a set of over 5,700 stocks accessible to global investors by being cross-listed in major developed markets; another group of around 32,000 individual stocks are locally accessible to domestic investors. We acknowledge that previous studies have used global industry portfolios, closed-end country funds, and the investable indices in emerging markets as globally-accessible assets used to replicate returns on only locally accessible assets (e.g., Bekaert and Urias, 1996; Carrieri, Chaieb and Errunza, 2008, 2011; Errunza and Ta, 2011). In this study, by contrast, we focus on the impact of the market openness and the secondary

cross-listing on the size, value, and momentum patterns in international stock returns to keep the accessibility criteria as transparent as possible.

We require that the stocks in the globally accessible sample need to be listed in the markets which are fully open to global investors or to be secondarily cross-listed in those as target markets. Within those target markets, we include secondary listings from overseas that can trade on many different venues or platforms. We confine the list to seven target markets: (i) *the U.S.*, which includes NYSE/AMEX, NASDAQ, and the Non-NASDAQ OTC markets;[34] (ii) *the U.K.*, which includes the London Stock Exchange, London OTC Exchange, London Plus Market, and SEAQ International;[35] (iii) *Europe*, which includes Euronext at Amsterdam, Brussels, Lisbon, Paris, and EASDAQ;[36] (iv) *Germany* in which the Frankfurt Stock Exchange is located; (v) *Luxembourg* in which the Luxembourg Stock Exchange is located; (vi) *Singapore*, which includes the Singapore Stock Exchange, Singapore OTC Capital, and Singapore Catalist;[37] and (vii) *Hong Kong* in which the Hong Kong Stock Exchange is located. The distinguishing feature of these target exchanges is that they are fully open to global investors, having minimum foreign investment restrictions and reasonably active trading in foreign cross-listed issues. We try to strike a balance between obtaining maximum breadth of stock exchange platforms accessible for international investors and avoiding problems related to differences in cross-listing trading

[34] Non-Nasdaq OTC markets include both the OTC Bulletin Board and the OTC Markets Group, for which its OTCQX International trading platform is designed for listings from overseas.

[35] The London Plus Stock Exchange (www.plusmarketsgroup.com) is a London-based stock exchange providing cash trading and listing services under the auspices of the Markets in Financial Instruments Directive (2004/39/EC, "MiFiD"), a European Union law providing for harmonized investment services. London OTC trading falls under the auspices of the London Stock Exchange (LSE) Group and is done under MiFiD with the exchange furnishing trade reporting and publication services. The Stock Exchange Automated Quotation (SEAQ) International is the LSE's electronic price quotations system for non-U.K. securities.

[36] EASDAQ was an electronic securities exchange based in Brussels founded originally as an equivalent to Nasdaq, was purchased by the American Stock Exchange in 2001 and then shut down in 2003.

[37] See www.sgx.com for details on main board versus Catalist listing requirements. A listing applicant must be sponsored by an approved sponsor of Catalist and must satisfy some disclosure and performance requirements. Singapore's OTC Capital (www.otccapital.com) is an unaffiliated trading platform for unlisted public companies.

mechanisms and conventions. For the Frankfurt Stock Exchange and OTCQX International trading platforms, for example, there are "unregulated" cross-listed stocks alongside the "regulated" cross-listed stocks, in which trading takes place without the sponsorship of the company.[38] We include both unregulated and regulated cross-listings in Frankfurt and OTCQX International.

The appendix describes the procedure for constructing the sample of globally accessible stocks. Our sample construction begins with all non-domestic stocks listed in the target exchanges. From the list containing over 30,000 stocks, we select those with available records of home market and a parent code in the database so that the cross-listed stocks in the target exchanges can be matched with their parent stocks listed in the home market. Because there are a few mismatches in Datastream, we verify the matching records. We correct the mismatched records for the cross-listed stocks if their true parent equities can be found in the global universe sample, keep those that have no parent equities but are only listed on the target exchanges, and drop those whose true parent equities are missing in the database. To ensure the validity of the sample, we drop the stocks whose Return Index (RI) records are not available in the database.[39] Furthermore, if one stock is cross-listed on more than one target exchange within the same target market, these multiple records are consolidated into one record. The sample at this point contains 22,612 stocks. Similar to the global equity universe, we exclude financial firms and confine the sample to firms from 46 countries and with available company account items from Worldscope. We then have 11,319 stocks secondarily cross-listed on at least one of the target markets. We then add

[38] If a company is already listed on an approved foreign stock exchange ("Like Exchanges"), it is exempt from the primary registration rules and can be dual listed on the Frankfurt Stock Exchange without an underwriter. There are over 200 such "Like Exchanges" approved by the Frankfurt Stock Exchange (www.franfurtstockexchange.de).

[39] To limit the effect of survivorship bias, we include dead stocks in the sample. For both dead and active stocks, we confirm their effective ending months according to two criteria: (i) consecutive constant RIs from the month until the end of the period, December 2010; and, (ii) zero trading volume from the month until the end of the period. If one stock has the same month for its base month and ending month, the stock is excluded from the sample.

domestic stocks from the seven target markets as long as three criteria are satisfied: they are among those stocks in the top 75% of market capitalization for the market; they have a minimum price of U.S. $5 and equivalent levels in terms of percentile rank for non U.S. markets; and, they are among those stocks with a minimum 75% public float for listed stocks. These filters leave a sample of 11,057 stocks which we label as “CL1” to denote the first group of cross-listed stocks.

To construct our final sample, we impose additional restrictions on how actively the secondarily cross-listed shares are traded, which we call our “viability” constraints. We only drop the cross-listed stocks for which trading in the target markets is too limited to be viably accessible for global investors. For each secondarily cross-listed stock in CL1, we compare (a) its monthly trading in the target markets with the total trading of all secondarily cross-listed stocks from the same country (using VA, turnover by value, from Datastream) and (b) its monthly trading volume (VO, turnover by volume, from Datastream) in the target markets relative to that of the same stock in the home market. The first viability constraint evaluates the annual percentage of its trading in target markets relative to all secondarily cross-listed stocks from the same country trading there. If the time-series average of the annual percentages during the sample period is required to be at least 0.5%, there are nearly 900 stocks that qualify, many of which are the most popularly traded stocks for global investors. For the stocks that fail to meet our first viability criterion, we use a second one based on the annual percentage of its own global trading volume in any of the target markets (Baruch, Karolyi, & Lemmon, 2007). If the time-series average of these annual percentages during the sample period is required to be at least 0.1%, there are around 5,300 stocks left in the sample. Merging these two cross-listed sets of stocks and qualified domestic set of stocks from the target markets leaves 5,747 stocks, which we call the "Main CL Sample."

Figure 3.4 presents its distribution across regions over the period from 1990 to 2010, reported by total market capitalization. On average, North America (47.66%) and Europe (29.56%) constitutes the bulk of the total market capitalization in the Main CL Sample, followed by Japan (10.50%), the Emerging Markets (8.49%), and Asia Pacific (3.79%). The cross-listed stocks constitute a significant fraction of the overall market capitalization in each home region (compare with Figure 3.1). By count, North America, Europe, Japan, Asia Pacific, and Emerging Markets represent 44.95%, 23.56%, 3.43%, 13.66%, and 14.41% of the sample population, respectively (shown in Figure 3.5). Figures 4 and 5 also exhibit the distribution of Main CL Sample stocks across countries within each region. In Europe, stocks from France, Germany, the Netherlands, and Switzerland are more likely to have shares secondarily cross-listed overseas but stocks from Austria, Greece, and the U.K. tend to stay in their home markets. In Asia Pacific, Hong Kong stocks are over-represented in the Main CL Sample relative to the global equity universe. Among emerging market countries, equities from China, India, and Taiwan are more likely to stay at home. On the other hand, equities from Russia, Mexico, and South Africa tend to go abroad.

Figure 3.6 illustrates the total market capitalization and the total number of the globally accessible sample, represented by the Main CL Sample, and breaks them down by regions *and* by year. The total count increases from less than 1,000 in the early 1990s to a peak of 4,123 in 2009 and then falls to 4,088 in 2010. In contrast to the counts, total market capitalization, as well as the market capitalizations from each region, has experienced more volatility over the period, reaching peaks in 2000 and 2007.

Figure 3.6 also shows the distribution of Main CL stocks by each *target market* and by year. Most notably, the U.S. as a target market for internationally cross-listed stocks is more resilient

than those in the U.K., Europe, and Germany, either by count or by market capitalization. Annual counts in the U.K. reach a peak of 670 in 2007 and decrease steadily to 347 in 2010. For Europe, the number of cross-listed stocks never goes up above 450 and it decreases steadily from 450 in 2001 to 261 in 2010. For the Frankfurt Stock Exchange, the annual count increases significantly from less than 270 in the early 1990s to 2,917 in 2008, but it falls during the most recent two years until down to 2,845 in 2010. Distinct from these markets, NYSE/AMEX, Nasdaq and the Non-Nasdaq OTC markets have attracted more foreign stocks cross-listed. Even after the 2008 financial crisis, the count is steadily rising from 2,087 in 2007 to 2,529 in 2010 (Iliev, Miller, and Roth, 2011). Although all target markets have shrunk in size around 2008, the cross-listed market capitalization in the U.S. drops by 28.01% from 2007 to 2009, much less than the 61.09% in the U.K., 48.31% in Europe, and 30.66% in Germany.

In addition to the Main CL Sample, we construct and evaluate two other definitions for the globally accessible sample, together with CL1, to ensure the reliability of the hybrid model we propose. First, we introduce an *absolute* viability constraint: for each stock in CL1 in a given year, if there is at least one month of non-zero trading in the target markets, the stock is included in the globally accessible sample for that year. The resulting sample has 9,605 stocks and is labeled "CL2a." Second, we consider more stringent screening on the two viability constraints: the screening ratios are up to 5% for the first relative viability constraint and 1% for the second one. Another new sample, denoted "CL2b," then contains 4,058 stocks. For each globally accessible sample, we group the stocks left in each respective region as the purely local set. Summary statistics on total counts and firm-level characteristics for the Main CL Sample are provided in Appendix Tables 1 and 2 (appendix tables are available upon request).

3.4 Building Factor Portfolios and Test Assets

We follow Fama and French (1993, 2012) in constructing proxy factors as returns on zero-investment portfolios that go long in stocks with high values of a characteristic and short in stocks with low values of the characteristic. These factors are explanatory returns in our asset pricing regression models. We also construct 5×5 size/B/M portfolios, the 5×5 size/momentum portfolios, and the 5×5 size/C/P portfolios that are used as test assets in our tests.

3.4.1 Building Factor Portfolios

Our first asset pricing tests are for 5×5 size/B/M portfolios and the explanatory returns are for 2×3 portfolios sorted on size and B/M. At the end of each June from 1990 to 2010, we allocate stocks in one region to two size groups – small stocks and big stocks. Big stocks are those in the top 90% of market capitalization for the region, and small stocks are those in the bottom 10%. The only difference between our sorting breakpoints and those of Fama and French (2012) is related to the B/M breakpoints. Fama and French (2012) use the 30th and 70th percentiles of B/M for the big stocks in each given region to avoid too much weight on micro-cap stocks. Value stocks are those with B/M ratios at or above the 70th percentile, growth stocks, those with B/M ratios at or below the 30th percentile, and the rest are neutral stocks. However, there are still differences in terms of accounting rule across countries within any one region. Given the fact that our globally accessible stocks are more likely to accept global standards for reporting that can be comparable across countries, we use B/M breakpoints based on the big stocks in the globally accessible sample from each region to avoid sorts that are dominated by the less comparable and tiny stocks in the region.

The global explanatory returns are constructed from the globally accessible sample. We use a universal size breakpoint, but use each region's B/M breakpoints to allocate the globally accessible stocks. Beyond the global factor returns, the hybrid model includes local factor returns that are based on the purely local stocks from the region for which the test is performed relative to the globally accessible stocks. Fama and French (2008, 2012) document that microcap stocks pose a challenge for asset pricing models and suggest factor returns should not be dominated by small stocks. Small stocks constitute the major component of the purely local samples. So, if the size breakpoint is the bottom 10th percentile of market capitalization of the purely local sample for each region, either the size factor or the value factor will be dominated by small stocks. Thus we use regional size cutoffs for the purely local portfolios. In addition, we adopt the same regional B/M breaks as in the globally accessible portfolios to avoid the microcap effect. Then, for each given region, the return spread factor portfolios of purely-local stocks relative to the globally-accessible stocks are the differences in the respective factor portfolio returns for the set of purely-local stocks in the region and for the globally-accessible stocks. For example, for the size-related spread factor portfolio, we compute the return difference between the factor portfolio for the locally-accessible stocks (measured, in turn, as the difference between an equally-weighted average of the small-growth, small-neutral, and small-value portfolios and an equally-weighted average of the big-growth, big-neutral, and big-value portfolios) and the globally-accessible stocks (measured similarly). The value- and momentum-related spread factor portfolios are built in the same way. The spread factor portfolios vary by region because the set of locally-accessible stocks from which they are built changes.

Another set of explanatory returns are 2×3 factor portfolios returns sorted on size and momentum, which will be introduced in our second asset pricing tests on size/momentum

portfolios. The momentum factor, WML, is formed using a 12-month/2-month strategy where each month's return is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. Similar to the size/B/M portfolios, the momentum breakpoints for the global explanatory returns are the 30th and 70th percentiles for the big stocks in the globally accessible sample from each region. And we use the regional momentum cutoffs based on big stocks for the given region when forming local explanatory returns. The momentum breakpoints from each region are employed in forming global portfolios. In our third set of tests on size/C/P portfolios, we build the set of explanatory returns that are for 2×3 portfolios sorted on size and C/P. The explanatory return associated with C/P is constructed by the same way as HML.

Table 3.2 presents summary statistics for factor portfolio returns for all stocks in the equity universe, for the globally-accessible stocks and for the spread factor portfolios of locally-accessible relative to the globally-accessible stocks; they are reported separately for the global experiments (Panel A) and the regional experiments (Panel B). The market excess returns are similar in magnitude in North America and Europe, but higher for the globally-accessible samples in three other regions and all four global experiments. The size premiums are always higher for the globally accessible samples everywhere likely because of the wider differences in size across regions than within regions. On the other hand, higher value premiums obtain for all stocks than either the globally- or locally-accessible subsets regardless of the region. In addition, Table 3.2 displays summary statistics for the local spread factor returns for each regional and global experiment. There are positive local market spread premiums in North America and Asia Pacific, but negative local market spread discounts in Europe, Japan and Emerging Markets. The global value spread premium, a respectable 0.40% (for B/M) and 0.44% (for C/P) on average per

month, is statistically reliably different from zero over the sample period. For other global and most of the regional experiments, the value spread factor portfolio returns are also positive and statistically significant. As for momentum spread factor portfolio returns, that in Japan is as low as -0.96% per month (*t* statistic of -3.02), while that in Europe is as high as 0.35% (*t* statistic of 1.90). The correlations (unreported, but available in Appendix Tables 3 and 4) between the spread factor portfolio returns and the respective factor portfolios for the globally-accessible are, as expected, relatively low, whether for the global or regional experiments and for the size-, value- and momentum-related factors.

3.4.2 Building Test Assets

Our first set of asset pricing tests evaluates 5×5 size/B/M portfolios. The size breakpoints for a region are the 3rd, 7th, 13th, and 25th percentiles of the region's aggregate market capitalization. The B/M breakpoints are defined by the 20th, 40th, 60th, and 80th percentiles for big stocks in the region. Table 3.3 displays the average excess returns and standard deviations for each set of 5×5 size/B/M test assets by global and regional experiment. Our results confirm the finding in Fama and French (2012) that the size pattern in value premiums poses a challenge for asset pricing models. The next two test assets are 5×5 size/momentum portfolios and 5×5 size/C/P portfolios. For the sake of brevity, average excess returns for these two types of test asset portfolios are reported in Appendix Tables 5 and 6.

3.5 Time-Series Regression Tests

Our first experiment involves time-series regression tests, as applied by Fama and French (1993, 1996, and 2012) and others, in which test assets are 5×5 size/B/M portfolios. We compare the

performance of global, local, and hybrid versions of the Fama-French three-factor model. Our criteria for success consist of the explanatory power (average adjusted R^2 across the test asset portfolios), the GRS statistic, the Sharpe Ratio, $SR(\alpha)$, the GLS CSR R^2, and summary statistics for the intercepts, including the difference between the highest and lowest regression intercepts ("H-L α") and the average absolute intercepts ("|α|").[40]

3.5.1 Main Experiment

Table 3.4 reports regressions to explain excess returns on the 5×5 portfolios from the sorts on size and B/M. Appendix Tables 7 and 8 furnish details on the intercepts and their *t*-statistics, as well as the betas for the hybrid model based on the Fama-French three-factor model. Panel A of Table 3.4 summarizes the results for the global version of the Fama-French three-factor model. The global factor model offers adequate explanatory power for the global test asset portfolios, but fares poorly for the returns on regional size/B/M test asset portfolios. The average R^2 is 0.92 for the global portfolios, but it is lower (only 0.83) if North America is excluded. Among the five regional tests asset portfolios, the average R^2 reaches only as high of 0.72 for Europe and is as low as 0.32 for Japan. The GRS statistics for the Global portfolios (3.12 and 2.67, for Developed Markets only) are well into the right tail of the relevant *F*-distribution and the average absolute intercepts average 0.16% per month.

Part of the reason for the model rejections may arise from the poor explanatory power of the regressions, as we see that the GRS statistics for the Global portfolios excluding North America are much lower (1.27 overall, 1.58 for Developed Markets only). For the regional test asset

[40] Lewellen, Nagel, and Shanken (2011) recommend also reporting the GLS cross-sectional R^2 in second-pass regressions of average returns on beta loadings. It has the advantage of not only accounting for cross-correlation in residuals across test asset portfolios but also offering an interpretation as the distance from the minimum-variance boundary of the maximally-correlated combination of factor-mimicking portfolios.

portfolios, however, we have not only poor explanatory power, but also high GRS statistics beyond the 99th percentile of the *F*-distribution (except for Japan and the Emerging Markets). Another possible reason for the high model rejection rates is the presence of extremely small stocks. In a separate part of Panel A, we also present the same statistics for only the 4×5 global test asset portfolios, excluding the five in the smallest size quintile. There is modest improvement in average R^2 but the GRS statistics and their Sharpe ratio ($SR(\alpha)$) core components are much lower.

Panel B of Table 3.4 reports results for the regressions of the purely local factor model in explaining excess returns on just the five regional test asset portfolios. The local three-factor model works well in Japan and Europe. Despite the fact that the GRS tests reject North America and Asia Pacific at the 99th percentile of the *F*-distribution, the purely local factor model performs better than the purely global factor model in all experiments, pushing up the average R^2s and lowering the average absolute intercepts. The microcap stocks in North America are still a challenge for the models; the GRS statistic without them is only 1.57, but then it rises to 2.12 if microcap stocks are included, which would constitute a rejection at the 99% level. For Emerging Markets, the purely local factor model works well if only judged by the GRS test. However, without a presumption of integrated pricing in the region, the power loss is significant with an average R^2 of only 0.65. The poor performance of the purely local factor model makes it useless for an application for which the focus is on emerging markets.

To now, we have re-established several key inferences from Fama and French (2012) for the three-factor model. Panel C of Table 3.4 presents the results of the new hybrid version of the Fama-French three-factor model. Our hybrid model works distinctly better than the purely global factor model for global test asset portfolio experiments. All the average R^2s are over 0.89 or even

higher, with and without microcap stocks. The average absolute intercepts for all the four global test asset portfolios are 0.14% or less, without microcap stocks, and 0.15% or less, with microcap stocks included. The Sharpe ratios, $SR(\alpha)$, for the intercepts drop for all four of the experiments. Consider, for example, that for the Global portfolios, the GRS statistic falls from 3.12 for the purely global factor model to 1.55 for the hybrid model. Excluding the microcap stocks, the hybrid model achieves yet a smaller GRS statistic, 0.92, below the 90th percentile of the relevant F-distribution. In terms of the CSR R^2, the hybrid model reaches 0.46, higher than 0.21 for the global factor model. And when microcap stocks are excluded, it yields a much higher level of 0.67, compared with 0.20 for the purely global factor model.[41] For the Developed Markets portfolios, shifting to the hybrid model pushes the average R^2 from 0.90 up to 0.95 without microcap stocks and from 0.89 to 0.95 with microcap stocks. It also lowers the average absolute intercepts and the GRS statistics. Diagnostics shown only in Appendix Table 7 (available upon request) illustrates that the only two remaining statistically significant intercepts all fall within the set of the smallest five quintile portfolios.

The improved performance from the hybrid model is more notable when we turn to the regressions on the Global and Developed Markets test asset portfolios excluding North America. For the Global portfolios excluding North America, the hybrid model improves upon the performance of the global factor model in explaining the average excess returns, lifting the average R^2s from 0.83 to 0.90 without microcap stocks and from 0.83 to 0.89 with microcap stocks, shrinking the average absolute intercepts from 0.25% to 0.14% without microcap stocks and from 0.24% to 0.15% with microcap stocks. In addition, the GRS statistics fall to 0.81 without microcap stocks and 1.10 with microcap stocks, and neither of them leads to the

[41] We also apply the model comparison tests proposed by Kan, Robotti and Shanken (2012) and the results show that the hybrid model outperforms the purely global model at the 10% level when microcap stocks are excluded.

rejection of model at conventional cutoff criteria. The hybrid model produces an even greater improvement over the purely global factor model when it is challenged to explain the average returns on the Developed Markets portfolios excluding North America. When microcap stocks are dropped, the average R^2 rises from 0.78 for the global factor model to 0.94 for the hybrid model, the cross-sectional R^2 goes up from 0.36 to 0.61, the average absolute intercept drops from 0.35% to 0.07%, the Sharpe ratio falls from 0.38 to 0.29, and the GRS is only 0.76. Even with microcap stocks, the hybrid model still performs well, improving on the purely global factor model by any of the evaluation criteria. In sum, the hybrid model is quite successful in capturing average returns on global portfolios.

For the regional test asset portfolios, the hybrid model and the purely local factor model produce similar regression fits. In Europe, Asia Pacific, and Japan, the average absolute intercepts for the hybrid model are close to those for the purely local factor model, and there are no significant differences in terms of the Sharpe ratio and the GRS statistic. In the Emerging Markets test, however, the hybrid model works better than the purely local factor model in shrinking the average absolute intercepts. Without microcap stocks, the average absolute intercept for the purely local factor model is 0.42%, which is much higher than that for the hybrid model of 0.18%. With microcap stocks, if the purely local factor model is replaced by the hybrid model, the average absolute intercept falls by more than half, from 0.43% to 0.23% per month. The superior performance of the hybrid model in the Emerging Markets is likely due to the hybrid model's introduction of an important feature: the dependence of emerging markets on developed markets. Indeed, in Appendix Table 8 (available upon request), the betas for the test asset portfolios in the Emerging Markets on the market, size, and value factor portfolios for the globally-accessible set are economically large and usually statistically important. The only

exception is the North America experiment: the GRS statistics rise to 2.20 without microcap stocks and 2.66 with microcap stocks, both implying a rejection of the model. The poor performance is due to the first five years of our sample, 1991-1995. Given the somewhat slower pace of globalization during the earlier period, not only stocks from Europe were less correlated with stocks from North America, but also the correlation between Japanese stock markets and America stock markets was as low as just 15%. What appears to be the problem is the greater representation of large-cap stocks from four regions outside North America in the globally-accessible sample, which adversely affects the performance of the global market factor in the hybrid model (Appendix Table 8). When the first five years are excluded, the hybrid model works as well as the purely local factor model in the North America experiments.[42]

3.5.2 Robustness Checks

We further test the reliability of the hybrid model by carrying out two rounds of robustness checks. We first check the hybrid versions of the Fama-French three-factor model which are built on other definitions of the globally-accessible sample according to the viability criteria. A second round of tests involves time-series regressions to see whether the inclusion of the Frankfurt Stock Exchange and non-Nasdaq OTC market – and especially its unusually large number of unsponsored secondary foreign listings, respectively, in their unregulated and OTCQX International segments - in the list of target exchanges for the globally-accessible sample changes the results.

Table 3.5 summarizes regressions to explain excess returns on size/B/M portfolios when the

[42] Another solution we investigated for the North American experiment was to construct three sets of factors in the hybrid model: globally-accessible stocks from outside the U.S. only, globally-accessible stocks from the U.S. only and then the locally-accessible stocks from U.S. In this case, the GRS statistic was 1.35 without microcap stocks and 2.14 with microcap stocks.

Main CL Sample is replaced by threealternative definitions of the globally-accessible set of stocks.[43] We first disregard the so-called viability constraints altogether and start with the largest globally accessible sample, denoted CL1. Recall that this sample represents 91% of the global market capitalization, so we expect this experiment is most likely to inhibit the performance of the hybrid model relative to the local models for regional experiments. Panel B of Table 3.5 shows that for all four global test asset portfolios, the tight regression fits affirm that the hybrid model is economically meaningful, and the GRS test indicates that using CL1 for the hybrid model works as well as using the Main CL Sample. Taking the Global portfolios as an example, the GRS statistic is 1.14 for the hybrid model built on CL1, slightly higher than 0.92 for that built on the Main CL Sample. However, the benefit of using CL1 in the global experiments comes at the cost of the relatively poorer regression fits for the regional test asset portfolios, especially those for North America and Europe. For the North America test, the hybrid model produces a larger average absolute intercept of 0.21% compared to only 0.13% with the Main CL Sample. In Europe, the GRS statistic rises as high as 1.76. The problems (witnessed by higher GRS statistics, higher average absolute intercepts, and larger Sharpe ratios) result from the depleted local factors in the two regions which include many fewer stocks than before. The purely-local samples in North America or Europe in this CL1 sample accounts for less than 10% of total market capitalization of the region.

Panel C of Table 3.5 reports the results for the hybrid model built on what we call "CL2a." Changing from *relative* viability constraints (at least 0.1% of global trading volume occurs in target markets *or* at least 0.5% of total trading value in target markets relative to all secondarily cross-listed stocks from the same country trading there) to an *absolute* viability constraint (at

[43] Table 5 illustrates only the case when microcap stocks are excluded, but all results are available.

least one month in a given year with non-zero trading volume in a target cross-listing market) on the cross-listing does not affect the performance of the hybrid model in explaining the average returns for global test asset portfolios and most of the regional test asset portfolios. The North America sample is the only exception in which the hybrid model now has a power problem, possibly because the absolute viability constraint breaks the consistency of our time-series explanatory returns. Some companies are identified as local stocks when there are no overseas trading records but as globally-accessible stocks when trading actually occurs in the target markets. Allowing these companies to switch between the two samples at a relatively high frequency may alter the profile of the returns of the explanatory factor portfolios. Panel D of Table 3.5 reports the regression results when CL2b is used. The more stringent relative viability constraints (above 1% of own-stock global trading volume in target markets *or* above 5% of all secondary cross-listing trading by country) shrink the globally accessible sample down to account for 62% of the total market capitalization for the global equity universe. The new CL2b performs similarly to the Main CL sample in the regional and global experiments.[44]

Given the looser secondary cross-listing rules on the Frankfurt Stock Exchange and OTCQX International, we repeat the experiments above for the case where these two markets are excluded from the list of target exchanges. Our results are not driven by their inclusion. To save space, the regression results are only shown in Appendix Table 9 (available upon request). When no viability constraints are imposed on this globally-accessible sample, the hybrid model provides good descriptions for our four global test asset portfolios. The GRS statistics are not higher than 1.17 without microcap stocks and not higher than 2.06 with microcap stocks. When the globally-accessible sample is screened by our relative viability constraints based on target

[44] In the Kan, Robotti, and Shanken (2012) model comparison tests (unreported), the hybrid model is the only model that is never statistically dominated in any of our analyses of Table 5.It outperforms the purely global model and the purely local model, respectively at the 5% and 10% levels, with a variety of portfolios employed as test assets.

markets other than Germany and OTCQX International, the hybrid model performs better than the purely global factor model for the global test asset portfolios, and works as well as the purely local factor model for most of the regional test asset portfolios. On the other hand, the hybrid model still fares poorly in North America. The early years of the sample appear to be the problem once again. In the Main CL sample, the GRS statistics increase to 2.47. If only focusing on the period of 1995-2010, the GRS statistics decline to 1.46.

With different adjustments on the viability constraints for cross-listed stocks, the hybrid model appears quite resilient in explaining the average returns in the global and regional test asset portfolios. But one open question is how robust our hybrid model is to the size, liquidity and float screens that we apply for the stocks in the seven target markets to qualify them as globally-accessible. After all, those stocks that are secondarily cross-listed in a target market may simply be those that meet those screens in their respective markets and so the extra criterion of cross-listing may be redundant. In this additional test, we redefine the globally-accessible set of stocks around the world to be those that meet the same size, liquidity and float screens as for the stocks in the target markets.[45] The new globally-accessible sample, when compared with the Main CL sample, has smaller counts but similar market capitalizations across five regions. However, the hybrid model built from this new sample, unlike that for the Main CL Sample, makes little or no improvement relative to the global model for the global test asset portfolios, especially where the focus is on Developed Markets. Consider, for instance, the case without microcap stocks for the Developed Markets portfolios, the average absolute intercept increases from 0.07% to 0.12%, the Sharpe ratio for the intercept goes up from 0.35 to 0.42, and the GRS statistic rises from 1.12 to 1.64. For the Developed Markets portfolios excluding North America, the average absolute

[45] The distribution of free floats varies substantially across countries outside the seven target markets. If using a universal float screening, there will be few or even no stocks selected for many countries as globally accessible stocks. Therefore, the median float (75% for U.S. and equivalent levels for other markets) is applied in this case.

intercept doubles from 0.07% to 0.15%, the Sharpe ratio from 0.28 to 0.42, and the GRS statistic from 0.76 to 1.65. In the regional experiment for North America, a hybrid model using this new globally-accessible sample fails to improve relative to the local factor model, instead pushing the GRS statistics up to 2.46, without microcap stocks, and as high as 2.84 when microcap stocks are included.

We acknowledge that there exist some data issues for this alternative globally-accessible sample. Less than half of stocks from markets outside the seven target exchanges have float records in Datastream, and those stocks are automatically dropped out of the globally-accessible sample. But we take from this that identifying those stocks that are secondarily cross-listed on one of the target markets likely furnishes a more complete assessment of the investability of stocks, especially for those from emerging markets.

In sum, the hybrid model not only captures strong common variation in global and regional stock returns, but also brings low pricing errors and rejection rates for a variety of regional and global test asset portfolios. Compared with the purely global factor model for global test asset portfolios, the hybrid model always achieves better performance: the explanatory power increases up to 0.89 or even higher, average absolute pricing errors have reduced to 0.14% or even lower, the GRS statistics are not rejected at the 90% level when microcap stocks are excluded. Compared with the purely local factor model for regional test asset portfolios, the hybrid model brings neither larger pricing errors nor higher model rejection rates, and it performs even better for Emerging Market test asset portfolios.

3.6 Some More Robustness Tests

3.6.1 Time-series Regression Tests for Size/Momentum Portfolios

Table 3.6 summarizes asset pricing tests in which the Carhart four-factor model is applied to explain excess returns on 4×5 size/momentum portfolios. The Fama-French three-factor model generally works poorly in such an experiment in terms of regression fit and GRS statistic (Fama and French, 2012, see their Tables 6 and 7). So, we turn to the Carhart four-factor model to build our hybrid model. The results are presented on the left side of the three panels in the table.

There are power problems with the global Carhart four-factor model for the global test asset portfolios. Reasonable performance is only achieved in the Global portfolio tests (all reported tests have microcap stocks removed): the average R^2 is 0.92, the average absolute intercept is 0.12%, the CSR R^2 is below 0.20, and the GRS statistic is 1.89, which is below the 99th percentile threshold. For the three other global test asset portfolios, the global four-factor factor model fares poorly, producing higher GRS statistics and large average absolute intercepts. For instance, for the Developed Markets portfolios, the GRS statistic is 2.05, which exceeds the 99th threshold of the F-distribution,. The test on the Developed Markets portfolios excluding North America has a relatively lower GRS statistic of 1.42, but this result is hampered by low power. As with earlier results on size/B/M portfolios, the global factor model fares poorly for the regional portfolio returns. By contrast, the local Carhart four-factor model is reasonable for applications in the regional test asset portfolios for North America and Japan. The regressions on Europe, Asia Pacific, and the Emerging Markets are relatively disappointing: the GRS test rejects the purely local factor model in these three regions.

The experiment for size/momentum portfolios produces the most disappointing results among all

asset pricing tests for the global or purely local versions of the Carhart model. But, even with this challenge, the hybrid model fares reasonably well. For the Global portfolios, the hybrid model and the global factor model perform similarly. Each of the test statistics are similar except the CSR R^2 which are notably higher for the hybrid model, but not statistically so by the Kan, Robotti, and Shanken (2012) tests. In the three other global test asset portfolios, the hybrid model better captures the returns than the global factor model. Using the Developed Markets portfolios excluding North America as an example, we see the regression fit improves from 0.77 for the global factor model to 0.94 for the hybrid model. The average absolute intercepts fall from 0.32% to 0.12% and the CSR R^2 jumps from 0.11 to 0.52, a statistically significant difference at 10%by the Kan, Robotti, and Shanken (2012) tests.

In the regional tests, the hybrid model produces high GRS statistics in Europe (2.91), Asia Pacific (2.12), and Emerging Markets (1.51), but these are all similar to the results for the purely local factor model. The regression fits and the average absolute intercepts are also close. As we discussed earlier, the relatively poor performance of the hybrid model in the North America experiment stems from the first five years of the sample, similar to the case with size/B/M test asset portfolios. The improvement of the hybrid model over the purely local factor model arises in the Emerging Markets test asset portfolios: the average absolute intercepts decline from 0.60% to 0.32%.

Echoing previous robustness checks on size/B/M portfolios, we use three other globally accessible samples to reconstruct the explanatory factor returns and get supporting evidence on the resilience of the hybrid model (all shown in Appendix Table 10). Among all four cross-listed samples, CL2a (which includes stocks with non-zero target market trading during the year) produces the lowest model rejection rates for all four global test asset portfolios. Compared with

the Main CL Sample in the regional experiments, CL2a improves the performance of the hybrid model in North America and Europe. For example, it shrinks the Sharpe ratio from 0.56 to 0.46 and the GRS statistic from 2.91 to 1.91 in the Europe experiment. In tests of other regions, the performance of CL2b (with more stringent viability constraints on the cross-listed stocks) comes close to those of the Main CL Sample. In addition, we are interested in whether the performance of the hybrid model is influenced by the inclusion of the unsponsored secondary foreign listings. Appendix Table 11 reports the regression results when the Frankfurt Stock Exchange and non-Nasdaq OTC markets are dropped from the list of target exchanges. The results are quantitatively similar to those reported in Table 3.6.

Preliminary results show that a hybrid version of the HKK (2011) three-factor model performs reasonably well for size/momentum portfolios.[46] We compare the Carhart four-factor model and the extended version of the HKK (2011) three-factor model in which an SMB factor in Fama and French (2012) is added; the key difference is that the value-based factor is constructed from C/P instead of B/M as a firm characteristic. The HKK (2011) extended four-factor model performs similarly to the Carhart four-factor model in explaining the average returns on the global and regional portfolios. Like the global Carhart four-factor model, the global HKK (2011) extended four-factor model works well for the Global portfolios: the average R^2 is 0.92, the average absolute intercept is 0.13%, and the GRS statistic is 1.88 (reported in Appendix Table 12). As before, for the three other global test asset portfolios, the global HKK (2011) extended four-factor model produces low power and large average absolute intercepts. In the regional scenarios, the local HKK (2011) extended four-factor model works well for North America and

[46] HKK (2011) propose and test a three-factor model that includes the C/P and momentum factors in addition to the global market portfolios and that produces the lowest pricing errors among various multifactor models in regressions for country, industry, and characteristic-sorted portfolios: $R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + c_i F_{C/P,t} + m_i F_{Mom,t} + \varepsilon_{i,t}$ substitutes for Eqn. (1).

Japan, but suffers loss of power and higher model rejection rates for Europe, Asia Pacific, and Emerging Markets. On the other hand, the hybrid version of the HKK (2011) extended four-factor model increases the average R^2 up to 88% and shrinks the average absolute intercepts down to less than 0.24% in the global tests, and it does not fare worse than the local version in the regional test asset portfolios.

We repeat previous robustness checks on size/momentum portfolios, including trying several alternative definitions of global accessibility and dropping the unsponsored cross-listed stocks on the Frankfurt Stock Exchange and OTCQX International. Once again, we uncover supporting evidence for the hybrid model. For the sake the brevity, regression results are provided in Appendix Tables 12 and 13.

3.6.2 Time-series Regression Tests for Size/C/P Portfolios

Table 3.6 also provides the regressions of the HKK (2011) extended four-factor model in explaining excess returns on 4×5 size/C/P portfolios. These are presented on the right hand side of the three panels in the table. As in Fama and French (2012), there is a size pattern in the average value premium in the sorts on C/P, but it is somewhat weaker than the sorts on B/M. For example, if the global HKK (2011) extended four-factor model is used in the test of the Global portfolios, the GRS statistics are 1.75 for the 4×5 portfolios.

Panel C of Table 3.6 indicates that the hybrid model similarly improves the regression fit of the global factor model for size/C/P test assets. Moreover, the average absolute intercepts drop to at or below 0.15%, the CSR R^2 all exceed 0.50, and the GRS statistics are all below 1.34. At the same time, the regressions of the hybrid model show uneven improvement relative to those of the

purely local factor model for the regional test asset portfolios. For example, if the purely local factor model is replaced by the hybrid model, the average absolute intercepts decrease significantly from 0.62% to 0.21% for the Emerging Markets and the CSR R^2 increase from 0.35 to 0.61. In the Europe test, however, the hybrid model fares worse than the purely local factor model. The average absolute intercept rises from 0.10% in the purely local factor model to 0.13% in the hybrid model. Despite that, the GRS test is not rejected if evaluated at the 95th percentile of the F-distribution. As before, the hybrid model suffers in the North American experiment because of the first five years.

We perform three more robustness checks with the size/C/P test asset portfolios (as reported in Appendix Tables 14 through 17). We first try alternative definitions for the globally-accessible sample for the Carhart four-factor model; there are measurable benefits to extend the global factor model to the hybrid model in most experiments. Second, we drop the cross-listed stocks from the Frankfurt Stock Exchange and OTCQX International and repeat the tests. Excluding them does not change the results. We also find that the hybrid model maintains its good performance when the global factors and local factors are adjusted by different viability constraints and size considerations. Finally, we implement the same tests for the HKK (2011) extended four-factor model. The results are quantitatively similar to those in Table 3.6. To conserve space, we report these results in Appendix Table 16. Our test does not permit us to adequately distinguish the Carhart four-factor model and the HKK (2011) extended four-factor model when it comes to explaining the size/C/P portfolios. The HKK (2011) model is another reasonable choice for applications in international asset pricing.

3.6.3 Time-series Regression Tests for Expanded Test Assets

Following a key prescription of Lewellen, Nagel, and Shanken (2010), Table 3.7 reports regressions employed on two expanded sets of test assets. Instead of using only 5×5 size/B/M portfolios (now with microcaps included), we augment them with 10 industry portfolios, which are constructed by using the FTSE/Dow Jones Industry Classification Benchmark (Level 1 Industrial Classification in Datastream) for the specific region for which the test is performed. These tests are shown on the left hand side of the panels. Another set of test assets we build are just 33 industry portfolios based on the Level 4 FTSE/Dow Jones Industry Classification Benchmark. These are shown on the right hand side of the three panels in the table.

The first thing to note is that adding industry portfolios worsens the performance of all the models, in terms of the regression fit, the average absolute intercepts, and the GRS statistics. But our choice of industry portfolios is based on the notion that they should provide a higher hurdle for the proposed model. And the superior performance of the hybrid model is a fairly robust empirical finding even in these new experiments. Specifically, for the 33 industry portfolios, the average absolute intercepts in the four sets of global portfolios are 0.16%, 0.16%, 0.19%, and 0.22%, respectively, for the hybrid model, whereas the global factor model gets higher levels of 0.27%, 0.28%, 0.30%, and 0.32%. The CSR R^2 more than double from around 0.15 for the global models in the 5×5 Size/B/M plus 10 industry portfolios to around 0.25 for the hybrid model. The magnitude of the improvement in CSR R^2 is even greater for the 33 Industry portfolios. With the 33 Industry portfolios in the five regional experiments, we see a notable jump in the CSR R^2 in Europe and the Asia Pacific. But in terms of the average absolute intercepts, the biggest improvement of the hybrid model over the local factor model still arises in the Emerging Markets among the regional experiments.

3.6.4 Time-series Regression Tests for Additional Portfolios and Individual Securities

In this section, we first build global test-asset portfolios that include just globally accessible stocks. Intuitively, we expect many global asset managers would impose such accessibility constraints to define their investment universe. In this setting, we further expect the traditional global factor model is most likely to succeed, so we propose a test to compare the ability of the traditional global factor and our new global factor model, in which the factor portfolios are built only from the globally accessible stocks, to explain the portfolio returns. Here, we mainly check the experiments on the Global portfolios and the Developed Markets portfolios.[47]

When compared to the traditional global factor model, the new global factor model yields lower average absolute intercepts, lower Sharpe ratios, smaller GRS statistics and higher R^2s. The results hold for all three sets of 5×5 test asset portfolios sorted on size/B/M, size/momentum, and size/C/P. Taking the size/B/M Developed Markets portfolios as an example, we find the average absolute intercept falls from 0.23% for the traditional global factor model to 0.12% for the new global factor model. In terms of SR(a), the new global factor model produces smaller values: 0.36 compared to 0.48 for the traditional global factor model. Accompanied with similar or even tighter regression fits, the GRS statistics drop from 2.36 for the traditional global factor model to 1.33 for the new global factor model. We cannot reject at the 90% level. The complete set of regression results is available in Appendix Tables 18.

We next move to supplementary tests using regressions on individual stocks to assess the explanatory powers of the local factor model and the hybrid model for their returns. Each month, beginning with November 1990, individual security regressions are estimated over 180 rolling 60-month periods. The last period ends in December 2010. In all regions, the hybrid Fama-

[47] If North America is excluded in the global test asset portfolios, there are only 2,333 stocks for the Developed Markets portfolios excluding North America and around 3,100 stocks for the Global portfolios excluding North America. Technically, the numbers of stocks are insufficient to construct portfolios.

French three-factor models achieve statistically significant increases in the average adjusted R^2. The incremental R^2s account for, on average over time, 11.73%, 8.39%, 6.76%, 2.58%, and 17.04% of the R^2s by the corresponding local models in the North America, Europe, Asia Pacific, Japan, and Emerging Markets tests. Furthermore, we decompose our hybrid model in order to evaluate the incremental R^2 from adding the global factors to the local factors. The global factors in the hybrid model increase the average adjusted R^2 by 2.29%, 1.22%, 1.00%, 0.81%, and 2.22% in North America, Europe, Asia Pacific, Japan, and Emerging Markets, respectively. The increase in the average adjusted R^2 due to the addition of global factors can be expressed relative to the total average adjusted R^2 for the hybrid model. The proportion of the explained variance attributable to global factors is 15.03%, 6.84%, 5.07%, 2.29%, and 15.03% in North America, Europe, Asia Pacific, Japan, and Emerging Markets, respectively, indicating the importance of global factors in the hybrid model.

One concern is that much of the success of the hybrid model is mechanical in that additional three (or four) factors are built over and above the base three (or four) factors in the global and local models. Most test statistics (such as, GRS and CSR R^2) for our model comparisons account for this fact in terms of different degrees of freedom, but they may still be inadequate in finite samples. To take on this challenge in another experiment we compare the hybrid model against a competing model in which local factors are constructed not based on fundamental factors such as size, B/M, C/P, or Momentum, but using principal component analysis (PCA). These factors are purely statistical and are designed to maximally capture the common variation among the stocks. To this end, we first orthogonalize all the stock returns for the specific region for which the test is performed relative to the global factors of the globally-accessible set. We next identify up to three principal components of the residuals and build local factor portfolios as determined

by the extracted principal factors, using portfolio weights given by the scaled eigenvectors.

Table 3.8 presents the results for the 4×5 Size/B/M test asset portfolios for each of the global and regional experiments. Our findings suggest that it is very hard, using the PCA local factors in addition to the global factors, to explain the common variation in returns as well as using the hybrid model by any of the evaluation criteria. For example, the average R^2s in North America, Europe, Asia Pacific, Japan, and Emerging Markets are 0.74, 0.77, 0.67, 0.76, and 0.60, respectively, for the PCA-based alternative model, compared with those of 0.90, 0.90, 0.81, 0.92, and 0.68 for the hybrid model. The GRS statistics and the average absolute intercepts are notably higher for the PCA-based alternative model and the CSR R^2 are much lower, in turn, among the global experiments.

3.6.5 Disaggregating Emerging Markets and Europe

Given the comparatively strong performance of the hybrid model in Emerging Markets, Panel A in Table 3.9 tries to pin down the improvement more precisely into three sub-areas by region of the world: Europe, the Middle East and Africa (EMEA), Latin America, and Southeast Asia. After all, there is considerable heterogeneity among countries that constitute Emerging Markets, which means that a "local" model may not be a fair benchmark against which to show improvement for our hybrid model.

The hybrid version of the Fama-French model dominates the equivalent global factor model in each of the three sub-areas with lower GRS statistics, lower average absolute intercepts, higher time-series and CSR R^2. In the comparisons between the local factor model and the hybrid model by sub-area, the differences are less clear. There is a notable decrease in the GRS statistics in the

EMEA region as well as in the average absolute intercepts: the average absolute intercepts shrink from 0.71% to 0.30%. In the test on Latin America the hybrid model furnishes similar GRS statistics and intercepts, but the CSR R^2 increases substantially from 0.17 to 0.44. The model comparisons for Southeast Asia yield almost equivalent results.

A similar argument about the heterogeneity of countries can be made in Europe in which global integration may have been facilitated by the introduction of a common currency among a subset of its members (Hardouvelis, Malliaropulos, and Priestley, 2006; Bekaert, Harvey, Lundblad, and Siegel, 2012). A logical question is whether our hybrid model can improve upon a local model redefined in Europe separately only among the original 11 members of the Euro bloc and only among those that remained outside the currency bloc. Panel B of Table 3.9 provides evidence using the Fama-French three-factor model and even distinguishes between the original Eurozone members before and after January 1999 when the new currency was launched.

Several observations emerge. First, the global factor model delivers relatively poor regression fit compared to the local and hybrid models. This obtains not only for the non-Eurozone members, but also those countries in the Euro bloc. Interestingly, among the Euro bloc countries, the global models experience a large decline in the GRS statistics and an increase in the time-series R^2. Second, we see considerable advantages using the hybrid model over the local model for the whole sample period and especially after January 1999 for the original Eurozone members. Specifically, the average absolute intercepts decrease from 0.18% for the local factor model to 0.11% for the hybrid model, the Sharpe ratio for the intercepts goes down from 0.45 to 0.32, and the GRS statistics drop sharply from 1.21 to 0.50. The hybrid model shows in a preliminary way some flexibility over a purely global and purely local model as it allows for an evolving role of financial globalization.

3.7 Conclusions

Using monthly returns for over 37,000 stocks from 46 developed and emerging market countries over a two-decade period, we test whether empirical asset pricing models capture the size, value, and momentum patterns in international stock returns. We specifically propose and test a new multi-factor model that includes factor portfolios based on firm characteristics and that builds separate factors comprised of globally-accessible stocks, which we call "global factors," and of locally-accessible stocks, which we call "local factors." Our new "hybrid" multi-factor model with both global and local factors not only captures strong common variation in global stock returns, but also achieves low pricing errors and rejection rates using conventional testing procedures for a variety of regional and global test asset portfolios formed on size, value, and momentum.

A critical ingredient of our analysis is how we categorize the equity universe into two subsets - the globally-accessible sample and purely-local sample of stocks – based on constraints as defined by whether or not the stock has shares actively traded in the markets fully open to global investors. To capture the impact of investability constraints on the size, value, and momentum patterns in international stock returns, we then build *separate* factor portfolios – global factors comprised of stocks only in the globally-accessible sample, and local factors comprised of the purely-local stocks from the specific region for which the test is perform – and propose a new "hybrid" multifactor model. We find that neither a purely global factor model nor a purely local factor model can work as well as the new "hybrid" when asked to explain average returns on global and regional size/value and size/momentum portfolios. The new "hybrid" model does not encounter the problems of the purely global factor models, such as high rates of rejections with

GRS tests and large average absolute intercepts. Rather, it improves the regression fit and reduces the pricing errors, with or without microcap stocks. And, at the same time, the new "hybrid" model fares reasonably relative to a purely local factor model, and works even better for emerging markets, in terms of explanatory power, model pricing errors and rejection rates. The robustness of the new "hybrid" model is confirmed by tests conducted with a variety of definitions of global accessibility, other double-sorted test portfolios, and other asset pricing models.

We interpret our findings in this study as a step forward in the international asset pricing literature with important implications for practitioners in guiding cost-of-capital calculations and risk control and performance evaluation analysis of global portfolios. Of course, we acknowledge several limitations in the scope of our work as well as in the implementation. There may be alternative ways in which stocks become globally accessible beyond secondarily cross-listing on overseas exchanges that we have not considered. Including other mechanisms for global investor accessibility, such as being included in one of MSCI or S&P global indexes (especially, in their investable indices in emerging markets), emerging market ETFs and closed-end country funds, would be valuable to explore how the returns of global factor portfolios have changed over time. We also cannot disregard the fact that simply being accessible does not necessarily mean global investors will actually pursue these opportunities. Although this fact is taken into consideration to a certain extent by imposing additional viability restrictions on how actively the cross-listed shares are traded in our experiments, a more comprehensive picture of institutional trading around the world would reveal the varying preferences and constraints face by different groups of institutional investors. One would also hope for a more reliable proxy for the measure of viability consideration than the relative (and absolute) criteria in this study. Third,

one could criticize our reliance on conventional test procedures, which is necessarily limiting. Finally, it also remains to be seen whether the new proposed "hybrid" model works for country, industry, and other characteristic-sorted test asset portfolios, as evaluated in HKK (2011).

There are also other possible avenues for future work. We can study the effect of exchange rate risks on the relative performance of global factors and local factors in the new "hybrid" model. All of our returns are U.S. dollar denominated at prevailing exchange rates. Because what constitutes globally-accessible stocks and purely-local stocks vary for investors by country of domicile, the need to hedge exchange rates varies and exchange rate risks are expected to play different roles in the risk prices of global factors and local factors. Exchange rate risk is certainly a potential problem in global asset pricing. A key contribution of Solnik's (1974) influential international asset pricing model is that currency risk can be priced and there is also growing evidence that the magnitude of currency-risk exposures can be quite large (Dumas and Solnik, 1995; De Santis and Gerard, 1997, 1998; Griffin and Stulz, 2001). Second, we can push the new "hybrid" structure to incorporate cross-sectional variation in real estate, commodities and bonds, which comprise a significant portion of global investment activity. Third, we can extend our unconditional testing framework for the hybrid model to a conditional one allowing for time variation in expected returns, variances and covariances, a potentially important factor for the transitioning emerging markets (Bekaert and Harvey, 1995; Bekaert, Harvey, Lundblad, and Siegel, 2011) for which our hybrid model performs especially well.

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Figure 3.1

Global Equity Universe, reported by Total Market Capitalization, 1990-2010

The figure shows the distribution of the global equity universe by region. Beside each region name is the time series average market capitalization from that region that qualifies for analysis, which is in U.S. dollars trillion, and its percentage of global market capitalization. The sample selection criteria are described in Table 3.1.

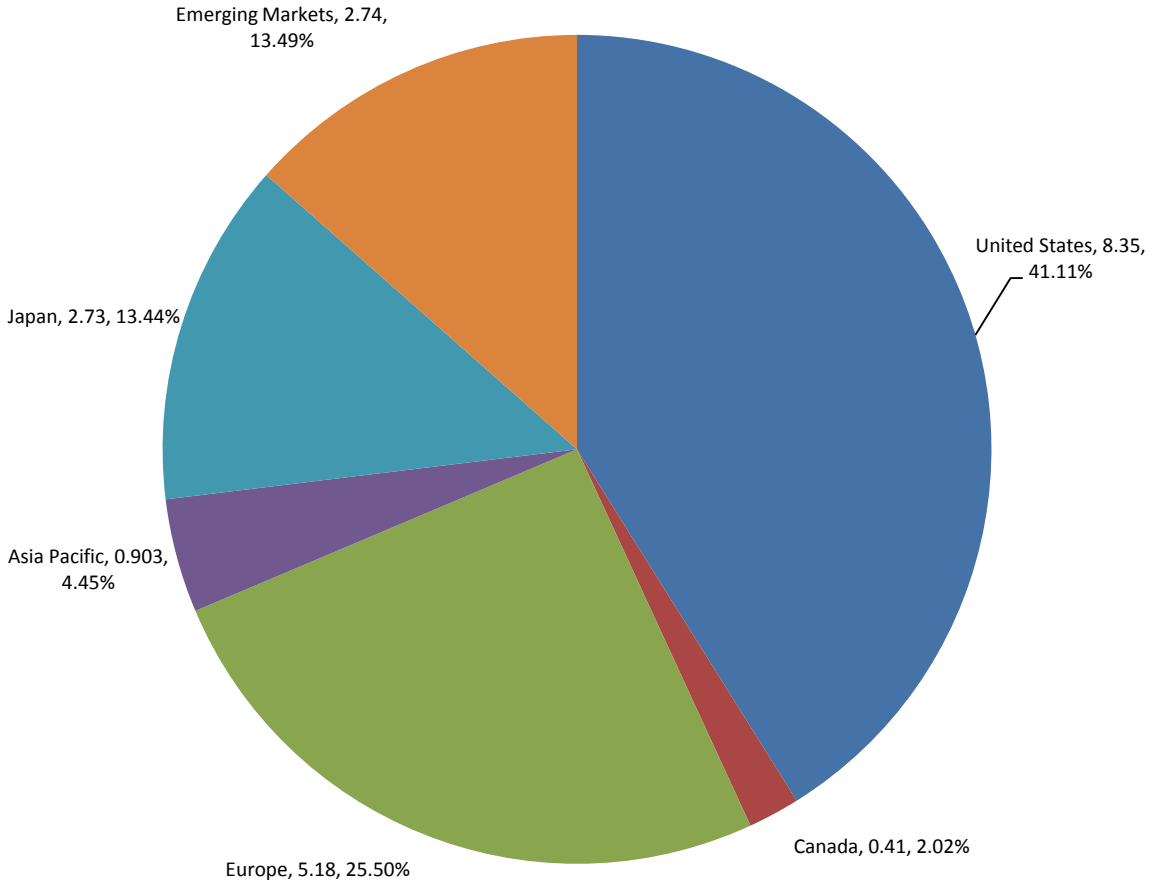
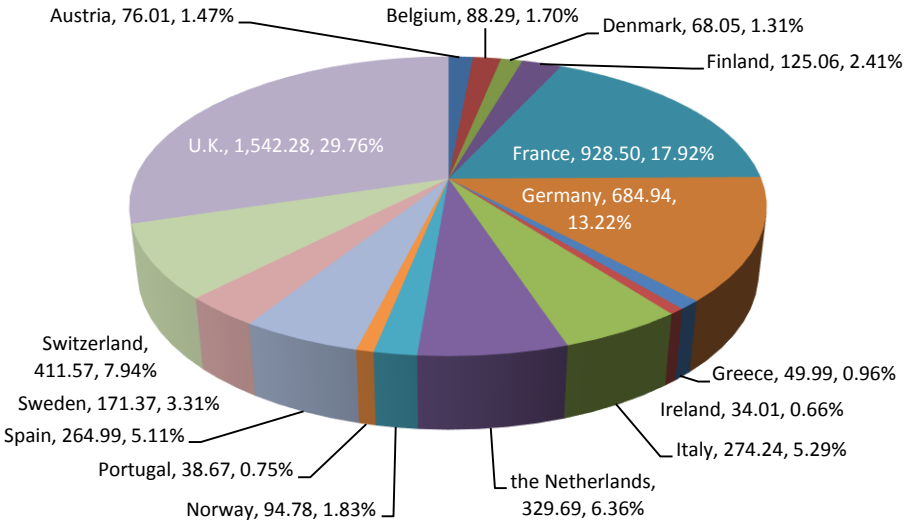
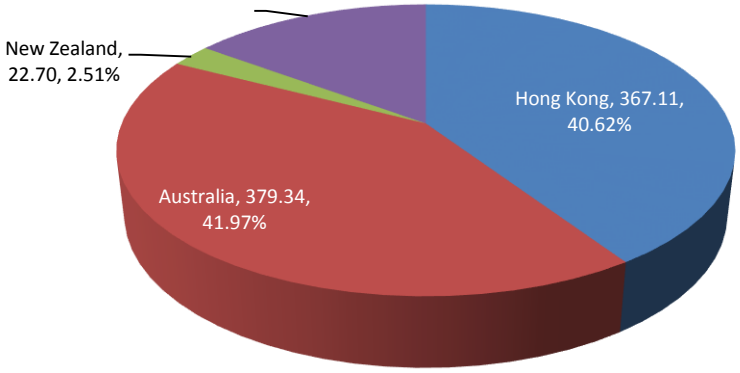


Figure 3.1, continued

Global Equity Universe, reported by Total Market Capitalization, 1990-2010

The figures show the distributions of Europe, Asia Pacific and Emerging Markets equity universes by country. Beside each country name is the average market capitalization from that country, which is in U.S. dollars billion, and the percentage of regional market capitalization. The sample selection criteria are described in Table 3.1.





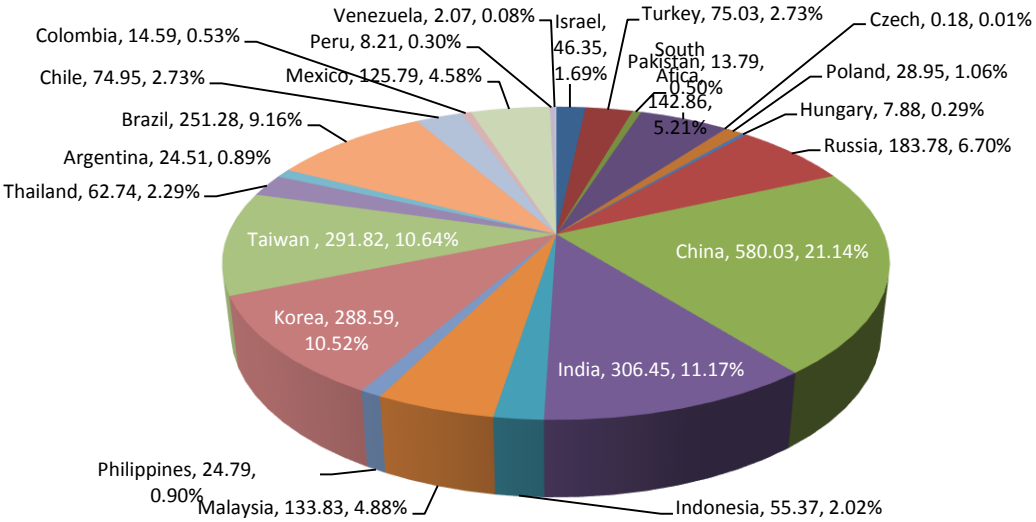


Figure 3.2

Global Equity Universe, reported by Total Number of Stocks, 1990-2010

The figure shows the distribution of the global equity universe by region. Beside each region name is the total number of sample stocks from that region that qualifies for analysis and the percentage of the total number that this count represents. The sample selection criteria are described in Table 3.1.

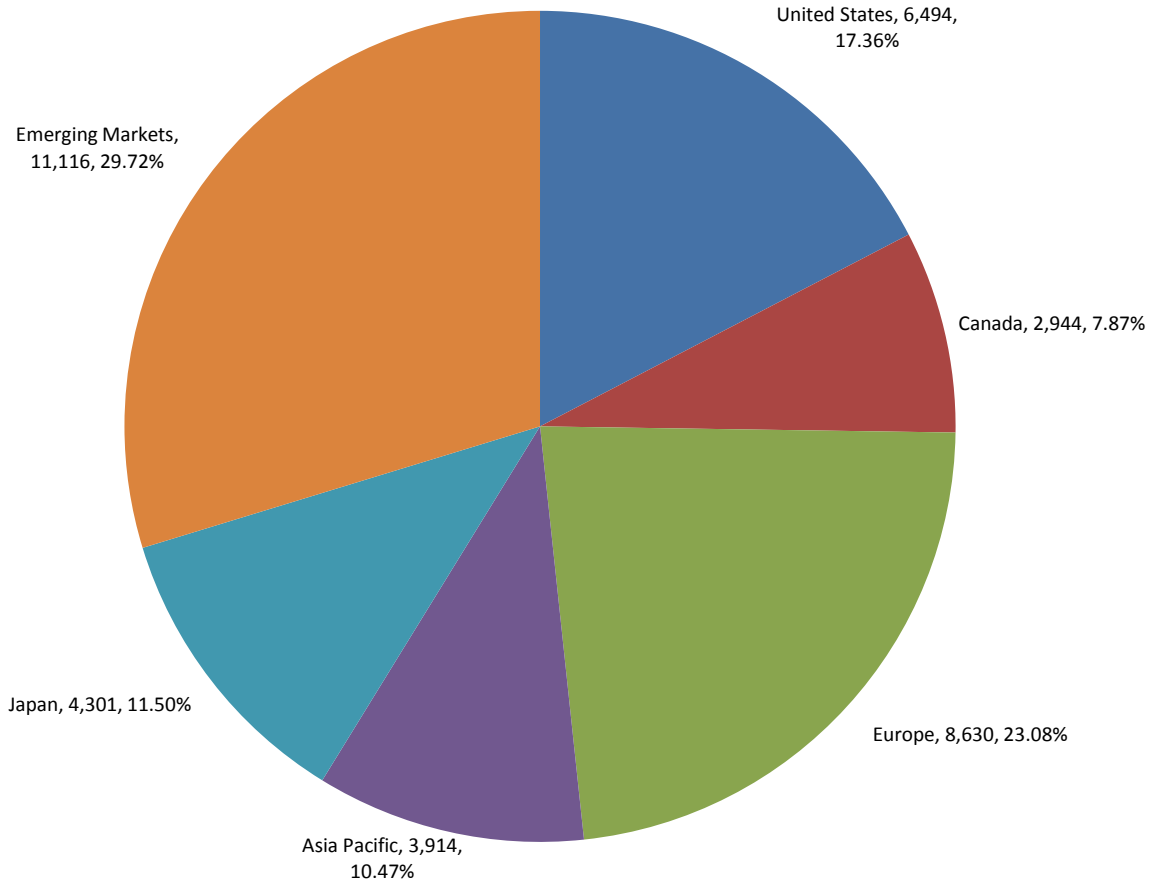
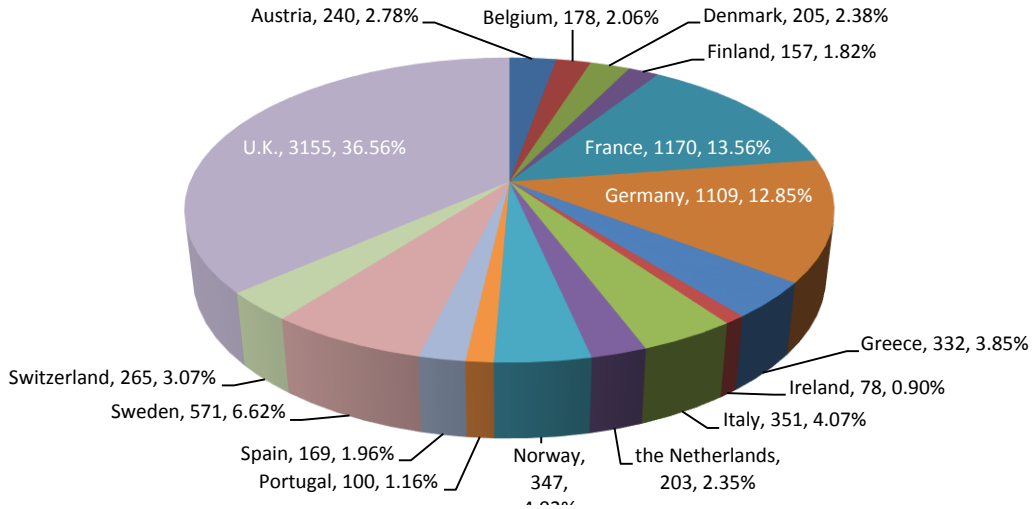
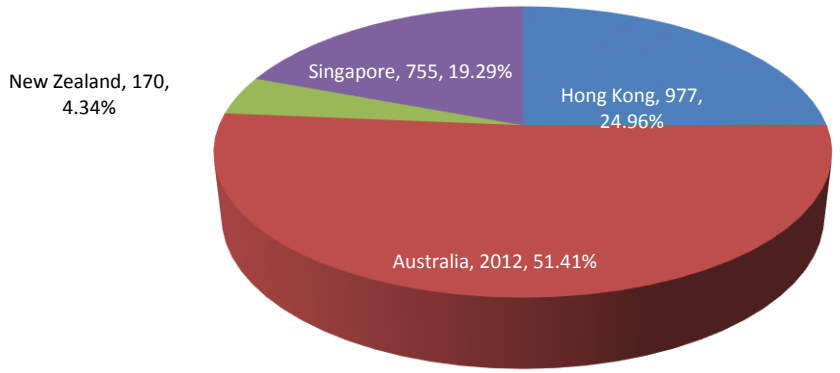


Figure 3.2, continued

Global Equity Universe, reported by Total Number of Stocks, 1990-2010

The figures show the distributions of Europe, Asia Pacific and Emerging Markets equity universes by region. Beside each country name is the total number of sample stocks from that country that qualifies for analysis and the percentage of the total number that this count represents. The sample selection criteria are described in Table 3.1.





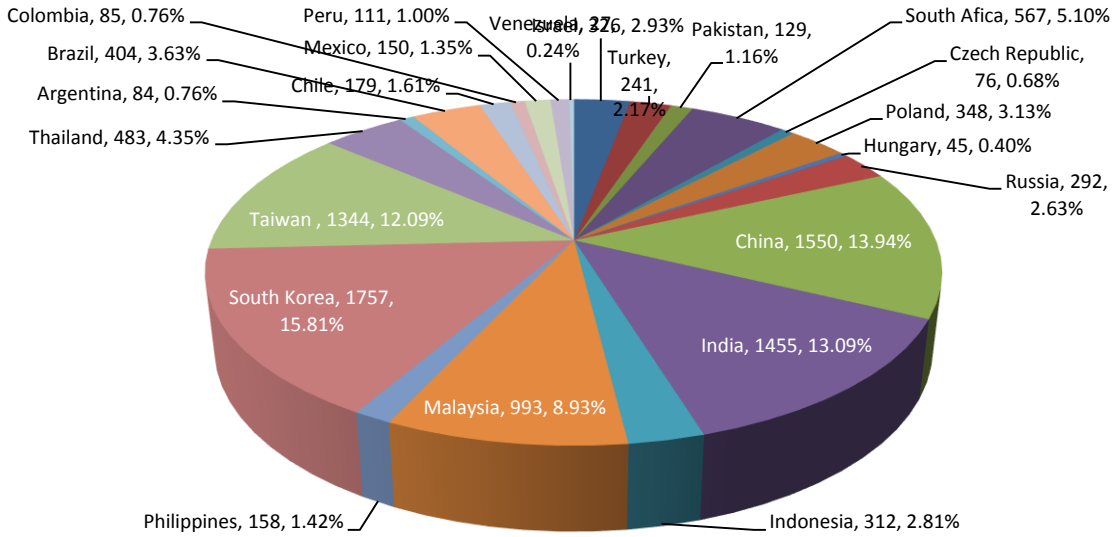
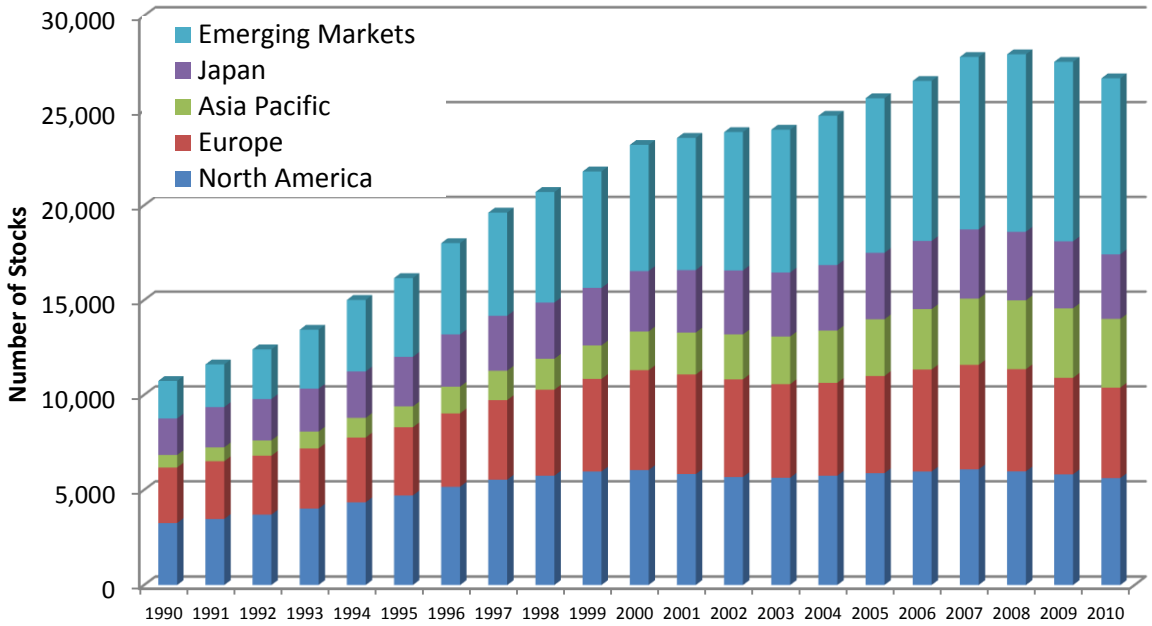


Figure 3.3

Global Equity Universe by Year, reported by Total Number of Stocks (above) and by Market Capitalization (below), 1990-2010

The figures show the distribution of our sample stocks from each region by year. The sample selection criteria are described in Table 3.1.



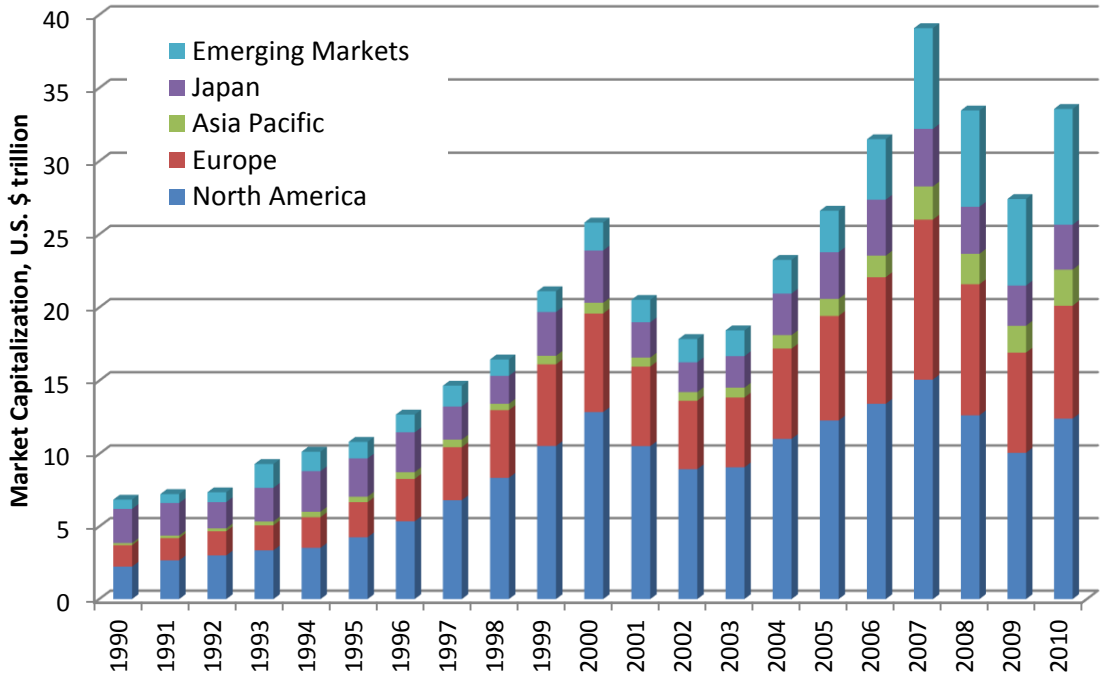


Figure 3.4

Globally Accessible Sample, reported by Total Market Capitalization, 1990-2010

The figure shows the distribution of the globally accessible sample by region. Beside each region name is the average market capitalization from that region, which is in U.S. dollars trillion, and its percentage of market capitalization. Here the sample is represented by the Main CL Sample and the sample selection criteria are described in the Appendix.

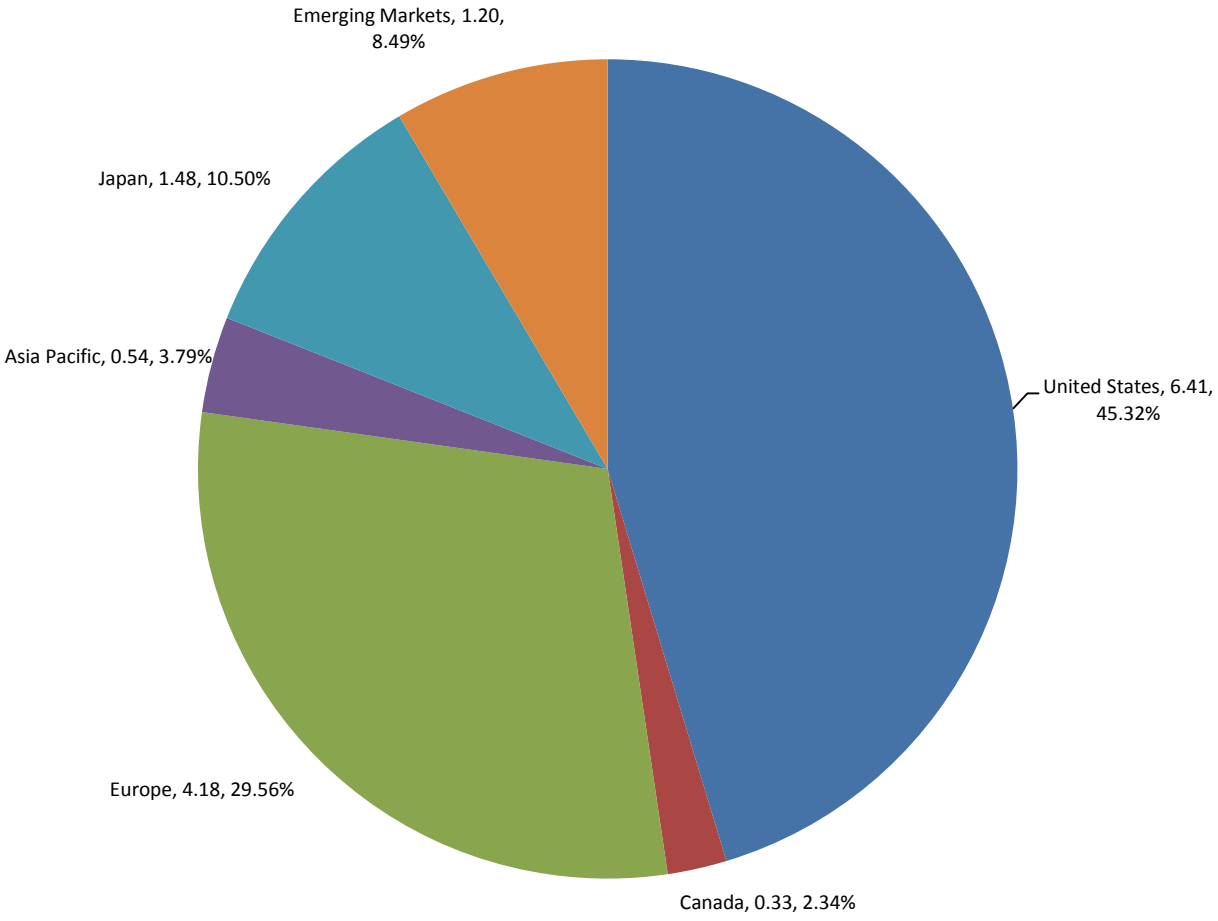
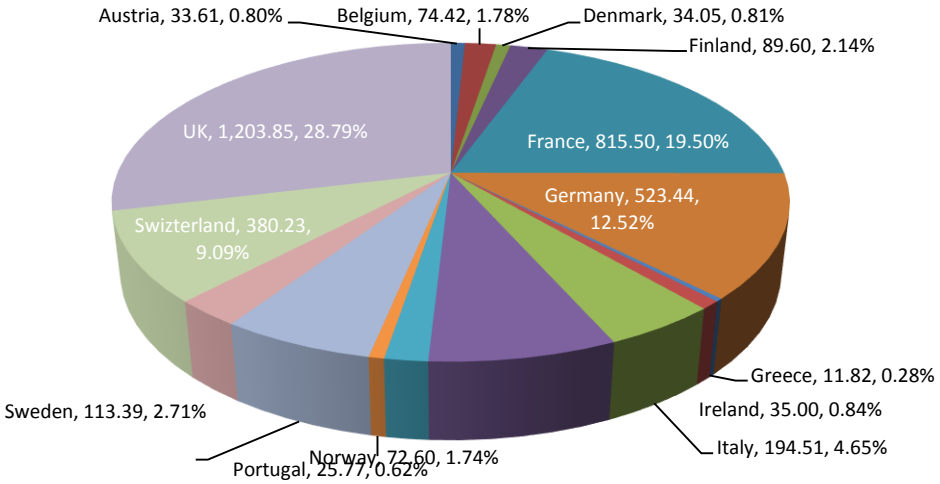
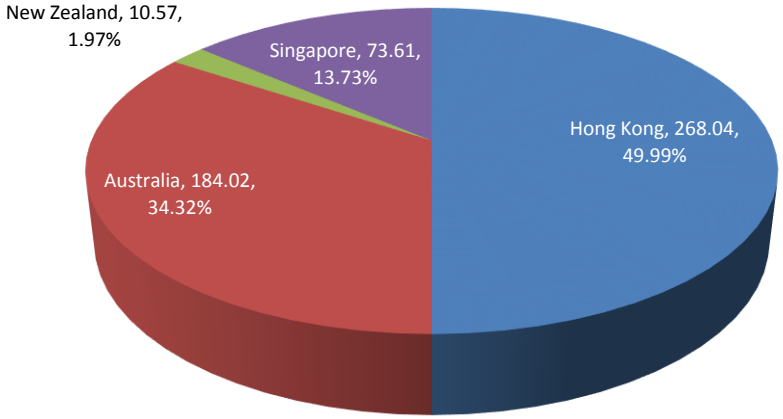


Figure 3.4, continued

Globally Accessible Sample, reported by Total Market Capitalization, 1990-2010

The figures show the distributions of Europe, Asia Pacific and Emerging Markets globally accessible samples by country. Beside each country name is the average market capitalization from that country, which is in U.S. dollars billion, and its percentage of market capitalization. Here the sample is represented by the Main CL Sample and the selection criteria are described in the Appendix.





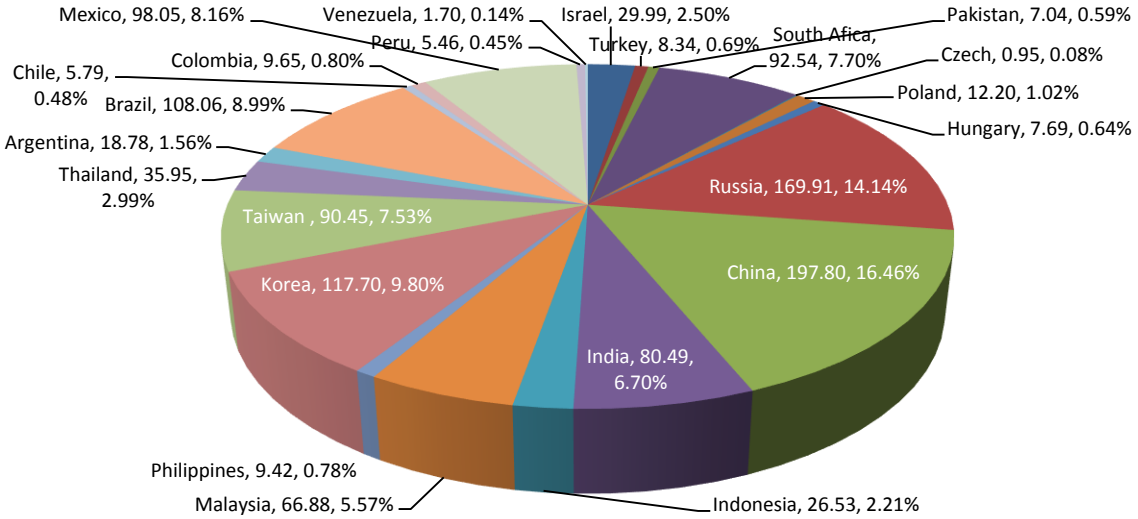


Figure 3.5

Globally Accessible Sample, reported by Total Number of Stocks, 1990-2010

The figure shows the distribution of the globally accessible sample by region. Beside each region name is the total number of sample stocks from that region that qualifies for analysis and the percentage of the total number that this count represents. Here the sample is represented by the Main CL Sample and the sample selection criteria are described in the Appendix.

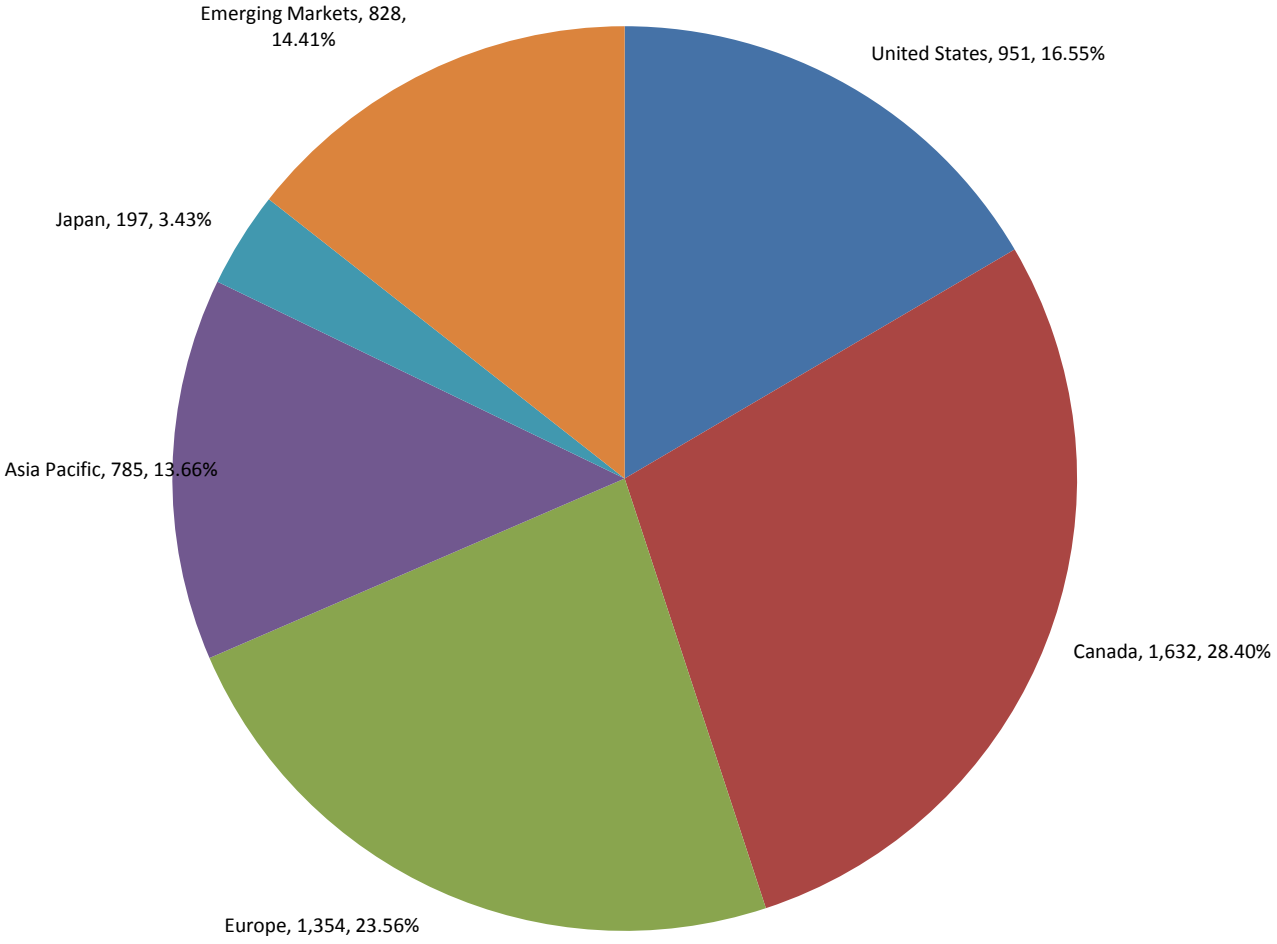
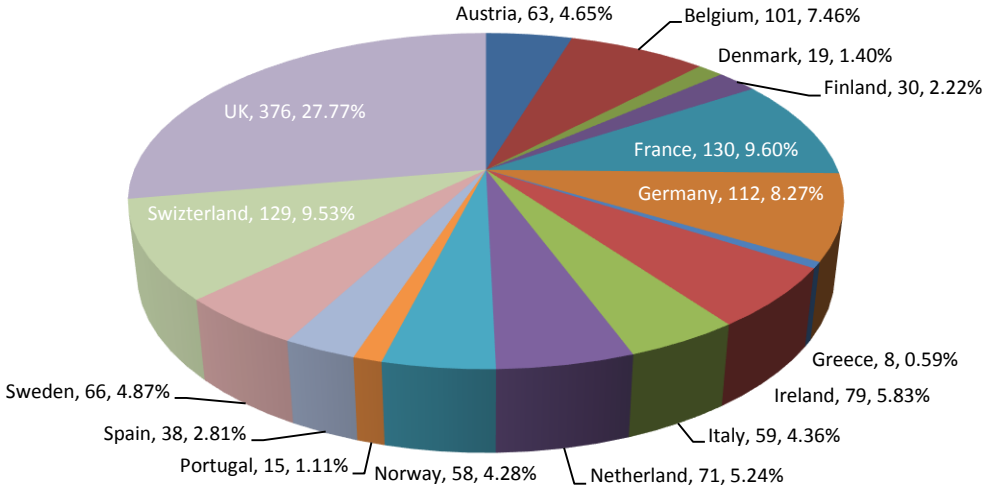
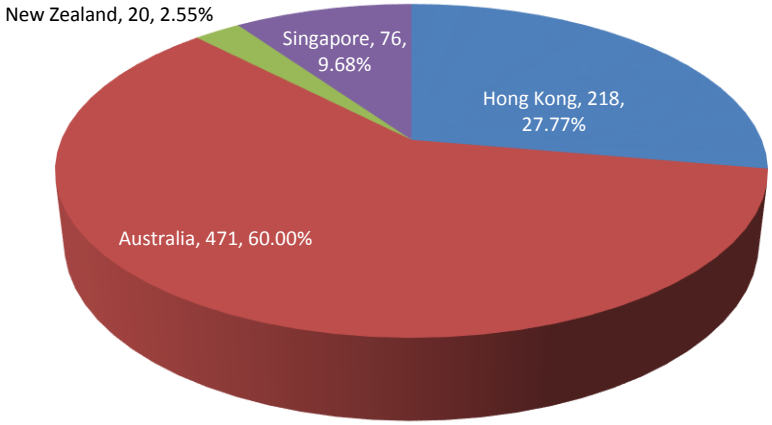


Figure 3.5, continued

Globally Accessible Sample, reported by Total Number of Stocks, 1990-2010

The figures show the distributions of Europe, Asia Pacific and Emerging Markets globally accessible samples by country. Beside each country name is the total number of sample stocks from that country that qualifies for analysis and the percentage of the total number that this count represents. Here the sample is represented by the Main CL Sample and the selection criteria are described in the Appendix.





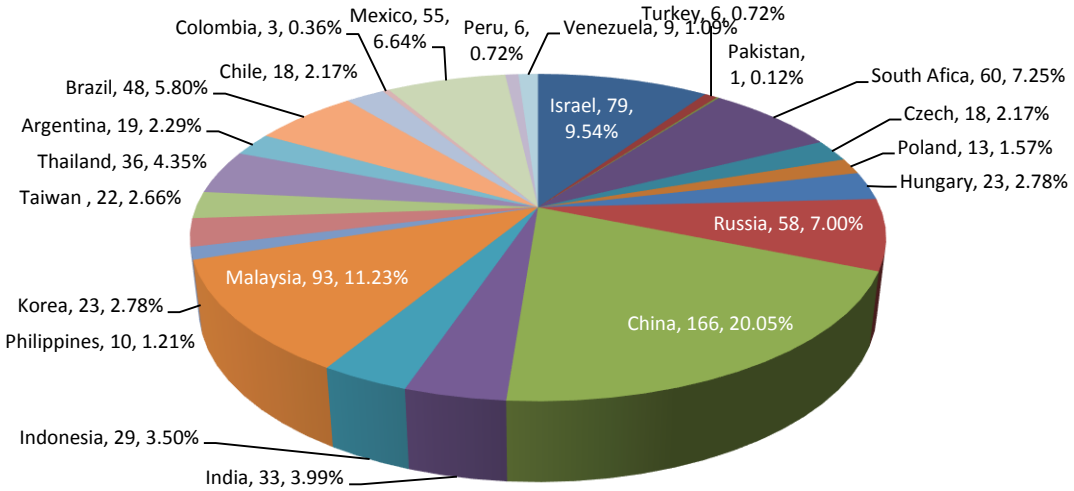
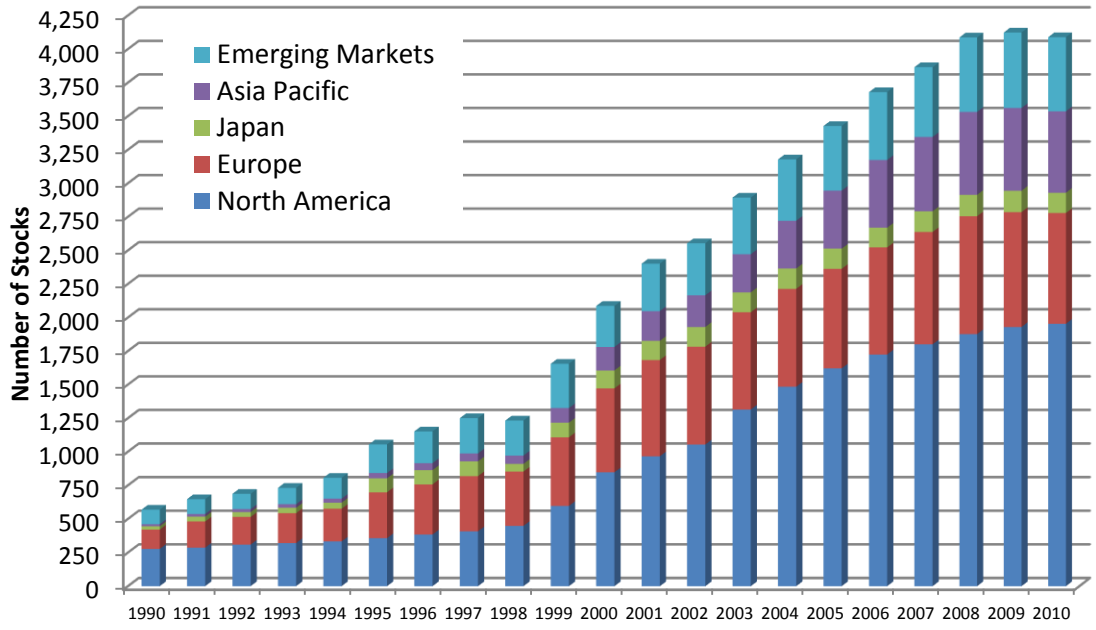


Figure 3.6

Globally Accessible Sample by Year, reported by Total Number of Stocks (above) and by Market Capitalization (below), 1990-2010

The figures show the distribution of globally accessible sample from each region by year. Here the sample is represented by the Main CL Sample and the sample selection criteria are described in the Appendix.



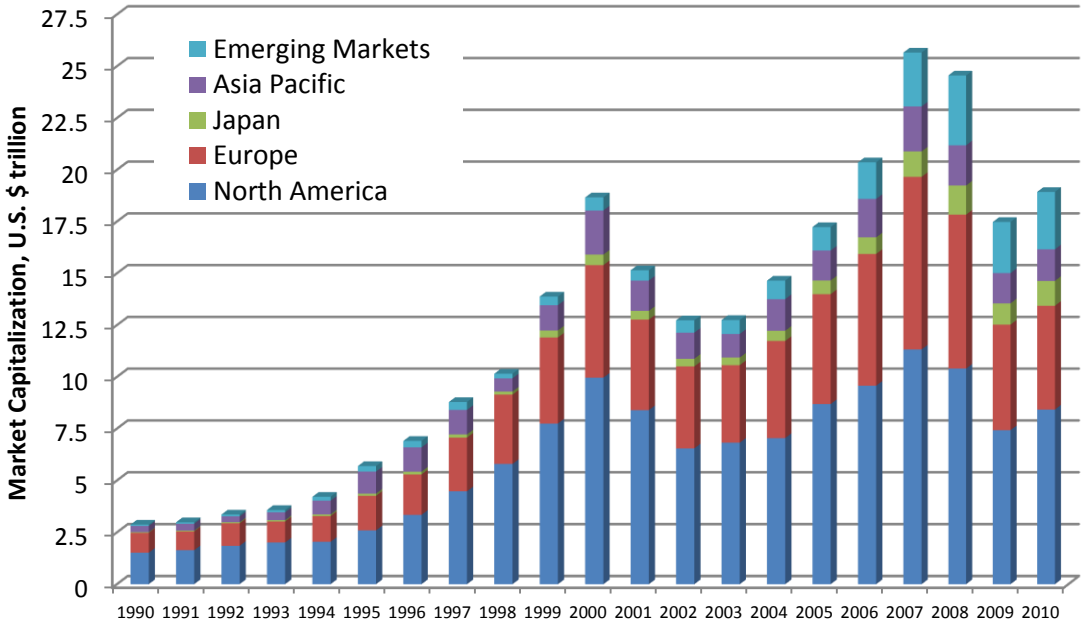
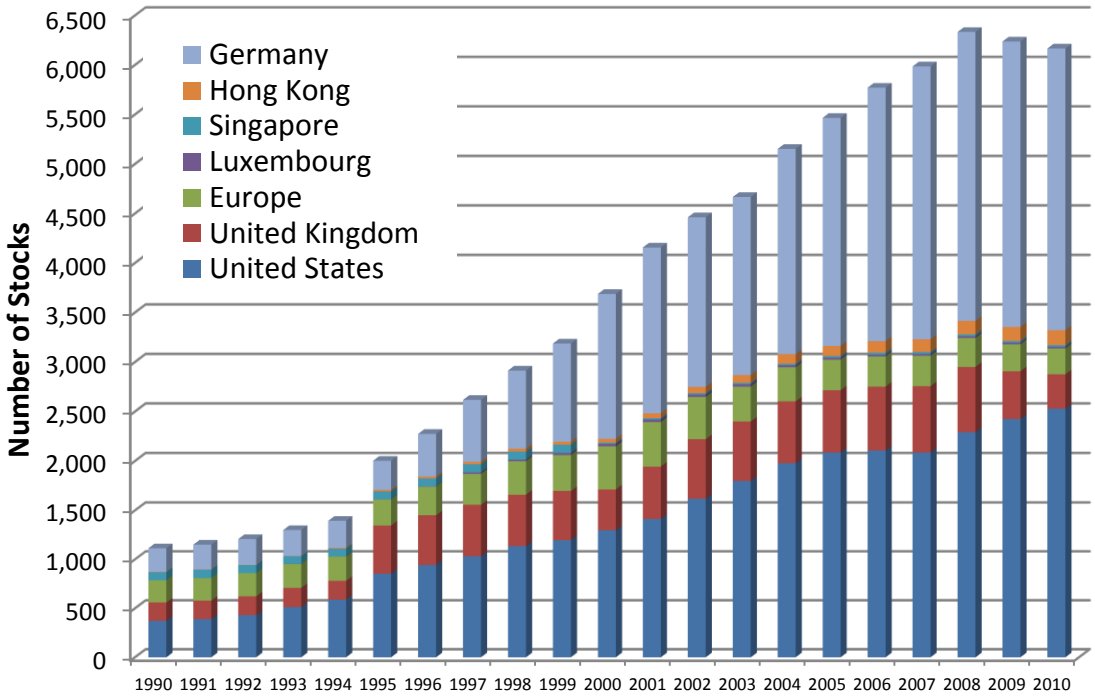


Figure 3.6, continued

Globally Accessible Sample by Year, reported by Total Number of Stocks (above) and by Market Capitalization (below), 1990-2010

The figures show the distribution of globally accessible sample from each target markets by year. Here the sample is represented by the Main CL Sample and the sample selection criteria are described in the Appendix.



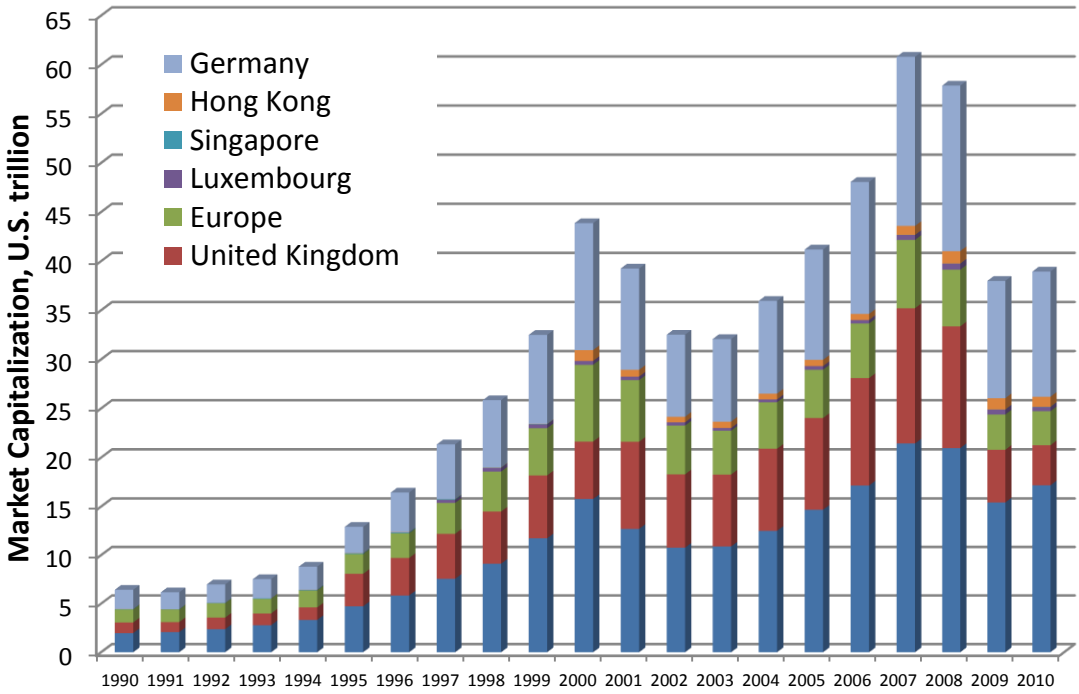


Table 3.1

Summary Statistics of Global Equity Universe by Country, Nov. 1989 – Dec. 2010

Country	Beginning Date	Total Number of Stocks	Size (U.S. $ mills.)	Book-to-Market (B/M)	Cash flow-to-Price (C/P)	Momentum (Mom, %)
North America		9,438				
United States	1989/11	6,494	256.70	0.47	0.09	6.60
Canada	1989/11	2,944	9.86	0.61	0.07	0.61
Europe		8,630				
Austria	1989/11	240	185.30	0.62	0.15	3.13
Belgium	1989/11	178	106.47	0.64	0.14	4.93
Denmark	1989/11	205	66.88	0.73	0.12	5.69
Finland	1989/11	157	133.66	0.83	0.14	10.81
France	1989/11	1,170	71.55	0.59	0.12	3.44
Germany	1989/11	1,109	78.98	0.51	0.10	-0.41
Greece	1989/11	332	45.31	0.64	0.09	12.45
Ireland	1989/11	78	184.90	0.57	0.10	7.71
Italy	1989/11	351	184.86	0.75	0.13	-0.92
Netherland	1989/11	203	228.09	0.55	0.14	7.10
Norway	1989/11	347	103.29	0.69	0.11	6.77
Portugal	1989/11	100	76.45	0.85	0.12	0.99
Spain	1989/11	169	430.65	0.68	0.12	6.57
Sweden	1989/11	571	50.14	0.61	0.10	5.55
Switzerland	1989/11	265	195.75	0.70	0.13	8.13
UK	1989/11	3,155	54.25	0.51	0.09	2.51
Asia Pacific		3,914				
Hong Kong	1989/11	977	70.57	0.91	0.09	3.89
Australia	1989/11	2,012	19.54	0.61	0.05	2.28
New Zealand	1989/11	170	49.80	0.71	0.11	10.79
Singapore	1989/11	755	71.72	0.77	0.10	6.07
Japan	1989/11	4,301	174.90	0.82	0.08	-2.19
Emerging Markets		11,116				
Israel	1989/11	326	21.18	0.71	0.12	6.43
Turkey	1989/11	241	57.24	0.56	0.15	12.13
Pakistan	1989/11	129	34.79	0.77	0.19	9.53
South Africa	1989/11	567	57.83	0.61	0.13	8.02
Czech Republic	1993/08	76	0.98	1.34	0.23	5.34
Poland	1992/01	348	30.50	0.74	0.10	40.97
Hungary	1991/02	45	37.57	0.86	0.14	4.21
Russia	1994/07	292	104.54	2.30	0.23	37.17
China	1991/02	1,550	247.05	0.62	0.08	26.48
India	1989/11	1,455	37.50	0.71	0.12	11.86
Indonesia	1990/05	312	40.90	0.76	0.12	5.42
Malaysia	1989/11	993	58.70	0.79	0.09	5.84
Philippines	1989/11	158	30.97	0.94	0.10	1.20
South Korea	1989/11	1,757	41.55	1.22	0.21	3.48
Taiwan	1989/11	1,344	156.80	0.64	0.08	-0.16
Thailand	1989/11	483	36.72	0.86	0.16	1.59
Argentina	1989/11	84	69.24	1.10	0.17	16.30
Brazil	1993/01	404	97.29	1.54	0.20	32.76

Table 3.1, continued

Country	Beginning date	Total number of Stocks	Size (U.S. $ mills.)	Book-to-Market (B/M)	Cash flow-to-Price (C/P)	Momentum (Mom)
Chile	1990/12	179	115.76	0.77	0.12	11.31
Colombia	1992/02	85	58.78	1.51	0.15	6.99
Mexico	1989/11	150	327.45	0.80	0.13	10.86
Peru	1991/02	111	10.59	1.10	0.15	11.93
Venezuela	1990/02	27	46.54	2.29	0.23	10.50
Total All		37,399				

This table reports summary statistics of our sample stocks for each country over the 198911-201112. We exclude financial firms and to be included in the analysis, each stocks has to have at least 12 monthly returns, is listed in its country's major exchange(s), and has sufficient information to calculate at least one of the characteristics including market value of equity (Size), book-to-market (B/M), cash flow-to-price (C/P). We also apply several screening procedures for Datastream data errors in monthly returns as suggested by Ince and Porter (2003) and others, as detailed in the text. The beginning date for each country is as shown. The total numbers of unique stocks are reported for each country. Mom is the time series average of the median lagged cumulative returns from *t-11* to *t-1* (skipping the most recent month). Also reported are the time-series average of annual medians for size, B/M, and C/P.

Table 3.2

Summary Statistics for Factor Portfolio Returns, Nov. 1990 – Dec. 2010

Panel A: Return Distributions of Factor Portfolios in the Global Experiments

Attributes	Market			Size			B/M			Mom			C/P		
	Equity Universe	Accessible	Local Spread	Equity Universe	Accessible	Local Spread	Equity Universe	Accessible	Local Spread	Equity Universe	Accessible	Local Spread	Equity Universe	Accessible	Local Spread
Global															
Mean	0.46	0.53	-0.24	0.09	0.48	-0.19	0.54	0.25	0.40	0.52	0.54	-0.04	0.60	0.36	0.44
Std Dev	4.47	4.29	1.78	2.45	2.69	2.28	2.50	2.89	2.04	4.37	4.98	2.44	3.03	2.90	2.11
t-Mean	1.59	1.93	-2.12	0.59	2.80	-1.28	3.39	1.35	3.06	1.84	1.68	-0.25	3.07	1.91	3.22
Developed Markets Only															
Mean	0.47	0.52	-0.23	0.04	0.51	-0.25	0.53	0.21	0.38	0.60	0.48	-0.22	0.64	0.26	0.42
Std Dev	4.46	4.22	1.72	2.38	2.43	2.21	2.39	2.90	1.67	4.13	5.26	1.86	2.67	3.02	1.86
t-Mean	1.62	1.91	-2.10	0.25	3.23	-1.78	3.42	1.12	3.58	2.26	1.42	-1.85	3.71	1.34	3.54
Global excl. North America															
Mean	0.33	0.46	-0.41	0.15	0.43	-0.29	0.73	0.42	0.37	0.60	0.50	0.05	0.73	0.50	0.42
Std Dev	4.79	4.81	2.76	2.17	2.66	2.81	4.32	2.43	2.56	4.13	4.39	3.73	3.42	2.15	2.85
t-Mean	1.06	1.49	-2.31	1.09	0.86	-1.63	2.62	2.70	2.26	2.26	1.76	0.21	3.34	3.64	2.30
Developed Markets Only excl. North America															
Mean	0.32	0.43	-0.43	0.05	0.42	-0.41	0.80	0.37	0.32	0.39	0.33	-0.21	0.72	0.35	0.35
Std Dev	4.85	4.76	2.97	2.29	2.30	2.73	4.31	2.60	2.17	4.27	4.59	3.06	2.59	2.35	2.34
t-Mean	1.04	1.41	-2.27	0.35	2.83	-2.36	2.88	2.23	2.27	1.43	1.13	-1.08	4.36	2.34	2.36

Table 3.2, continued

Panel B: Return Distributions of Factor Portfolios in the Regional Experiments

Attributes	Market			Size			B/M			Mom			C/P		
	Equity Universe	Accessible	Local Spread	Equity Universe	Accessible	Local Spread	Equity Universe	Accessible	Local Spread	Equity Universe	Accessible	Local Spread	Equity Universe	Accessible	Local Spread
North America															
Mean	0.68	0.66	0.11	0.33	0.79	-0.02	0.26	-0.06	0.17	0.40	0.68	-0.18	0.35	-0.02	0.12
Std Dev	4.58	4.16	2.53	3.67	3.79	2.47	3.34	4.23	2.04	5.99	6.53	2.65	3.85	4.36	2.09
t-Mean	2.32	2.48	0.70	1.39	3.23	-0.12	1.22	-0.23	1.28	1.03	1.63	-1.05	1.43	-0.06	0.93
Europe															
Mean	0.58	0.56	-0.11	-0.16	0.23	-0.54	0.64	0.31	0.38	0.83	0.49	0.35	0.67	0.37	0.47
Std Dev	4.91	4.82	2.68	2.48	2.44	3.02	2.68	3.10	2.16	4.59	5.21	2.90	2.33	2.79	2.30
t-Mean	1.83	1.81	-0.61	-1.00	1.47	-2.78	3.70	1.58	2.72	2.80	1.46	1.90	4.51	2.09	3.21
Asia Pacific															
Mean	0.74	0.85	0.19	-0.11	0.37	-0.59	0.65	0.19	0.49	1.07	0.91	0.40	0.63	0.43	0.40
Std Dev	5.87	6.22	3.85	3.38	4.37	2.97	3.21	5.15	3.38	5.14	5.32	4.48	2.98	3.96	3.14
t-Mean	1.96	2.12	0.78	-0.52	1.31	-3.10	3.18	0.57	2.26	3.23	2.67	1.40	3.27	1.70	1.97
Japan															
Mean	-0.04	0.12	-0.72	-0.15	0.30	-0.51	0.48	0.40	0.20	-0.44	-0.12	-0.96	0.32	0.33	-0.08
Std Dev	6.07	6.07	5.24	4.29	3.40	3.83	2.72	3.53	2.86	5.38	6.23	4.95	2.32	3.53	2.70
t-Mean	-0.10	0.30	-2.14	-0.53	1.38	-2.06	2.77	1.76	1.09	-1.29	-0.31	-3.02	2.17	1.47	-0.45
Emerging Markets															
Mean	0.32	0.77	-0.34	0.37	0.41	0.16	0.64	0.64	0.43	1.05	0.96	0.56	0.95	0.95	0.72
Std Dev	6.33	6.71	5.30	3.45	3.61	4.07	3.95	4.40	4.45	7.38	5.99	8.67	4.96	4.28	5.72
t-Mean	0.79	1.78	-1.00	1.66	1.75	0.60	2.53	2.26	1.51	2.22	2.50	1.00	2.99	3.46	1.97

Table 3.2, continued

This table shows the summary statistics for explanatory returns. It includes five regional portfolios for North America, Europe, Japan, Asia Pacific (excluding Japan) and Emerging Markets. Four sets of global portfolios are also reported, including Global portfolios that combine all the five regions, Developed Markets portfolios that combine the first four regions, Global portfolios excluding North America, Developed Markets portfolios excluding North America. For each scenario, it shows the explanatory returns for three samples, the whole sample ("Equity Universe" in the table), the subset of globally-accessible stocks, the Main CL Sample, which stands for the globally accessible sample ("Accessible" in the table) and the subset of locally-accessible stocks relative to the globally-accessible stocks ("Local Spread" in the table). We form portfolios at the end of June of each year *t* by sorting stocks in a region into two market cap and three book-to-market (B/M) or cash flow-to-price (C/P) groups. Big stocks are those in the top 90% of market cap for the region, and small stocks are those in the bottom 10% (Fama and French, 2011). The B/M or C/P breakpoints for the five regions are the 30th and 70th percentiles of B/M for the big stocks from the globally accessible sample for each given region. The global portfolios use global size breaks, but we use the B/M or C/P breakpoints for the five regions to allocate the stocks of these regions to the global portfolios. The independent 2×3 sorts on size and B/M (or C/P) produce six value-weighted portfolios, SG, SN, SV, BG, BN and BV, where S and B indicate small or big and G, N, and V indicate growth, neutral and value. The factor portfolios based on size is the equally-weighted average of the returns on the three small stock portfolios for the region minus the equally-weighted average of the returns on the three big stock portfolios where all the six portfolios are all based on B/M. The factor portfolios based on B/M (or C/P) are calculated as the equally-weighted average of value-growth returns for small and big stocks, SV-SG and BV-BG. The 2×3 sorts on size and lagged momentum are similar, but the size/momentum portfolios are formed monthly. For portfolios formed at the end of month *t*, the lagged momentum return is a stock's cumulative return for *t-11* to *t-1*. The independent 2×3 sorts on size and momentum produce six value-weighted portfolios, SL, SN, SW, BL, BN and BW, where S and B indicate small and big, and L, N, and W indicate losers, neutral, and winners. The factor portfolios based on momentum is constructed as the equally-weighted average of WML_S=SW-SL and WML_B=BW-BL. B/M(C/P) breakpoints are the same for all three samples within each scenario, the globally accessible sample uses its own size and momentum breakpoints, and the purely local sample uses regional size and momentum breakpoints. For each given region, the return spread factor portfolios of purely-local stocks relative to the globally-accessible stocks are the differences in the respective factor portfolio returns for the set of purely-local stocks in the region and for the globally-accessible stocks. For example, for the size-related spread factor portfolio, we compute the return difference between the factor portfolio for the locally-accessible stocks (measured, in turn, as the difference between an equally-weighted average of the SG, SN, and SV portfolios and an equally-weighted average of the BG, BN, and BV portfolios) and the globally-accessible stocks (measured similarly). The value- and momentum-related spread factor portfolios are built in the same way. All returns are in U.S. dollars. Market is the return on a value-weighted market portfolio globally or for the region minus the U.S. one month Treasury bill yield. Mean and Std Dev are the mean and standard deviation of the return, and t-Mean is the ratio of Mean to its standard error.

Table 3.3

Summary Statistics for the 25 size/B/M Excess Returns, Nov. 1990 – Dec. 2010

	Mean					Standard Deviation				
	Low	2	3	4	High	Low	2	3	4	High
Global										
Small	0.06	0.55	1.36	0.93	1.25	6.55	5.95	8.42	5.06	4.91
2	0.09	0.59	0.64	0.76	0.94	6.02	5.51	5.03	4.89	4.97
3	0.15	0.37	0.56	0.62	0.83	5.75	5.37	5.18	4.84	5.06
4	0.40	0.47	0.59	0.60	0.81	6.05	5.02	5.00	4.74	5.08
Big	0.28	0.49	0.46	0.62	0.54	4.87	4.44	4.43	4.38	4.73
Developed Markets Only										
Small	0.05	0.58	0.88	0.84	1.10	6.66	5.72	5.88	5.08	4.65
2	0.11	0.42	0.58	0.70	0.80	6.50	5.61	5.02	4.70	4.87
3	0.14	0.37	0.46	0.58	0.75	6.16	5.50	5.32	4.74	5.00
4	0.42	0.36	0.59	0.59	0.74	6.29	4.97	4.81	4.80	5.09
Big	0.26	0.49	0.42	0.63	0.51	4.86	4.38	4.44	4.28	4.74
Global excl. North America (NA)										
Small	-0.15	0.30	0.66	0.66	1.00	6.77	5.71	5.32	5.00	5.16
2	-0.11	0.36	0.88	0.63	0.74	6.03	5.58	8.01	5.08	5.26
3	-0.05	0.25	0.34	0.51	0.75	5.73	5.57	5.25	5.19	5.40
4	0.12	0.32	0.40	0.47	0.70	5.70	5.34	5.27	5.22	5.60
Big	0.02	0.30	0.43	0.54	0.65	5.32	4.98	4.89	4.91	5.27
Developed Markets Only excl. North America (NA)										
Small	-0.15	0.23	0.43	0.54	0.76	6.84	5.46	5.25	4.86	4.87
2	-0.31	0.19	0.31	0.47	0.47	6.18	6.08	5.03	4.90	5.08
3	-0.12	0.12	0.28	0.50	0.53	6.04	5.49	5.35	5.11	5.41
4	0.02	0.20	0.33	0.37	0.60	6.10	5.21	5.21	5.27	5.58
Big	-0.04	0.29	0.37	0.55	0.64	5.30	4.96	4.96	4.87	5.39
North America										
Small	0.89	1.14	1.45	1.32	1.64	8.90	7.34	7.68	6.56	6.00
2	0.61	0.94	1.03	1.00	1.20	8.37	7.22	6.51	5.48	5.75
3	0.96	0.67	0.85	0.92	1.11	8.42	6.51	5.75	4.93	5.31
4	0.89	0.75	0.93	0.77	0.99	7.71	5.75	5.29	5.06	5.20
Big	0.54	0.67	0.53	0.79	0.55	5.21	4.61	4.42	4.23	4.72
Europe										
Small	-0.20	0.07	0.51	0.50	0.87	6.59	5.62	5.40	5.16	5.14
2	0.14	0.28	0.40	0.72	0.96	6.47	5.62	5.55	5.32	5.66
3	0.19	0.38	0.41	0.72	0.90	6.46	5.71	5.37	5.51	5.92
4	0.35	0.39	0.66	0.68	0.75	6.06	5.19	5.28	5.47	5.81
Big	0.26	0.52	0.58	0.84	0.86	5.34	4.79	5.29	5.17	5.63
Asia Pacific										
Small	0.68	0.93	1.30	1.45	2.11	11.34	9.80	8.78	8.11	8.78
2	0.17	0.93	0.60	1.03	1.12	8.23	8.21	8.06	7.41	7.93
3	-0.15	0.32	0.77	1.03	0.94	7.97	6.84	7.25	7.11	7.32
4	0.99	1.08	0.79	0.94	0.92	7.14	8.28	6.41	6.13	7.38
Big	0.54	1.02	0.56	0.77	1.24	6.39	6.31	6.54	5.77	7.94

Table 3.3, continued

	Mean					Standard Deviation				
	Low	2	3	4	High	Low	2	3	4	High
Japan										
Small	-0.46	-0.05	-0.06	0.18	0.09	10.07	7.89	7.57	7.20	6.98
2	-0.55	-0.13	-0.15	-0.05	-0.02	8.90	8.19	7.50	7.10	6.97
3	-0.47	-0.21	-0.14	-0.08	0.03	8.39	8.19	7.19	7.03	7.05
4	-0.51	-0.12	-0.09	-0.03	0.19	7.82	7.11	6.68	6.63	6.77
Big	-0.48	-0.06	0.12	0.21	0.39	6.90	6.32	5.78	5.66	6.33
Emerging Markets										
Small	0.13	0.55	1.45	1.04	1.72	10.09	7.66	8.50	7.27	7.55
2	0.36	0.92	0.73	1.02	1.31	7.77	7.42	7.30	6.82	7.55
3	0.26	0.86	0.56	1.00	1.41	7.32	7.33	7.43	6.92	7.14
4	0.19	0.46	0.56	0.74	1.22	6.78	6.77	6.61	6.50	7.39
Big	0.37	0.40	0.63	0.57	0.91	6.42	6.72	6.32	6.89	7.17

This table shows the summary statistics for the 25 size/B/M excess returns. At the end of June of each year we construct 25 size/B/M portfolios for each region. The size breakpoints are the 3rd, 7th, 13th, and 25th percentiles of aggregate market cap for a region. The B/M quintile breakpoints use the big stocks (top 90% of market cap) of a region. Regional quintile B/M breakpoints are used to allocate the stocks of these regions to the global test asset portfolios. The intersections of the 5×5 independent size and B/M sorts for a region produce 25 value-weighted size/B/M portfolios.

Table 3.4

Summary Statistics for Regression Tests of the Fama-French Three-Factor Model Using Monthly Excess Returns on 25 Size/B/M Portfolios, With (5×5) and Without (4×5) Microcap Stocks: Nov. 1990 – Dec. 2010

Panel A: Global Benchmark: Global Fama-French Three-factor Model

	Test Assets	4×5 Size/B/M						5×5 Size/B/M					
		H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS	H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS
Global	Global	0.39	0.11	0.41	0.94	0.20	1.74	1.13	0.16	0.62	0.92	0.21	3.12
	Developed Only	0.43	0.13	0.39	0.90	0.24	1.62	0.77	0.16	0.57	0.89	0.26	2.67
	Global excl. NA	0.68	0.25	0.34	0.83	0.51	1.24	0.80	0.24	0.39	0.83	0.46	1.27
	Developed only excl.NA	0.69	0.35	0.38	0.78	0.36	1.51	0.81	0.34	0.44	0.77	0.30	1.58
Regional	North America	0.86	0.35	0.44	0.71	0.12	2.00	0.94	0.41	0.54	0.70	0.15	2.41
	Europe	0.57	0.19	0.37	0.73	0.17	1.41	0.74	0.21	0.50	0.72	0.17	2.01
	Asia Pacific	1.45	0.25	0.44	0.58	0.13	2.00	2.09	0.30	0.51	0.56	0.21	2.08
	Japan	0.93	0.56	0.29	0.33	0.28	0.90	1.06	0.56	0.36	0.32	0.21	1.06
	Emerging Markets	0.77	0.18	0.30	0.55	0.34	0.94	1.16	0.23	0.39	0.52	0.36	1.25

Panel B: Regional Benchmark: Local Fama-French Three-factor Model

Test Assets	4×5 Size/B/M						5×5 Size/B/M					
	H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS	H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS
North America	0.43	0.11	0.39	0.91	0.15	1.57	0.74	0.14	0.51	0.91	0.14	2.12
Europe	0.43	0.11	0.35	0.92	0.33	1.24	0.51	0.12	0.46	0.92	0.25	1.71
Asia Pacific	1.10	0.26	0.42	0.81	0.25	1.79	1.73	0.30	0.49	0.80	0.24	1.95
Japan	0.32	0.10	0.26	0.92	0.42	0.75	0.49	0.10	0.31	0.92	0.31	0.81
Emerging Markets	0.58	0.42	0.30	0.65	0.41	0.98	1.13	0.43	0.40	0.63	0.41	1.34

Panel C: Hybrid Model Based on Main CL Sample

	Test Assets	4×5 Size/B/M						5×5 Size/B/M					
		H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS	H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS
Global	Global	0.30	0.08	0.32	0.94	0.67	0.92	0.80	0.11	0.46	0.92	0.46	1.55
	Developed Only	0.35	0.07	0.35	0.95	0.46	1.12	0.72	0.09	0.53	0.95	0.41	2.05
	Global excl. NA	0.72	0.14	0.29	0.90	0.74	0.81	1.14	0.15	0.38	0.89	0.59	1.10
	Developed only excl.NA	0.28	0.07	0.28	0.94	0.61	0.76	0.51	0.08	0.42	0.94	0.49	1.27
Regional	North America	0.62	0.13	0.46	0.90	0.40	2.20	0.72	0.15	0.57	0.90	0.20	2.66
	Europe	0.48	0.12	0.35	0.90	0.38	1.22	0.71	0.13	0.51	0.91	0.17	2.06
	Asia Pacific	0.94	0.23	0.39	0.81	0.30	1.44	1.66	0.30	0.51	0.79	0.30	1.92
	Japan	0.54	0.08	0.25	0.92	0.55	0.65	0.54	0.09	0.35	0.93	0.45	0.97
	Emerging Markets	0.64	0.18	0.29	0.68	0.51	0.82	1.20	0.23	0.40	0.64	0.48	1.22

Table 3.4, continued

The regressions use the global, local and hybrid version of the Fama-French three-factor model to explain the returns on four sets of global portfolios and five sets of regional portfolios on North America, Europe, Japan, Asia Pacific(excluding Japan), and Emerging Markets formed on size and B/M. The 5×5 results include microcap portfolios, the 4×5 results exclude microcap portfolios. The GRS statistic tests whether all intercepts in a set of 25 (5×5) or 20 (4×5) regressions are zero; H-L α is the difference between the highest and lowest intercepts for a set of regressions; $|\alpha|$ is the average absolute intercepts; *SR(α)* is the Sharpe ratio for the intercepts; R^2 is the average time-series adjusted R^2; CSR R^2 is the GLS cross-sectional R^2. With 25 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.41; 95%: 1.56; 97.5%: 1.69; 99%: 1.86 and 99.9%: 2.26. With 20 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.45; 95%: 1.62; 97.5%: 1.78; 99%: 1.95 and 99.9%: 2.41. Three classes of models are investigated:

$$\text{Global Fama-French Three-factor Model: } R_i - R_f = \alpha_i^G + \beta_i^G\left(R_m^G - R_f\right) + s_i^G F_{Size}^G + h_i^G F_{B/M}^G + \varepsilon_i$$

$$\text{Local Fama-French Three-factor Model: } R_i - R_f = \alpha_i^L + \beta_i^L\left(R_m^L - R_f\right) + s_i^L F_{Size}^L + h_i^L F_{B/M}^L + \varepsilon_i$$

$$\text{Hybrid Fama-French Three-factor Model: } R_i - R_f = \alpha_i^H + \beta_i^A\left(R_m^A - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^A F_{Size}^A + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^A F_{B/M}^A + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + \varepsilon_i$$

The superscript "G" on the market and factor portfolios implies that they are constructed from all stocks around the world and the superscript designation of "L" on the market and factor portfolios implies that they are constructed only from local - or regional, in our experiments - stocks. The superscript "H" denotes the intercept for the hybrid model. The superscript "A" denotes a market or factor portfolio comprised of stocks only in the globally-accessible sample, which is represented by the sample of secondary cross-listings in this study, and the superscript "Ā-A" denotes a market or factor spread portfolio of the difference in the market or factor for purely-local stocks from the specific region (those not secondarily cross-listed overseas for which the test is performed) and that of the globally accessible stocks. The Main CL Sample is used here.

Table 3.5

Summary Statistics for Regression Tests of the Hybrid Version of the Fama-French Three-Factor Model Using Monthly Excess Returns on 20 Size/B/M Portfolios When Different CL Samples are Used to Construct the Global Factors: Nov. 1990 – Dec. 2010

	Test Assets	4×5 Size/B/M					
		H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS
		Panel A: Main CL Sample (two viability constraints on target market trading)					
Global	Global	0.30	0.08	0.32	0.94	0.67	0.92
	Developed Only	0.35	0.07	0.35	0.95	0.46	1.12
	Global excl. NA	0.72	0.14	0.29	0.90	0.74	0.81
	Developed only excl.NA	0.28	0.07	0.28	0.94	0.61	0.76
Regional	North America	0.62	0.13	0.46	0.90	0.40	2.20
	Europe	0.48	0.12	0.35	0.90	0.38	1.22
	Asia Pacific	0.94	0.23	0.39	0.81	0.30	1.44
	Japan	0.54	0.08	0.25	0.92	0.55	0.65
	Emerging Markets	0.64	0.18	0.29	0.68	0.51	0.82
		Panel B:CL1 (no viability constraints on target market trading)					
Global	Global	0.42	0.07	0.34	0.95	0.46	1.14
	Developed Only	0.35	0.07	0.38	0.94	0.27	1.23
	Global excl. NA	0.74	0.12	0.29	0.90	0.63	0.80
	Developed only excl.NA	0.26	0.12	0.35	0.93	0.64	1.06
Regional	North America	0.57	0.21	0.44	0.87	0.59	1.93
	Europe	0.43	0.19	0.44	0.89	0.61	1.76
	Asia Pacific	0.94	0.26	0.41	0.78	0.30	1.57
	Japan	0.63	0.16	0.33	0.91	0.43	1.13
	Emerging Markets	0.59	0.13	0.27	0.74	0.48	0.70
		Panel C: CL2a (non-zero target market trading in trailing 12 months)					
Global	Global	0.44	0.09	0.40	0.94	0.44	1.65
	Developed Only	0.45	0.11	0.42	0.93	0.23	1.75
	Global excl. NA	0.74	0.11	0.39	0.90	0.61	1.54
	Developed only excl.NA	0.50	0.12	0.40	0.93	0.55	1.60
Regional	North America	0.53	0.11	0.36	0.83	0.47	1.36
	Europe	0.43	0.10	0.34	0.90	0.50	1.18
	Asia Pacific	0.93	0.23	0.40	0.80	0.32	1.55
	Japan	0.60	0.19	0.34	0.91	0.44	1.17
	Emerging Markets	0.54	0.12	0.26	0.67	0.57	0.69
		Panel D:CL2b (more stringent viability constraints on the Main CL Sample)					
Global	Global	0.33	0.07	0.33	0.94	0.70	1.02
	Developed Only	0.37	0.07	0.38	0.95	0.42	1.38
	Global excl. NA	0.69	0.13	0.31	0.89	0.68	0.90
	Developed only excl.NA	0.35	0.08	0.33	0.93	0.65	1.05
Regional	North America	0.56	0.13	0.46	0.90	0.30	2.20
	Europe	0.46	0.13	0.39	0.89	0.40	1.51
	Asia Pacific	0.99	0.25	0.40	0.81	0.26	1.57
	Japan	0.48	0.08	0.25	0.92	0.54	0.63
	Emerging Markets	0.61	0.18	0.29	0.69	0.52	0.82

Table 3.5, continued

The regressions use the hybrid model to explain the returns on four sets of global portfolios and five sets of regional portfolios on North America, Europe, Japan, Asia Pacific(excluding Japan), and Emerging Markets formed on size and B/M. The global factor portfolios are based on other globally accessible samples, where the Main CL Sample refers to the sample with two relative viability constraints, CL1 refers to the sample without viability constraints, CL2a is the sample with absolute viable constraint, CL2b is the sample where more stringent screenings are imposed on the two viability constraints. Note that the regression results for the Main CL Sample are repeated from Table 4 for comparison. The selection criteria are described in the Appendix. The 4×5 results exclude microcap portfolios. The GRS statistic tests whether all intercepts in a set of 20 (4×5) regressions are zero; H-L α is the difference between the highest and lowest intercepts for a set of regressions; $|\alpha|$ is the average absolute intercept; *SR(α)* is the Sharpe ratio for the intercepts; R^2 is the average time-series adjusted R^2; CSR R^2 is the GLS cross-sectional R^2. With 20 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.45; 95%: 1.62; 97.5%: 1.78; 99%: 1.95 and 99.9%: 2.41. The hybrid model based on the Fama-French three-factor model is:

$$R_i - R_f = \alpha_i^H + \beta_i^A\left(R_m^A - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^A F_{Size}^A + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^A F_{B/M}^A + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + \varepsilon_i$$

The superscript "H" denotes the intercept for the hybrid model. The superscript "A" denotes a market or factor portfolio comprised of stocks only in the globally-accessible sample, which is represented by the sample of secondary cross-listings in this study, and the superscript "Ā-A" denotes a market or factor spread portfolio of the difference in the market or factor for purely-local stocks from the specific region (those not secondarily cross-listed overseas for which the test is performed) and that of the globally accessible stocks.

Table 3.6

Summary Statistics for Regression Tests of the Carhart Four-Factor Model on 20 Size/Momentum Portfolios and the Hou-Karolyi-Kho Extended Four-Factor Model on 20 Size/C/P Portfolios: Nov. 1990 – Dec. 2010

Panel A: Global Benchmark: Global Carhart Four-Factor Model (*left*) and Global Hou-Karolyi-Kho Extended Four-Factor Model (*right*)

	Test Assets	4×5 Size/Momentum						4×5 Size/C/P					
		H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS	H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS
Global	Global	0.57	0.12	0.43	0.92	0.17	1.89	0.42	0.10	0.42	0.93	0.31	1.75
	Developed Only	0.71	0.14	0.45	0.89	0.17	2.05	0.45	0.09	0.41	0.89	0.29	1.70
	Global excl. NA	0.89	0.25	0.44	0.81	0.05	1.96	0.54	0.20	0.38	0.84	0.49	1.44
	Developed only excl.NA	0.71	0.32	0.37	0.77	0.11	1.42	0.61	0.30	0.38	0.79	0.53	1.43
Regional	North America	0.82	0.45	0.37	0.72	0.43	1.37	0.70	0.52	0.41	0.70	0.29	1.68
	Europe	1.22	0.23	0.51	0.73	0.11	2.68	0.76	0.13	0.38	0.72	0.39	1.43
	Asia Pacific	1.61	0.34	0.52	0.58	0.08	2.74	1.24	0.24	0.46	0.58	0.34	2.15
	Japan	1.57	0.49	0.43	0.34	0.18	1.84	0.49	0.59	0.27	0.33	0.29	0.73
	Emerging Markets	2.53	0.47	0.44	0.45	0.08	1.96	1.08	0.30	0.38	0.54	0.34	1.47

Panel B: Regional Benchmark: Local Carhart Four-Factor Model (*left*) and Local Hou-Karolyi-Kho Extended Four-Factor Model (*right*)

Test Assets	4×5 Size/Momentum						4×5 Size/C/P					
	H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS	H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS
North America	0.54	0.10	0.30	0.91	0.36	0.94	0.39	0.09	0.36	0.90	0.33	1.35
Europe	0.98	0.20	0.55	0.91	0.11	2.98	0.36	0.10	0.37	0.92	0.59	1.34
Asia Pacific	0.84	0.23	0.47	0.83	0.28	2.17	1.08	0.22	0.44	0.81	0.44	1.91
Japan	0.63	0.19	0.36	0.92	0.11	1.37	0.46	0.10	0.30	0.92	0.37	0.95
Emerging Markets	0.84	0.60	0.43	0.62	0.26	1.90	1.04	0.62	0.40	0.66	0.35	1.71

Panel C: Hybrid Model Based on Main CL Sample: Hybrid Carhart Four-Factor Model (*left*) and Hybrid Hou-Karolyi-Kho Extended Four-Factor Model (*right*)

	Test Assets	4×5 Size/Momentum						4×5 Size/C/P					
		H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS	H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS
Global	Global	0.44	0.13	0.44	0.93	0.52	1.74	0.40	0.10	0.38	0.94	0.50	1.29
	Developed Only	0.53	0.12	0.45	0.95	0.38	1.80	0.33	0.07	0.34	0.94	0.56	1.10
	Global excl. NA	0.99	0.19	0.47	0.89	0.44	2.07	0.50	0.15	0.38	0.90	0.68	1.34
	Developed only excl.NA	0.63	0.12	0.40	0.94	0.52	1.50	0.43	0.11	0.37	0.93	0.90	1.30
Regional	North America	0.73	0.21	0.42	0.90	0.50	1.77	0.63	0.15	0.42	0.89	0.45	1.77
	Europe	0.81	0.19	0.56	0.90	0.59	2.91	0.49	0.13	0.39	0.91	0.72	1.39
	Asia Pacific	0.79	0.24	0.48	0.83	0.50	2.12	1.46	0.23	0.48	0.81	0.61	2.07
	Japan	0.74	0.14	0.40	0.93	0.20	1.53	0.46	0.10	0.28	0.92	0.47	0.77
	Emerging Markets	1.17	0.32	0.40	0.64	0.49	1.51	0.78	0.21	0.34	0.69	0.61	1.09

Table 3.6, continued

The regressions use the global, local and hybrid version of the Carhart four-factor model (*left*) and the Hou-Karolyi-Kho extended four-factor model (*right*) to explain the returns on four sets of global portfolios and five sets of regional portfolios on North America, Europe, Japan, Asia Pacific(excluding Japan), and Emerging Markets formed on size and momentum (*left*) and those on size and C/P (*right*). The 4×5 results exclude microcap portfolios. The GRS statistic tests whether all intercepts in a set of 20 (4×5) regressions are zero; H-L α is the difference between the highest and lowest intercepts for a set of regressions; |α| is the average absolute intercept; *SR(α)* is the Sharpe ratio for the intercepts; R^2 is the average time-series adjusted R^2; CSR R^2 is the GLS cross-sectional R^2. With 20 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.45; 95%: 1.62; 97.5%: 1.78; 99%: 1.95 and 99.9%: 2.41. Six classes of models are investigated:

Global Carhart Four-factor Model: $R_i - R_f = \alpha_i^G + \beta_i^G\left(R_m^G - R_f\right) + s_i^G F_{Size}^G + h_i^G F_{B/M}^G + m_i^G F_{Mom}^G + \varepsilon_i$

Local Carhart Four-factor Model: $R_i - R_f = \alpha_i^L + \beta_i^L\left(R_m^L - R_f\right) + s_i^L F_{Size}^L + h_i^L F_{B/M}^L + m_i^L F_{Mom}^L + \varepsilon_i$

Hybrid Carhart Four-factor Model: $R_i - R_f = \alpha_i^H + \beta_i^A\left(R_m^A - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^A F_{Size}^A + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^A F_{B/M}^A + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + m_i^A F_{Mom}^A + m_i^{\bar{A}-A} F_{Mom}^{\bar{A}-A} + \varepsilon_i$

Global Hou-Karolyi-Kho extended four-factor Model: $R_i - R_f = \alpha_i^G + \beta_i^G\left(R_m^G - R_f\right) + s_i^G F_{Size}^G + c_i^G F_{C/P}^G + m_i^G F_{Mom}^G + \varepsilon_i$

Local Hou-Karolyi-Kho extended four-factor Model: $R_i - R_f = \alpha_i^L + \beta_i^L\left(R_m^L - R_f\right) + s_i^L F_{Size}^L + c_i^L F_{C/P}^L + m_i^L F_{Mom}^L + \varepsilon_i$

Hybrid Hou-Karolyi-Kho extended four-factor Model: $R_i - R_f = \alpha_i^H + \beta_i^A\left(R_m^A - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^A F_{Size}^A + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + c_i^A F_{C/P}^A + c_i^{\bar{A}-A} F_{C/P}^{\bar{A}-A} + m_i^A F_{Mom}^A + m_i^{\bar{A}-A} F_{Mom}^{\bar{A}-A} + \varepsilon_i$

The superscript "G" on the market and factor portfolios implies that they are constructed from all stocks around the world and the superscript designation of "L" on the market and factor portfolios implies that they are constructed only from local - or regional, in our experiments - stocks. The superscript "H" denotes the intercept for the hybrid model. The superscript "A" denotes a market or factor portfolio comprised of stocks only in the globally-accessible sample, which is represented by the sample of secondary cross-listings in this study, and the superscript "Ā-A" denotes a market or factor spread portfolio of the difference in the market or factor for purely-local stocks from the specific region (those not secondarily cross-listed overseas for which the test is performed) and that of the globally accessible stocks. The Main CL Sample is used here.

Table 3.7

Summary Statistics for Regression Tests of the Fama-French Three-Factor Model Using Monthly Excess Returns on 25 Size/B/M Portfolios and Industry Portfolios: Nov. 1990 – Dec. 2010

Panel A: Global Benchmark: Global Fama-French Three-factor Model

	Test Assets	5×5 Size/B/M + 10 Industry						33 Industry					
		H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS	H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS
Global	Global	1.13	0.18	0.77	0.87	0.13	3.28	1.46	0.27	0.60	0.67	0.03	2.16
	Developed Only	1.07	0.18	0.69	0.85	0.12	2.66	1.51	0.28	0.60	0.66	0.03	2.13
	Global excl. NA	1.01	0.24	0.58	0.80	0.17	1.84	1.46	0.30	0.56	0.67	0.04	1.85
	Developed only excl.NA	1.23	0.31	0.63	0.75	0.13	2.24	1.55	0.32	0.49	0.63	0.05	1.44
Regional	North America	1.21	0.38	0.59	0.66	0.11	1.93	1.76	0.31	0.48	0.47	0.11	1.37
	Europe	1.34	0.22	0.64	0.70	0.09	2.31	1.53	0.27	0.51	0.57	0.03	1.57
	Asia Pacific	2.09	0.27	0.55	0.56	0.14	1.69	2.70	0.36	0.46	0.46	0.09	1.25
	Japan	1.26	0.51	0.43	0.32	0.15	1.03	1.78	0.49	0.32	0.27	0.04	0.62
	Emerging Markets	1.16	0.26	0.54	0.51	0.12	1.63	1.88	0.32	0.50	0.42	0.05	1.47

Panel B: Regional Benchmark: Local Fama-French Three-factor Model

Test Assets	5×5 Size/B/M + 10 Industry						33 Industry					
	H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS	H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS
North America	0.78	0.15	0.57	0.83	0.11	1.83	1.46	0.23	0.48	0.56	0.13	1.42
Europe	0.83	0.15	0.60	0.87	0.16	1.99	1.31	0.27	0.56	0.68	0.08	1.87
Asia Pacific	2.03	0.30	0.54	0.78	0.18	1.56	2.98	0.37	0.59	0.62	0.22	2.01
Japan	0.71	0.12	0.39	0.85	0.19	0.86	1.36	0.26	0.39	0.64	0.12	0.90
Emerging Markets	1.23	0.45	0.56	0.62	0.27	1.79	2.04	0.54	0.58	0.50	0.15	2.04

Panel C: Hybrid Model Based on Main CL Sample

	Test Assets	5×5 Size/B/M + 10 Industry						33 Industry					
		H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS	H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS
Global	Global	0.80	0.12	0.62	0.88	0.39	1.86	0.85	0.16	0.51	0.70	0.14	1.37
	Developed Only	0.99	0.12	0.65	0.89	0.25	2.07	1.04	0.16	0.51	0.69	0.32	1.34
	Global excl. NA	1.17	0.16	0.56	0.86	0.36	1.62	0.95	0.19	0.57	0.73	0.15	1.74
	Developed only excl.NA	1.87	0.14	0.64	0.89	0.21	2.02	1.43	0.22	0.53	0.73	0.19	1.52
Regional	North America	0.83	0.18	0.66	0.83	0.10	2.38	1.36	0.28	0.56	0.56	0.16	1.84
	Europe	1.30	0.17	0.65	0.86	0.17	2.22	1.46	0.26	0.55	0.68	0.24	1.72
	Asia Pacific	1.66	0.27	0.58	0.78	0.27	1.67	3.02	0.35	0.55	0.64	0.34	1.61
	Japan	0.91	0.13	0.44	0.86	0.27	1.02	1.43	0.22	0.40	0.67	0.13	0.90
	Emerging Markets	1.80	0.26	0.53	0.65	0.35	1.47	2.50	0.33	0.54	0.54	0.13	1.62

Table 3.7, continued

The regressions use the global, local and hybrid version of the Fama-French three-factor model to explain the returns on four sets of global portfolios and five sets of regional portfolios on North America, Europe, Japan, Asia Pacific(excluding Japan), and Emerging Markets formed on size and B/M together with 10 industry portfolios (*left*) and 33 industry portfolios (*right*). The 5×5 results include microcap portfolios The 10 industry portfolios (*left*) are constructed by using the FTSE/Dow Jones Industry Classification Benchmark (Level 1 Industrial Classification In Datastream) to aggregate individual stocks from the specific region for which the test is performed into ten groups representing the industries Oil and Gas, Basic Materials, Industrials, Consumer Goods, Healthcare, Consumer Services, Telecommunications, Utilities, Financials and Technology. Similarly, the 33 industry portfolios (*left*) are constructed by using the FTSE/Dow Jones Industry Classification Benchmark (Level 4 Industrial Classification In Datastream). The GRS statistic tests whether all intercepts in a set of 35 (5×5+ 10) or 33 regressions are zero; H-L α is the difference between the highest and lowest intercepts for a set of regressions; $|\alpha|$ is the average absolute intercept; $SR(\alpha)$ is the Sharpe ratio for the intercepts; R^2 is the average time-series adjusted R^2; CSR R^2 is the GLS cross-sectional R^2. With 35 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.35; 95%: 1.48; 97.5%: 1.60; 99%: 1.73 and 99.9%: 2.05. With 33 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.36; 95%: 1.49; 97.5%: 1.61; 99%: 1.75 and 99.9%: 2.08. Three classes of models are investigated:

$$\text{Global Fama-French Three-factor Model: } R_i - R_f = \alpha_i^G + \beta_i^G\left(R_m^G - R_f\right) + s_i^G F_{Size}^G + h_i^G F_{B/M}^G + \varepsilon_i$$

$$\text{Local Fama-French Three-factor Model: } R_i - R_f = \alpha_i^L + \beta_i^L\left(R_m^L - R_f\right) + s_i^L F_{Size}^L + h_i^L F_{B/M}^L + \varepsilon_i$$

$$\text{Hybrid Fama-French Three-factor Model: } R_i - R_f = \alpha_i^H + \beta_i^A\left(R_m^A - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^A F_{Size}^A + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^A F_{B/M}^A + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + \varepsilon_i$$

The superscript "G" on the market and factor portfolios implies that they are constructed from all stocks around the world and the superscript designation of "L" on the market and factor portfolios implies that they are constructed only from local - or regional, in our experiments - stocks. The superscript "H" denotes the intercept for the hybrid model. The superscript "A" denotes a market or factor portfolio comprised of stocks only in the globally-accessible sample, which is represented by the sample of secondary cross-listings in this study, and the superscript "Ā-A" denotes a market or factor spread portfolio of the difference in the market or factor for purely-local stocks from the specific region (those not secondarily cross-listed overseas for which the test is performed) and that of the globally accessible stocks. The Main CL Sample is used here.

Table 3.8

Summary Statistics for Regression Tests of the Alternative Model Based on Principal Component Analysis(PCA) Using Monthly Excess Returns on 20 Size/B/M Portfolios: Nov. 1990 – Dec. 2010

		H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS	H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS
		Panel A: Hybrid Model						*Panel B: PCA-based Alternative Model*					
Global	Global	0.30	0.08	0.32	0.94	0.67	0.92	0.75	0.27	0.46	0.90	0.38	2.18
	Developed Only	0.35	0.07	0.35	0.95	0.46	1.12	0.74	0.23	0.48	0.88	0.48	2.37
	Global excl. NA	0.72	0.14	0.29	0.90	0.74	0.81	0.80	0.47	0.42	0.75	0.45	1.83
	Developed only excl.NA	0.28	0.07	0.28	0.94	0.61	0.76	1.01	0.49	0.54	0.82	0.42	3.02
Regional	North America	0.62	0.13	0.46	0.90	0.40	2.20	0.42	0.15	0.40	0.74	0.35	1.59
	Europe	0.48	0.12	0.35	0.90	0.38	1.22	0.90	0.30	0.42	0.77	0.14	1.78
	Asia Pacific	0.94	0.23	0.39	0.81	0.30	1.44	1.56	0.57	0.53	0.67	0.19	2.90
	Japan	0.54	0.08	0.25	0.92	0.55	0.65	0.95	0.39	0.34	0.76	0.39	1.19
	Emerging Markets	0.64	0.18	0.29	0.68	0.51	0.82	0.97	0.64	0.39	0.60	0.24	1.52

Table 3.8, continued

The regressions use the alternative model built on principal component analysis(PCA) to explain the returns on four sets of global portfolios and five sets of regional portfolios on North America, Europe, Japan, Asia Pacific(excluding Japan), and Emerging Markets formed on size and B/M. The local factors in the PCA-based alternative model is constructed as follow: first orthogonalize the stock returns for the specific region for which the test is performed relative to the global factors of the globally-accessible set, next identify up to three principal components of the residuals, then the local factor portfolios are determined by the extracted principal factors, with portfolio weights given by the scaled eigenvector. The PCA-based alternative model therefore consists of three global factors and three "local" principal component factors. Panel B reports the regression results of the PCA-based alternative model and, for comparison, Panel A supplements those of the hybrid model proposed in this chapter, which is also reported in Panel C, Table 4. The 4×5 results exclude microcap portfolios. The GRS statistic tests whether all intercepts in a set of 20 (4×5) regressions are zero; H-L α is the difference between the highest and lowest intercepts for a set of regressions; $|\alpha|$ is the average absolute intercept; $SR(\alpha)$ is the Sharpe ratio for the intercepts; R^2 is the average time-series adjusted R^2; CSR R^2 is the GLS cross-sectional R^2. With 20 portfolios and 242 monthly returns, critical values of the GRS statistic for all models are: 90%: 1.45; 95%: 1.62; 97.5%: 1.78; 99%: 1.95 and 99.9%: 2.41. Two classes of models are investigated:

PCA-based Candidate Fama-French Three-factor Model: $R_i - R_f = \alpha_i^H + \beta_i^A\left(R_m^A - R_f\right) + +s_i^A F_{Size}^A + h_i^A F_{B/M}^A + \lambda_i^{PCA,1} F_1^{PCA} + \lambda_i^{PCA,2} F_2^{PCA} + \lambda_i^{PCA,3} F_3^{PCA} + \varepsilon_i$

Hybrid Fama-French Three-factor Model: $R_i - R_f = \alpha_i^H + \beta_i^A\left(R_m^A - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^A F_{Size}^A + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^A F_{B/M}^A + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + \varepsilon_i$

The superscript "H" denotes the intercept for the hybrid model. The superscript "PCA" on the local principal component factor portfolios implies that they are constructed only from local - or regional, in our experiments – stocks and determined by the principal components of the residual extracted from regression of local stock returns on the global factors of the globally-accessible set. The superscript "A" denotes a market or factor portfolio comprised of stocks only in the globally-accessible sample, which is represented by the sample of secondary cross-listings in this study, and the superscript "Ā-A" denotes a market or factor spread portfolio of the difference in the market or factor for purely-local stocks from the specific region (those not secondarily cross-listed overseas for which the test is performed) and that of the globally accessible stocks. The Main CL Sample is used here.

Table 3.9

Summary Statistics for Regression Tests of the Hybrid Model on Europe and Emerging Markets: Nov. 1990 – Dec. 2010

Panel A: Emerging Markets

	Test Assets	4×5 Size/B/M					
		H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS
Global	EMEA	1.64	0.41	0.39	0.34	0.21	1.57
	Latin America	1.44	0.41	0.43	0.34	0.46	1.96
	Southeast Asia	0.69	0.18	0.25	0.45	0.22	0.63
Local	EMEA	1.28	0.71	0.38	0.45	0.45	1.52
	Latin America	1.40	0.31	0.41	0.55	0.17	1.76
	Southeast Asia	0.62	0.13	0.23	0.75	0.28	0.59
Hybrid	EMEA	1.44	0.30	0.33	0.52	0.42	1.09
	Latin America	1.46	0.29	0.40	0.53	0.44	1.64
	Southeast Asia	0.67	0.13	0.24	0.74	0.37	0.58

Panel B: Europe

	Test Assets	4×5 Size/B/M					
		H-L α	$\lvert\alpha\rvert$	$SR(\alpha)$	R^2	CSR R^2	GRS
Global	Non Eurozone Members	0.56	0.11	0.24	0.64	0.34	0.60
	Original Eurozone Members	0.72	0.24	0.41	0.68	0.14	1.72
	- Before Jan. 1999	*1.12*	*0.24*	*0.67*	*0.46*	*0.50*	*1.63*
	- After Jan. 1999	*0.76*	*0.25*	*0.40*	*0.76*	*0.32*	*0.87*
Local	Non Eurozone Members	0.43	0.11	0.25	0.84	0.37	0.64
	Original Eurozone Members	0.57	0.17	0.37	0.88	0.30	1.47
	- Before Jan. 1999	*0.77*	*0.19*	*0.63*	*0.85*	*0.34*	*1.36*
	- After Jan. 1999	*0.79*	*0.18*	*0.45*	*0.90*	*0.23*	*1.21*
Hybrid	Non Eurozone Members	0.58	0.14	0.30	0.83	0.41	0.94
	Original Eurozone Members	0.64	0.14	0.35	0.87	0.44	1.22
	- Before Jan. 1999	*1.05*	*0.22*	*0.68*	*0.82*	*0.37*	*1.63*
	- After Jan. 1999	*0.59*	*0.11*	*0.32*	*0.90*	*0.76*	*0.50*

Table 3.9, continued

The regressions use the global, local and hybrid version of the Fama-French three-factor model to explain the returns on seven sets of portfolios formed on size and B/M (Panel A for Emerging Markets and Panel B for Europe). The 4×5 results exclude microcap portfolios. The GRS statistic tests whether all intercepts in a set of 20 (4×5) regressions are zero; H-L α is the difference between the highest and lowest intercepts for a set of regressions; $|\alpha|$ is the average absolute intercepts; *SR(α)* is the Sharpe ratio for the intercepts; R^2 is the average time-series adjusted R^2; CSR R^2 is the GLS cross-sectional R^2. Three classes of models are investigated:

Global Fama-French Three-factor Model: $R_i - R_f = \alpha_i^G + \beta_i^G\left(R_m^G - R_f\right) + s_i^G F_{Size}^G + h_i^G F_{B/M}^G + \varepsilon_i$

Local Fama-French Three-factor Model: $R_i - R_f = \alpha_i^L + \beta_i^L\left(R_m^L - R_f\right) + s_i^L F_{Size}^L + h_i^L F_{B/M}^L + \varepsilon_i$

Hybrid Fama-French Three-factor Model:

$$R_i - R_f = \alpha_i^H + \beta_i^A\left(R_m^A - R_f\right) + \beta_i^{\bar{A}-A} R_m^{\bar{A}-A} + s_i^A F_{Size}^A + s_i^{\bar{A}-A} F_{Size}^{\bar{A}-A} + h_i^A F_{B/M}^A + h_i^{\bar{A}-A} F_{B/M}^{\bar{A}-A} + \varepsilon_i$$

The superscript "G" on the market and factor portfolios implies that they are constructed from all stocks around the world and the superscript designation of "L" on the market and factor portfolios implies that they are constructed only from local - or regional, in our experiments - stocks. The superscript "H" denotes the intercept for the hybrid model. The superscript "A" denotes a market or factor portfolio comprised of stocks only in the globally-accessible sample, which is represented by the sample of secondary cross-listings in this study, and the superscript "Ā-A" denotes a market or factor spread portfolio of the difference in the market or factor for purely-local stocks from the specific region (those not secondarily cross-listed overseas for which the test is performed) and that of the globally accessible stocks. The Main CL Sample is used here.

APPENDIX

Procedure for Constructing the Globally Accessible Sample

Target Market	U.S.	U.K.	Europe	Germany	Luxembourg	Singapore	Hong Kong
Target Exchanges	NYSE/AMEX, NASDAQ, Non NASDAQ OTC New York, NASDAQ/NMS, NYSE Arca	London London OTC London Plus Market SEAQ International	Euronext Amsterdam Brussels Lisbon Paris Easdaq	Frankfurt	Luxembourg	Singapore Catalist Singapore OTC Singapore	Hong Kong
Exclusion Criteria							
• *Non domestic stocks only*	9,632	4,114	5,165	14,542	430	300	314
• *Target market currency denominated only*	9,585	4,114	5,165	14,542	430	215	284
• *ADRs, GDRs, or equity only*	8,900	3,112	4,212	13,899	404	212	246
• *Available records of home market only*	9,181	3,086	4,205	13,873	363	212	246
• *Qualified records of parent code only*	8,857	3,078	4,205	12,591	363	211	246
• *Available RI records only*	7,586	2,413	2,997	12,186	143	179	216
• *Exclude dual record in one target market*	6,421	1,995	2,217	11,463	133	171	212
• *Qualified countries only*	6,320	1,791	2,165	11,292	126	170	210
• *Available records from Worldscope only*	5,080	1,517	1,058	9,986	101	160	201
• *Non-financial stocks only*	4,392	1,283	690	8,680	82	120	175
• *Exclude special cases*	4,354	1,273	689	8,622	81	120	175
• *Total across regions*						11,319	
• *Additional domestic stocks included*						11,335	
• *Qualified stocks only*	CL1			11,057			
• *Viability Constraints*	Main CL Sample			5,747		• *Relative viability constraints(I or II)*	
	CL2a			9,605		• *Absolute viability constraint*	
	CL2b			4,058		• *Stringent Relative viability constraints(I or II)*	

Appendix, continued

This table shows the procedure on how to construct the globally accessible sample and the total number of stocks is reported for each step. The list of target exchanges is as shown and each exclusion criterion is explained in the table below. To be included in the global accessible sample, each stock has to be also cross listed in any of the 7 target markets with the types of ADRs, GDRs or equity, has sufficient information to identify its home market and parent codes, have at least one monthly returns, has sufficient information to calculate at least one of the characteristics including Size, B/M and C/P. "CL" stands for cross-listing.

Definitions of Exclusion Criteria

Exclusion Criteria	Description
• *Non domestic stocks only*	If one stock is only listed in its home market, it is excluded from the sample. And these stocks are excluded as follow, ▪ Stocks are from U.S. and only listed in the target exchanges within the U.S.; ▪ Stocks are from U.K. and only listed in the target exchanges within the U.K.; ▪ Stocks are from Portugal and only listed in Euronext Lisbon; ▪ Stocks are from France and only listed in Euronext Paris; ▪ Stocks are from Netherland and only listed in Euronext Amsterdam; ▪ Stocks are from Luxembourg and only listed in Luxembourg; ▪ Stocks are from Singapore and only listed in the target exchanges within Singapore; ▪ Stocks are from Hong Kong and only listed in Hong Kong Stock Exchange
• *Target market currency denomination only*	If one stock is denominated with a currency other than that of the host market, it is excluded from the sample. This exclusion criterion only applies to stocks cross-listed in the U.S., Singapore and Hong Kong.
• *ADRs, GDRs, or equity only*	If one stock is recorded as other instrument types than ADRs, GDRs or equity from Datastream, it is excluded from the sample.
• *Available records of home market only*	If one stock has no available records of home market from Datastream, it is excluded from the sample.
• *Qualified records of parent code only*	If one stock has no available records of parent code in each major exchange from Datastream, it is excluded from the sample.
• *Available RI records only*	If one stock has no available Return Index (RI) from Datastream, it is excluded from the sample.
• *Exclude dual record case in one target market*	If one stock is cross listed on more than one target exchange within one given target market, it is counted as only one stock in the sample.
• *Qualified countries only*	If one stock is from countries other than the country list in Table 1, it is excluded from the sample.
• *Available records from Worldscope only*	If one stock has no available company account item from Worldscope, it is excluded from the sample.
• *Non-financial stocks only*	If one stock is financial stock, it is excluded from the sample.
• *Exclude special cases*	Special cases include but is not limited to that the ADR (or GDR), instead of the home equity, is primary quoted in Datastream.
• *Total across regions*	If one stock is listed in more than one target market, it is counted as only one stock in the sample.
• *Additional domestic stocks included*	Domestic stocks from the seven target markets are included as long as three criteria are satisfied: a. size (in the top 75% of market cap for the market); b. liquidity (a minimum price of $5 for U.S. and equivalent levels in terms of percentile rank for non U.S. markets); and c. float (a minimum 75% public float for listed stocks)
• *Qualified stocks only*	If one stock has less than 12 monthly returns, it is excluded from the sample.
• *Viability Constraints*	Viability constraints are evaluated by the Turnover (VO) from Datastream and it includes records in the home market and those in the target markets.
• *Relative viability constraint I*	For each cross-listed stock in the sample, there should be at least 0.5% of annual oversea trading value relative to all secondarily cross-listed stock trading from its country of domicile
• *Relative viability constraint II*	For each cross-listed stock in the sample, there should be at least 0.1% of annual global trading volume occurred in any of the target markets on average during the sample period
• *Absolute viability constraint*	For each cross-listed stock in the sample in a given year, if there is at least one month of non-zero trading occurred in the target markets, the stock is included in the sample for that year
• *Stringent Relative viability constraints(I or II)*	The screening ratios are 5% for relative viability constraint I and 1% for relative viability constraint II.

CHAPTER 4

WHAT FACTORS DRIVE TRADING AROUND THE WORLD?

4.1 Introduction

Over the past two decades, financial economists have become increasingly fascinated with the trading decisions of investors. Although there have been many rich explanations for the level of trading volume, such as tax-driven trading, liquidity trading, portfolio rebalancing and speculation, less effort has been devoted to improving our understanding of the commonality in trading activity across different stocks. Decomposing trading activity to measure how much of the trading process is driven by systematic factors and how much is because of firm-specific causes is valuable for modeling asset pricing and trading volume. Understanding commonality of trading around the world is also important for global asset managers concerned with diversifying their investment and trading strategies.

Considerable evidence has shown that the systematic variation of stock returns are related with firm-level characteristics such as size, book-to-market equity, cash flow to price, momentum while we know little about the theoretical foundation for the co-movement in stock trading. To fill the gap, Lo and Wang (LW hereafter, 2000 and 2006) have developed a multi-factor model for turnover based on mutual fund separation theorem. This model suggests that the number of return factors and the number of turnover factors should be the same. And the turnover factors in turnover model are nothing but the turnover on the K return factors. Although their model gives rise to a decomposition of turnover into systematic and idiosyncratic components, difficulties

still exist in implementing conventional procedures of multifactor estimation due to severe heteroscedasticity and nonstationarity in turnover data. In order to overcome these problems, Cremers and Mei (CM hereafter, 2007) employ two statistical procedures developed by Bai and Ng (BN hereafter, 2002 and 2004) and document that there are four or five systematic factors driving stock turnover in the NYSE and AMEX for the period of 1962-2001. This chapter is motivated in the same spirit but broadens the investigation to over 30,000 stocks from 48 countries using weekly turnovers over the 1977 to 2010 period. Given the widespread acceptance of the common factors in return, do these factors also drive the systematic trading around the world? The purpose of this chapter is to answer this important question.

The global perspective helps to illuminate how the co-movement in trading activity varies across countries and over time. Furthermore, it furnishes a better understanding of the relationship between the commonality in return and the commonality in trading. Are the cross-country and time-series patterns in the commonality in trading similar to those for the commonality in returns? This extensive study enables us not only to determine how well classic multifactor models perform in developed or emerging markets in terms of capturing the systematic turnover, but also to identify which factors in stock returns are important for explaining the common variation in stock turnover for each country.

This chapter uncovers several new findings on the commonality of trading around the world. First, the results suggest, the systematic turnover factors together capture 31% of the variation of individual stock turnover on average, lower than the 36% of systematic variation in individual stock excess returns. The average level of commonality in trading varies substantially across countries, with greater values for less developed countries, which is consistent with the findings and argument of Morck, Yeung and Yu (2000). In general, there are two to four pervasive return

factors while three to eight systematic turnover factors exist. In terms of time-series dynamics, I show that in North America the commonalities of both excess return and turnover are U-shaped over the last ten years.

Secondly and perhaps more importantly, the return-based factors work poorly in capturing the common variation in stock turnovers around the world. Although the factors associated with size, book-to-market, and cash-flow-to-price help capture the cross-sectional variation in stock turnover, these common factor-mimicking portfolios, together with the market portfolio, can only explain up to 67% of the co-movement of trading, much lower than their performance in capturing over 90% of the cross-sectional variation in stock returns. Additionally, the component of systematic trading unrelated with return motives varies substantially across markets, with larger gaps for North America, Japan and most emerging markets.

In terms of time-series dynamics, it shows that, according to LW (2000, 2006) model, trading due to systematic risk in returns can account for 64% of all systematic turnover variation on average. I further compare the performances of three asset pricing models – namely, CAPM, the Fama and French (FF hereafter, 1993) three-factor model and the Hou-Karolyi –Kho (HKK hereafter, 2011) model. CAPM market turnover captures on average 37% of all systematic turnover in individual stock trading. Two additional FF factor turnovers increase the mean performance of the 48 countries by 23% in capturing systematic turnover; two additional HKK (2011) factor turnovers increase by 16%. I continue to identify which factors in returns are important for explaining the common variation in stock turnover. For all the major factors that have been suggested in the empirical asset pricing literature, a zero-investment factor-mimicking portfolio (in the spirit of Huberman, Kandel and Stambaugh, 1987, using the methodology of FF, 1992, Chan, Karceski and Lakonishok, 1998 and HKK, 2011) is constructed by going long in

stocks that have high values on an attribute and short in stocks with low values of the attribute. Examining the turnover behavior of different factor mimicking portfolios can help us evaluate and interpret the trading implications related to these stock characteristics. Results show that factors associated with size, book-to-market, and cash flow to price are important in driving the systematic turnover in individual stock trading. I finally assess the performance of different models, which combine these factor-mimicking portfolios with the market portfolio, in capturing the systematic turnover in individual stock trading. A universal four-factor model, which includes a market turnover factor and three other factor turnovers associated with size, book-to-market, and cash-flow-to-price, can explain on average up to 67% of the common variation in stock turnovers around the world. The results indicate that the return-based factors fare poorly in the regression of individual stock turnovers and there are around 33% left in the commonality of trading that cannot be explained by the return motives.

Cross-country analysis shows that the explanatory power of the return-based multifactor model varies substantially across countries and markets, with better performance for European developed markets and China. When the FF three-factor model is used in the regression of individual stock turnovers, 27% of the systematic turnover is unexplained in U.K., Norway and Sweden while over 52% is left in U.S, 48% in the Tokyo stock exchange, and 54% in Taiwan, South Korea and other emerging markets. When the optimal four-factor model is applied, in terms of the average R^2 from regression for each country and market, 20% of the systematic turnover in the U.K., Norway and Sweden cannot be explained by these return-based factors while over 40% is left in North America, 43% in the Tokyo stock exchange, and 36% left in the emerging markets. Here, China is a special case in that there is only 20% of all systematic turnover in individual stock trading left beyond what the return-based factors can capture, despite

that its commonality of trading ranks highest in the world. One possibility that might explain the superior performance of the return-based factors in European markets is that their total commonality in trading is small and therefore it is easy for the return-based factors to approach the optimal level. Why the return-based factors work even worse in the United States and Japan remains an open-ended question.

The remainder of the chapter is organized as follows. Section 2 provides a description of the data, followed by the methodology for decomposing turnover. Section 3 briefly describes the decomposition results. Section 4 shows how return factors explain the turnover file and Section 5 concludes.

4.2. Data and Methodology for Decomposing Turnover

This section explains the data sources, the screening procedures, and the methodology of turnover decomposition.

4.2.1 Data Sources and Screens

I collect the weekly total return index (RI), the weekly trading turnover (VO; expressed in thousands of shares), the number of outstanding shares (NB), and the market capitalization (MV; expressed in millions of U.S. dollars) for individual stocks from Datastream. The choice of a weekly horizon is a compromise between maximizing sample size and minimizing the day-to-day volume and return fluctuations that have less direct economic relevance (LW, 2000 and CM, 2007). According to convention, I measure weekly turnovers and returns from Wednesday-day

close to the following Wednesday close[48].

My sample includes 42,080 stocks from 48 countries from Dec. 29, 1976 to June, 30, 2010. According to the classification by the International Finance Corporation (IFC) of the World Bank Group, 22 out of the 48 countries are developed (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Italy, Japan, Luxembourg, the Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, the U.K., and the U.S.) and 26 markets are developing (Argentina, Brazil, Chile, China, Colombia, Czech Republic Greece, Hungary, India, Indonesia, Israel, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Portugal, Russian Federation, Sri Lanka, South Africa, South Korea, Taiwan, Thailand, and Turkey, and Venezuela).

Because my focus is on the implications of portfolio theory for trading behavior, I restrict the sample to stocks from major exchanges, which I define as the exchanges on which the majority of stocks in that country are listed. However, multiple exchanges are included in samples for China (Shanghai and Shenzhen exchanges), Japan (Osaka and Tokyo exchanges), and the United States (NYSE, AMEX and NASDAQ). I exclude preferred stocks, warrants, REITs, depositary receipts, and other stocks with special features[49].

To limit the effect of survivorship bias, I include dead stocks in the sample. For both dead and active stocks, I confirm the ending date if it satisfies two conditions: 1) consecutive constant RIs

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[1] Seasonal patterns in weekly autocorrelations have been examined in detail by Keim and Stambaugh (1984), Bessembinder and Hertzel (1993), and Boudoukh et al. (1994). Bessembinder and Hertzel (1993) find, for example, that the patterns in autocorrelations across weekdays are related to the importance of weekend returns versus nonweekend returns in autocorrelation patterns and are robust to alternative market microstructures.

[49] The exclusion of these stocks is done manually by examining the names of the individual stocks, as neither Datastream nor Worldscope provide codes for discerning non-common shares from common shares. I drop stocks with name including “REIT”, “REAL EST”, “GDR”, “PF”, “PREE”, or “PRF” as these terms may represent REITS, GDRs, or preferred stocks. I drop stocks with name including “duplicate”, “dual purposes”, “TRUST”, “INCOME FD”, “INCOME FUND” due to various special features.

from that day until the end of the period, June, 30, 2010; 2) zero VOs from that day until the end of the period. Panel A in Table 4.1 shows a brief summary by year. The second column of the sheet provides the number of firms with status of dead or suspended listed in Datastream, the third column gives the number of firms that are actually dead according to the two conditions stated above, the fourth column provides the number of firms that were alive until June 2010, and the fifth column sums up all the previous three columns.

I use the following screens and adjustments. The stocks whose either VOs or RIs are unavailable from Datastream are dropped from the sample. For weekly returns, I apply several screening procedures suggested by Ince and Porter (2003) and HKK (2011). In addition, I require a minimum price of $1 (and equivalent value for foreign currencies) at previous week-end for a stock to be included in the analysis to minimize potential biases arising from low-price and illiquid stocks. Panel B in Table 4.1 confirms that the final sample has consistent value-weighted market returns with the MSCI country index returns.

Panel C in Table 4.1 presents the number of firms in raw sample, unbalanced sample, and balanced sample. The first column provides the number of securities traded on the exchanges. The second column provides the unbalanced sample, which includes the number of securities with <50% missing observations in turnovers and no problematic data[50].The third column provides the balanced sample, including the number of securities with neither missing observations in turnover nor problematic data. The last column provides average weekly turnovers estimates for the whole sample period, which are comparable to earlier studies such as

[50] Two types of problematic data (CM, 2007) are considered. The first type includes stocks that have constant turnovers in the period. The second are those stocks that have likely data entry problems as evidenced by an unusually large standard deviation (specifically, 10 times the average standard deviation. See also the discussion on the so-called Z-flag in LW. As they argue, such large standard deviations probably indicate data errors).

LW (2000) and CM (2007). This chapter standardizes the turnover data by first de-meaning, and then normalizing, each stock turnover series by its sample standard deviation over the relevant period.

Consistent with CM (2007) and LW (2000), the time series data have been divided into seven five-year sample periods. I further limit my final sample by just allowing positive turnovers for the sample period to prevent the problem of missing data. Table 4.2 presents a brief summary for seven five-year sample sub-periods. For each sub-period, the first column provides the simple average weekly turnover and the second column provides the number of firms which satisfies the positive turnover condition from the balanced sample. 48 out of 51 markets meet with the sub-period screening criteria. Additionally, I impose the condition of no less than 50 firms for each sample; thirty-three out of fifty-one markets are available for turnover decomposition.

To ensure that the accounting variables are known before the returns, I match the accounting data for fiscal year-end in year $t-1$ with weekly returns from July of year t to June of year $t+1$. Among the accounting ratios, L/B (Worldscope data item WC08226), D/P (WC09404), and E/P (WC09204) are directly obtained from Worldscope. I take the inverses of the price-to-book ratio (WC09304) and the price-to-cash-flow ratio (WC09604) to calculate the B/M and C/P ratios, respectively. Size is defined as the market value of equity at the last Wednesday of June of year t, and momentum (Mom) for month t is the cumulative raw return from month $t-6$ to month $t-2$, skipping month $t-1$ to mitigate the impact of microstructure biases such as bid-ask spread or nonsynchronous trading. In addition, I select the stocks with complete financial accounting information to construct the characteristic-based portfolios: book-to-market equity, cash flow-to-price, and dividend-to-price.

4.2.2 Methodology for Decomposing Turnover

LW (2000, 2006) provide a multifactor model for turnover:

$$\tau_{jt} = \tau_j + \delta_{j1} g_{1t} + \cdots + \delta_{jK} g_{Kt} + \xi_{jt}$$

(1)

where τ_{jt} is the turnover of stock *j* in period *t* (number of shares traded divided by the total number of shares outstanding), δ_{jk} is the exposure of firm *j* to economy wide trading shocks g_{kt}, and τ_j is a constant. Using terms common for discussing returns, I call δ_{jk} turnover betas. ξ_{jt} has mean zero and is assumed to be orthogonal to g_{kt}. In addition, I assume ξ_{jt} satisfies the regularity conditions as given in BN (2002, 2004). Appendix A shows the detailed decomposition method proposed by BN (2002, 2004).

4.3 Decomposition Results

4.3.1 The Commonality in Turnover and Excess Return

Decomposition results suggest that there is a strong presence of commonality in turnover and excess return for each country. On average, the systematic turnover factors together capture 31% of the variation of individual stock turnover, lower than the percentage of systematic variation in individual stock excess return, 36%. The asymmetry between the commonality of trading and excess returns around the world is different from what CM (2007) find for the NYSE and AMEX. It might indicate that there are more firm-specific components incorporated in trading volume rather than the price for other foreign markets.

Figure 4.1 illustrates the cross-country variation in commonality in turnover and excess return.

The figure sorts the average R^2, a measurement of commonality in turnover, over the sample period for the thirty-three markets in out sample, from high to low. The average level of commonality in trading varies substantially across countries, with greater values for less developed countries. China stands out, with an average R^2 of 64%. Among other less-developed countries, such as Taiwan, Turkey, Malaysia, commonality average around 31-54%, whereas developed countries like Australia, Finland, Canada and the U.K. have an average commonality of just around 13-19%. The cross-sectional variation from less-developed countries to developed countries also can be found from the commonality of excess return in Figure 4.1. This evidence is consistent with the information argument by Grossman and Stiglitz (1980), Shleifer and Vishny (1997) and Morck, Yeung and Yu (2000).

Figure 4.2 shows the trend of the commonality in turnover and excess return using the Hodrick-Prescott filter (Hodrick and Prescott, 1997). Panel A exhibits the non-overlapping yearly time-series of R^2. In addition, the overlapping weekly R^2s are obtained by regressing the past year stock turnover and excess return on the corresponding extracted factors, which are reported in Panel B. Although Morck, Yeung and Yu (2000) attribute the stock price synchronicity to market inefficiency, the U-shape of the R^2 over time, in both developed and emerging economies, does not necessarily mean that the market's information environment has weakened for all the zones. Instead, the evidence from North America is consistent with recent finding on liquidity and institutional herding (Hasbrouck and Seppi, 2001; Sias, 2003; Kamara, Lou and Sadka, 2008; Brunnermeier and Pedersen, 2009; Karolyi, Lee and Dijk, 2010). In the U.S. and Canada, the correlated trading by institutional investors has strengthened the co-movement of stock price. Especially, the Financial Crisis in 2006-2008 has increased the commonality in turnover, the comprehensive measure of the degree of correlated trading.

Additionally, the commonalities in both turnover and excess return spiked during macroeconomic shocks (such as the 1989-91 Economic Recession, and the 1994 economic crisis in Mexico), liquidity shocks (such as the Financial Crisis of 2007-2010, and the 1997 Asian Financial Crisis), corporate events (such as the WorldCom Bankruptcy, and the Enron Scandal in 2001), and other shocks (such as the Black Monday in 1987, the September 11 attacks, and the Indian Ocean tsunami in 2004). This finding is consistent with the models by Roll (1988) and Morck, Yeung and Yu (2000) which argue that macroeconomic instability and financial crises interrupt the functioning of stock market, prevent firm-specific information from being capitalized into stock prices, and increase the synchronicity of stock movement.

However, these commonalities in turnover and in excess return are not necessarily correlated with each other in some certain periods. Still taking U.S. NYSE& AMEX as an example, Figure 4.3 shows the commonality in turnover is more sensitive than the commonality in excess return, especially during the 1989-91 Economic Recession, the 1994 Economic Crisis in Mexico, the 1998-2001 North America Economic Crisis, and the Indian Ocean tsunami in 2004. Sometimes the commonality in turnover spiked even earlier, as in the subprime crisis.

I consider two plausible explanations for the variances. First, because stock trading incorporates more information than the price, such as market sentiment, investor attention and non-public information transmissions, the commonality in turnover, to some extent, will tend to react more dramatically than the commonality in excess return. Second, the super-sensitivity of the commonality in turnover is related to the correlated trading by institutional investors. When the market experiences shocks, institutional investors will trade multiple stocks in a similar way due to changes in the information environment or to liquidity shocks they face. Because these investors hold many different stocks at the same time, they are likely to trade them

simultaneously to minimize trading costs and to maintain a well-diversified portfolio. Accordingly, correlated trading will increase even before the market registers the shocks into the price. My conception of the commonality in turnover includes these additional market forces and therefore can represent the optimal degree of correlated trading in the market.

In conclusion, the commonalities in excess return and turnover describe how the market has functioned across countries and over time. Especially, the commonality in turnover indicates the pattern of information transmission across the stocks.

4.3.2 The Number of Factors in Turnover and Excess Return

Table 4.3 gives the results of the test of the number of factors in standardized turnover and excess return. There are more systematic turnover factors than return factors. For most of the countries, there are two to four pervasive return factors while three to eight systematic turnover factors exist. Table 4.4 summarizes the explanatory power for each principal component. The first principal component of turnover typically explains between 6% (Australia, 95-00) and 68% (Shenzhen stock exchange in China, 95-00), in average 17%, of the variation of the standardized turnover. Over time the numbers of systematic turnover factors have significantly increased. Furthermore, the sixth to eighth components still explain a fair amount of turnover variation, in average 2%. Compared with the results of excess return, the explanatory powers of systematic factors in turnover are relatively lower either for the individual stock turnover (Panel A, Table 4.4) or for all systematic turnover in individual stock trading (Panel B, Table 4.4)

There are other two main findings from Table 4.3. Asian markets have more factors than other countries and markets. It motivates to the discussion on the role of government policy,

psychological bias and other non-fundamental factors in driving the cross-sectional variation of the correlated trading in local capital markets. Secondly, the number of factors has increased for almost all the markets over time. Even for the most recent ten years, there are more factors of common variation in turnover in thirteen markets, twelve markets still having the constant number of factors while only three markets having fewer number of factors. The evidence might be related with the increasing openness of local capital market for foreign investors.

In order to better investigate how the number of factors changes over each week, not just across each five-year sub-period, additional work has done by decomposing the weekly stock turnovers over the past years to estimate the optimal number of systematic factors for each week. The result shows that the number of turnover and excess return factors in developed markets has risen during the period of macroeconomic instability and financial crises. It is reasonable given that the constraints for the institutional tend to tight during these periods.

In addition, BN (2004) PANIC analysis shows that the turnover decomposition breaks persistent turnover into two components: a persistent systematic component and a stationary idiosyncratic component. The number (in red) from Table 4.3 denotes that the corresponding systematic factor is stationary. For example, as for the most recent five years for Shenzhen stock exchange in China, the first three systematic factors are stationary while the last two systematic factors are not. This not only gives us a better way to understand the dynamics of turnover at the firm level but also indicates another way to find the proxies for the systematic factors.

4.4 Can Fundamental Factors Fully Explain the Correlated Trading around the World?

It is well recognized that fundamental factors can capture common variation in stock returns.

This goal of this section is to check how fundamental factors explain stock turnover and its systematic co-variation. There are good reasons to think the systematic patterns in stock returns and trading activity are linked. If the market is perfectly efficient, systematic information incorporated in the trading volume should be reflected in the stock return on one hand, and, on the other hand, the risk factors driving the stock returns should also be expected to capture the cross-sectional variation in trading volume. Since the stock prices have been shown to be driven by the common factors associated with these characteristics, the same factors are expected to play a similar role in driving the corresponding trading volume.

4.4.1 Four Empirical Asset Pricing Models

As the first step, I compare the performance of three asset-pricing models: (a) CAPM; (b) the FF (1993) three-factor model; (c) the HKK (2011) model; and (d) the LW (2000) model, by the ability of turnover on their return factors to explain individual stock turnover.

First two columns in Table 4.5 report the average R^2 from regressing individual stock turnover on the CAPM market turnover over the all available sample periods for each market. The CAPM market turnover is the value-weighted turnover across all individual firms in each sub-period, using market capitalization weights for all firms. The second column reports that the CAPM market turnover on average explains 12% of individual stock turnover over the sample periods across all the countries. In comparison, CAPM market return can explain 29% of individual stock excess return. The Table 4.also reports the relative performance of the CAPM market turnover. I measure performance by computing the average R^2 in the second column divided by the average R^2 in the last column, which is obtained from regressing individual stock turnover on their principal components. We can see that the CAPM market turnover here captures on average

37% of all systematic turnover in individual stock trading.

Next two columns in Table 4.5 report the average R^2 from regressing individual stock turnover on turnovers of the FF (1993) three return factors. The FF (1993) three portfolios are a value-weighted market portfolio plus "small minus big" (SMB) portfolio and "high minus low" (HML) portfolio. Portfolio turnover is defined by computing a value-weighted average of individual stock turnover, with the weights being the absolute value of the portfolio weights. We can see that the FF (1993) factor turnovers typically explain 8-50% of individual stock turnover, capturing about 32-82% of all systematic turnover in individual stock trading. Therefore, the two additional FF (1993) factor turnovers increase the mean performance by 23% in capturing systematic turnover.

Table 4.5 next shows the average R^2 from regressing individual stock turnover on turnovers of the HKK (2011) return factors. The three HKK (2011) portfolios are a value-weighted market portfolio plus two value-weighted factor mimicking portfolios (FMP hereafter): that is, "price to cash flow" and "momentum". We can see that the HKK (2011) factor turnovers typically explain 6-47% of the individual stock turnover, which capture 30-75% of all systematic turnover in individual stock trading. The two additional HKK factor turnovers increase the mean performance by 16% in capturing systematic turnover.

The average R^2 from regressing individual stock turnover on turnovers of return factors extracted from the LW (2000) model is also presented in Table 4.5. The return factor portfolios here are determined by the principal component factors extracted from the return data, with portfolio weights given by the scaled eigenvector. The number of return factors used is reported in Table 4.3. Thus, the corresponding turnover for each factor portfolio is simply the weighted average

of individual turnover, using again the absolute value of scaled eigenvectors as weights. We can see that the LW (2000) turnover typically explain 8-52% of individual stock turnover, while they capture on average 37-93% of all systematic turnover in individual stock trading. Therefore, the LW (2000) turnovers on return factor portfolios outperform those of FF (1993) in capturing systematic turnover by adding 4%. Ideally, if the LW (2000) mutual fund separation holds, we would expect the LW (2000) turnovers to capture 100% of individual stock turnover. Thus, the average 64% of the systematic turnover by LW (2000) turnover indicates that the remainder 36% can be thought of as the distance to the true LW (2000) return-turnover model.

Table 4.6 shows the average R^2 from regressing individual stock excess return on return factors derived from the three asset-pricing models. And Table 4.7 summarizes the regressions results. It is shown that, on average, the factor mimicking portfolio performs well in explaining the cross-sectional variation in excess returns. For example, FF (1993) three factor models capturing 90% of all systematic excess stock return, which is 29% higher than the explanatory power on the systematic turnover co-variation. The results complement those of CM (2007) and earlier empirical studies, which emphasize the role of portfolio rebalancing in determining turnover. On the other hand, the results also suggest that existing asset-pricing models have quite limited explanation for trading activity.

Figure 4.4 presents the average performance by FF (1993) three-factor model for each market, sorted from high to low. The ability of turnover on their fundamental return factors in explaining stock turnover varies across markets, with greater values for developed European markets and China. Switzerland and Osaka stand out, with an average performance of over 80%, which means that only 20% of the common variation of stock turnover could not be explained by FF (1993) three factors. China also has a relatively high performance ratio of 75%. The strong

motive of portfolio rebalancing in trading activity might be related with its homogenous market structure since it is a highly regulated market. In contrast, North American and relatively open emerging markets, like, Brazil, Taiwan, and Thailand, have an average performance of just 46%. This evidence initiates the later analysis on institutional herding and psychological bias since there are more different trading motives in these markets.

4.4.2 A Horserace of Return-based Factors

Previous evaluations discuss the role of accounting ratios (fundamental factors), statistical factors and the return on a market index (the market factor) for the cross-section of stock turnover. In order to further explore which firm-level characteristics best account for systematic turnover co-variation around the world, this section continues to explore other fundamental factors and two additional sets of empirical factors that are based on past return (technical factors) and macroeconomic variates (macroeconomic factors). Together, these make up all the major possible candidates for stock return co-variation that have been discussed in the literature.

I follow FF (1993) and Chan, Karceski and Lakonishok (1998) in constructing proxy factors as returns on zero-investment portfolios that go long in stocks in stocks with high values of a characteristic and short in stocks with low values of a characteristic. And I judge how well different FMPs can explain common variation in turnover across size quintile portfolios as test assets (with the F-test of Gibbons, Ross and Shanken, 1989) and individual stocks as R^2 discussed in previous section.

i. Fundamental Factors

D/P is the ratio of dividends to market value of equity. E/P is the ratio of earnings to market value of equity. L/B is the leverage ratio. In each case I exclude a firm if it has a zero or negative value for the particular value for the particular accounting ratio. For each of the characteristics, quintile portfolios at the end of June of each year *t* using accounting information from fiscal year ending in year *t-1*, and their value-weighted turnovers are calculated from July of year *t* to June of *t+1*, as in FF (1992,1993). The FMP turnovers are calculated as the highest-quintile turnover minus the lowest-quintile turnover.

ii. Technical Factors

This set of factors is inspired by earlier findings that a firm's past return helps to predict future returns (DeBondt and Thaler, 1985; Brock, Lakonishok and LeBaron, 1992; Jegadeesh and Titman, 1993, 1995; Chan, Jegadeesh, and Lakonsishock, 1996). The most obvious trading strategies are those based on the past return pattern of stocks. Momentum and contrarian strategies are two opposite example of those. Two of the simplest and most widely used technical rules are also investigate: moving average-oscillator and trading range break-out.

The momentum FMP is formed following Jegadeesh and Titman's (1993) 6-month/6-month strategy where each month's turnover is an equal-weighted average of six individual strategies of buying the winner quintile and selling the loser quintile and rebalanced monthly. In order to minimize the bid-ask bounce effect, one month is skipped between ranking and holding periods in constructing the momentum FMP. The contrarian FMP is formed following Jegadeesh and Titman's (1995) and Lo and MacKinlay (1990) one week strategy which each week's turnover is weighted average of selling the winner stocks relative to the equally-weighted index and buying the loser quintile in past week. The portfolio weight ($w_{i,t}$) assign to stock *i* at time *t* is

$$w_{i,t} = -\frac{1}{N}\left(r_{i,t-1} - \widehat{r_{t-1}}\right)$$

(2)

where N is the number of stocks and $\widehat{r_{t-1}}$ is the equally-weighted index return at time *t-1*.

The rule of moving average-oscillator initiates buy (sell) signals when the short moving average is above (below) the long moving average by an amount larger than the band. The moving-average FMP is formed following Brock, Lakonishok and LeBaron (1992) two week strategy which each two-weeks' turnover is weighted average of buying the upper part[51] and selling the lower part where the short period is one week and the long period is twenty-one weeks. With the rule of trading range break, buy (sell) signals are generated when the price level moves above (below) local maximums (minimums). The local maximums (minimums) are computed over the preceding twenty-one weeks. The trading-range-break FMP is formed as two-week strategy which each two-weeks' turnover is average of buying the upper part[52] and selling the lower part.

iii. Macroeconomic Factors

Because stock returns reflect the state of the economy, various measures of macro-economic conditions serves as the basis for the third set of factors. The first variable is the growth rate of monthly industrial production (IP). Next is the change in unemployment rate (UE), and the third one is the change in monthly expected inflation (CPI). In forming FMP, the relevant attribute is a stock's loading on the factor, which is estimated from a regression using the most recent past sixty months of data prior to the portfolio formation data. The excess return on the market portfolio is included as an explanatory variable along with the particular macroeconomic variable

[51] It refers to when the short moving average is above its long moving average.
[52] It refers to when the price level is above its local maximum.

in order to control for market-wide movements in stock prices. The regression slope on the pre-specified factor serves as the attribute on which stocks are ranked and assigned to portfolios.

Motivated by Chan, Karceski and Lakonishok (1998), I check the volatilities of turnover on the mimicking portfolios. By summarizing the largest standard deviations of turnovers on the factor portfolios during each sub-period for each market, I find that C/P, E/P and size FMPs are the three factor portfolios that mostly ranked as the largest volatility in factor portfolio turnover. Additionally, the contrarian FMP beats other alternatives of technical factors in terms of the standard deviation. It is understandable because only this factor portfolio is constructed by the weekly return performance. Among three macroeconomic FMPs, the CPI FMP has relatively larger volatility in turnover for most of the markets. Table 4.8 reports the average standard deviation of FMPs across all the possible sub-periods for all of the markets. Among the eight out of thirty-three markets, C/P (denoted by CHL in the table) FMP has the highest standard deviation in turnover on average. It is also the same case for E/P (denoted by EPG in the table) FMP. The last row of Table 4.8 reports the average standard deviation of these factor portfolio turnovers across all the markets. It shows that CPI FMP exhibits largest turnover volatility, then it might be contributing a substantial common component to turnover movements.

Furthermore, given previous statistical results that the turnover tends to have more systematic factors than the return, it is reasonable to start from looking for a four-factor model. I proceed in four steps.

The first step is to find the model that fits the best across sub-periods. In order to find the most powerful model in explaining the cross variation of turnover among different stocks within the market, I perform a horse race on all the possible combinations of fundamental factors,

momentum and contrarian factors, which are extensively studies in multifactor asset pricing models. The second column of Table 4.9 reports the list of models that achieve the highest equally-weighted average R^2 across sample periods in the individual stock turnover regressions for each of the markets. The important factors for most of the market include size, B/M, C/P, E/P, L/B and contrarian (denoted by CON in the table) factors.

The second step evaluates the explanatory powers of each possible model across different markets with the aim to find the universal four-factor model that fit the best around the world. It turns out that the model combing market factor, size factor, B/M factor and C/P factor together (MSBC model, thereafter) is the one that has the highest equally-weighted average R^2 in regression of individual stock turnovers on mimicking portfolios across markets. MSBC model explain on average 21% of individual stock turnover, capturing about 67% of all systematic turnover in individual stock trading. And Carhart's (1997) four-factor model, which adds the momentum to the FF three-factor model, achieves the second highest R^2.

As the third step, I employ *F*-test of Gibbons, Ross and Shanken (1989) to judge how well different combinations of FMPs can explain average turnover across size quintiles as test assets. It turns out none of these return-based factors could help GRS statistics fall below the critical value. Despites all models fares poorly in the test, MSBC model has the second lowest average GRS statistic, which is only slightly lower than the model including market factor, size factor, B/M factor and leverage ratio factor.

The last step is to find the most appropriate macroeconomic factor. Another run of horse race finds that adding CPI to MSBC model could contribute additional 2% in average R^2 and therefore the extended five-factor model captures 73% of the co-movement of trading.

To sum up, the horse race of various proposed factors finds that the model including market factor, size, B/M and C/P factors is the relatively desirable choice that fits across country and over each sample periods, resulting in capturing additional 8% of all systematic turnover in individual stock trading than the FF (1993) three-factor model.

4.4.3 A Cross-country Analysis

Given the fact that return-based factor model fares poorly in explaining the trading activity around the world, I next investigate whether they perform relatively better in some specific markets with the aim to find out what characteristics of these markets help to explain the failure of return motives in driving cross-sectional variation in the commonality in turnover.

The explanatory power of the return-based multifactor model varies substantially across markets, with better performance for European developed markets and China. When the FF (1993) three-factor model is used in the regression of individual stock turnovers, there are 27% of the systematic turnover left unexplained in U.K., Norway and Sweden while 45% left in the NYSE and AMEX, 48% in Tokyo stock exchange, 58% left either in the NASDAQ, Taiwan, India, and Thailand. I also try other models, including the HKK (2011) three-factor model, the Carhart's (1997) four-factor model, and the MSBC model. The ranking and the range are still similar as shown in Table 4.10. For instance, when applying the optimal market-specific four factor model in terms of the average R^2 from turnover regression, the difference of the performance ratios across markets is still substantially large, from almost 90% for Spain to 52% for the NASDAQ. Although it is reasonable to disregard the cases of Spain and Osaka stock exchange because of their smaller sample sizes, there are still on average 20% of the systematic turnovers that could

not be explained the common return factors in U.K., Norway and Sweden. On the other hand, the unexplained component of the systematic turnover still stay up to 38% in the NYSE&AMEX, 42% in Tokyo stock exchange, 43% for countries like Taiwan, India and Thailand, and 48% in the NASDAQ.

North America, Japan and emerging markets always lag behind on the list because there are larger amount of the commonality in trading, mostly higher than 47%, that could not be captured by their return-based factors. In contrast, the factor models have stable better performance in Norway, Sweden, Denmark and U.K. I first relate this finding with the previous that there is higher level of commonality in trading in less developed countries. If a country has a lower level of commonality in trading, it might be relatively easy to capture its commonality by the factor model. However, the rank of the commonality level is not reversely consistent with that one of the performance ratios. And the argument only seems sensible for the emerging markets and European markets but not for North America and Japan. Furthermore, China is a special case in that there is only 20% of all systematic turnover in individual stock trading left beyond what the return-based factors could capture despite that its commonality of trading ranks in the top around the world.

I further test the correspondence between the stock return and trading activity. That is to say, if one market is worse fit by the factor pricing model than other markets, taking FF (1993) three-factor model as an example, then this market is expected to incorporate more components that can't be explained by size or value premium and therefore the FF (1993) three-factor model would achieve lower power in explaining the trading activity in this market relative to other markets. However I fail to find evidence to support the hypothesis. Figures 4 to 8 show that, for those countries which have higher performance ratios in excess returns regression, it doesn't

necessarily mean that they have similarly higher performance ratios in turnover regressions. On the other hand, if the factor model gives higher performance ratios for the country in turnover regression, it does not necessarily mean that the market is better fit by the corresponding factor pricing model.

4.5 Conclusions

This chapter seeks to identify which factors are important for driving the time-series and cross-section variation in stock turnovers around the world. It is an experiment of linking the systematic pattern in trading activity with the systematic pattern in stock returns. The key finding is that on average 33% of the co-movement of trading around the world could not be explained by these common factors in return. The difference between the return-motivated commonality in trading and the true commonality in trading varies substantially across markets, with larger gaps for North America, Japan and emerging markets.

This chapter confirms CM (2007)'s finding on the NYSE and AMEX stocks but also uncovers several new findings on the commonality of trading. From weekly data of over 30,000 individual stocks from 48 markets over the 1977 to 2010 period, I employ two statistical procedures developed by BN (2002, 2004) for decomposing individual stocks from 48 countries into systematic and firm-specific components to turnover and return panels. Totally the systematic turnover factors capture 31% of the variation of individual stock turnover while systematic return factors could explain 36% of the variation in individual stock excess return. The average level of commonality in trading varies substantially across countries, with greater values for less developed countries. Furthermore, the decomposition breaks turnover into a persistent systematic component and stationary idiosyncratic components and in general there are two to four

pervasive return factors while three to eight systematic turnover factors exist.

To further identify the factors driving the trading, this chapter compares the performance of three asset-pricing models: (a) CAPM, (b) the FF (1993) three-factor model, (c) the HKK (2011) three-factor model and (d) the LW (2000) model, by the ability of turnover on their return factors in explaining individual stock turnover. CAPM market turnover capture on average 37% of all systematic turnover in individual stock trading. Two additional FF (1993) factor turnovers increase the mean performance by 23% in capturing systematic turnover and two additional HKK (2011) factor turnover increase by 16%. According to LW (2000, 2006) model, trading due to systematic risk in returns can only on average account for 64% of the all systematic turnover variation in the weekly time series. This chapter continues to evaluate the performance of fundamental factors, technical factors, macroeconomic factors and statistical factors that have been suggested in the existing empirical asset pricing literature, in capturing the systematic co-variation in stock turnovers by constructing the zero-investment FMPs based on these firm-level characteristics. It shows that factors associated with size, book-to-market ratio, and cash flow to price ratio are important in driving the systematic turnover in individual stock trading. The model, which includes market factor, size, book-to-market ratio and cash flow to price ratio factors, is proposed based on its relatively better ability of fitness across country and over sub-period in explaining on average 67% of all systematic turnover in individual stock trading.

This chapter continues to check the cross-country evidence on how the return-based factor model explains the trading activity around the world and find that the explanatory power varies substantially across market, with better performance for European developed markets and China. North America, Japan and emerging markets always lag behind on the ranking list because there is a larger amount of the commonality in trading, mostly higher than 47% of the systematic

turnover, which could not be explained by their return-based factors. The economic interpretation of the results is intriguing. If the market is perfectly efficient, systematic information incorporated in the trading volume should be reflected in the stock return on one hand, and, on the other hand, the risk factors driving the stock returns should also be expected to capture the cross-sectional variation in trading volume. However this chapter fails in find sufficient evidence to support this hypothesis.

I consider two plausible explanations for the failures. First, as previous researchers proposed, the general failure around the world can be attributed to irrational motives which might constitute one part of the commonality in trading but doesn't necessarily result in increasing the commonality in return. Trading could arise naturally from the portfolio rebalancing needs of investors in response to changes in asset valuations. Apart from this motive, there are two schools of thought that develop theories for trading activity. In the first set of models, trading occurs due to the profit motives of privately informed investors, as well as non-informational reasons. These models generally examine trading among privately informed traders, uninformed traders, and liquidity traders. In these models, investors try to infer information from trading activity and market prices. One example of this strand is institutional herding. The second school of thought models trading as induced by differences of opinion; investor share the same public information but interpret it differently, a scenario which induces trading activity. Investor might be also trading by some kind of group psychology stories, like institutional herding or overconfidence. Second, the extent of commonality in a country is inversely related to the measures of its economic and institutional development. The commonality in trading volume is greater in countries with weaker legal protections for investors and a more opaque information environment, like emerging markets. Given the higher level of the commonality in trading, it is

hard for the factor model to capture all of the systematic turnover in individual stock trading. Here China is an interesting case. Its commonality of trading ranks the highest among all the thirty-three markets, which goes up to over 64% of individual stock turnover. At the same time the return-based factor model performs relatively well, only leaving 20% of all systematic turnover unexplained. Given the prominent performance of its first principal component and its market portfolio, I conjecture that the strong motive of portfolio rebalancing in trading activity might be related with its homogenous market structure since it is a highly regulated market.

The question left unanswered in this chapter is why there are much larger components of the systematic turnover in North America and Japan that are unrelated with return motives while their commonalities in trading are similar with other developed countries. Without detailed trading records by different types of investors in these markets, we are unlikely to find convincing explanations for the puzzle in North America and Japan. We also cannot disregard the influence of measurement problems. For instance, the weekly frequency level of my analysis of commonality may be not appropriate for these two markets. We also have little understanding of the commonality in trading across asset classes, including bonds and other derivatives. Additionally, the preliminary experiment of the major common factors in return is tentative and incomplete. For example, I might omit some important factors in driving the common variation in stock turnovers, like the return on assets (Chen, Novy-Marx and Zhang, 2010). I invite further theoretical and empirical work to explore these issues.

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Figure 4.1

The Commonality in Turnover and Excess Return

This figure depicts the average local commonality in turnover (Panel A) and excess return (Panel B) in 33 countries, respectively, over the period Jan 1977 to June 2010. The commonality in turnover (excess return) is measured by the R^2 of weekly regressions of the individual stock turnover (excess return) on the selected systematic turnover (excess return) factors.

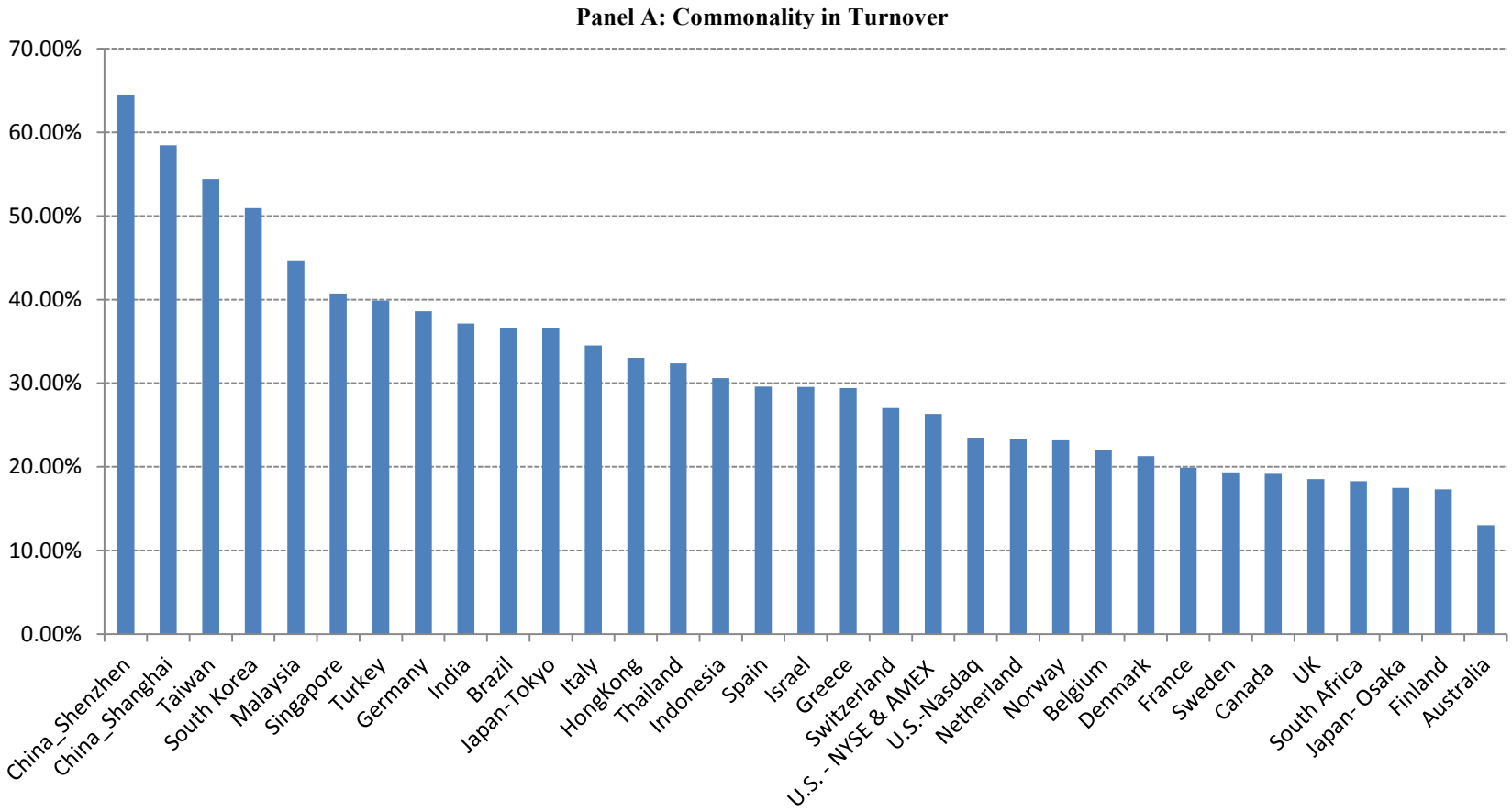


Figure 4.1, continued

Panel B: Commonality in Excess Return

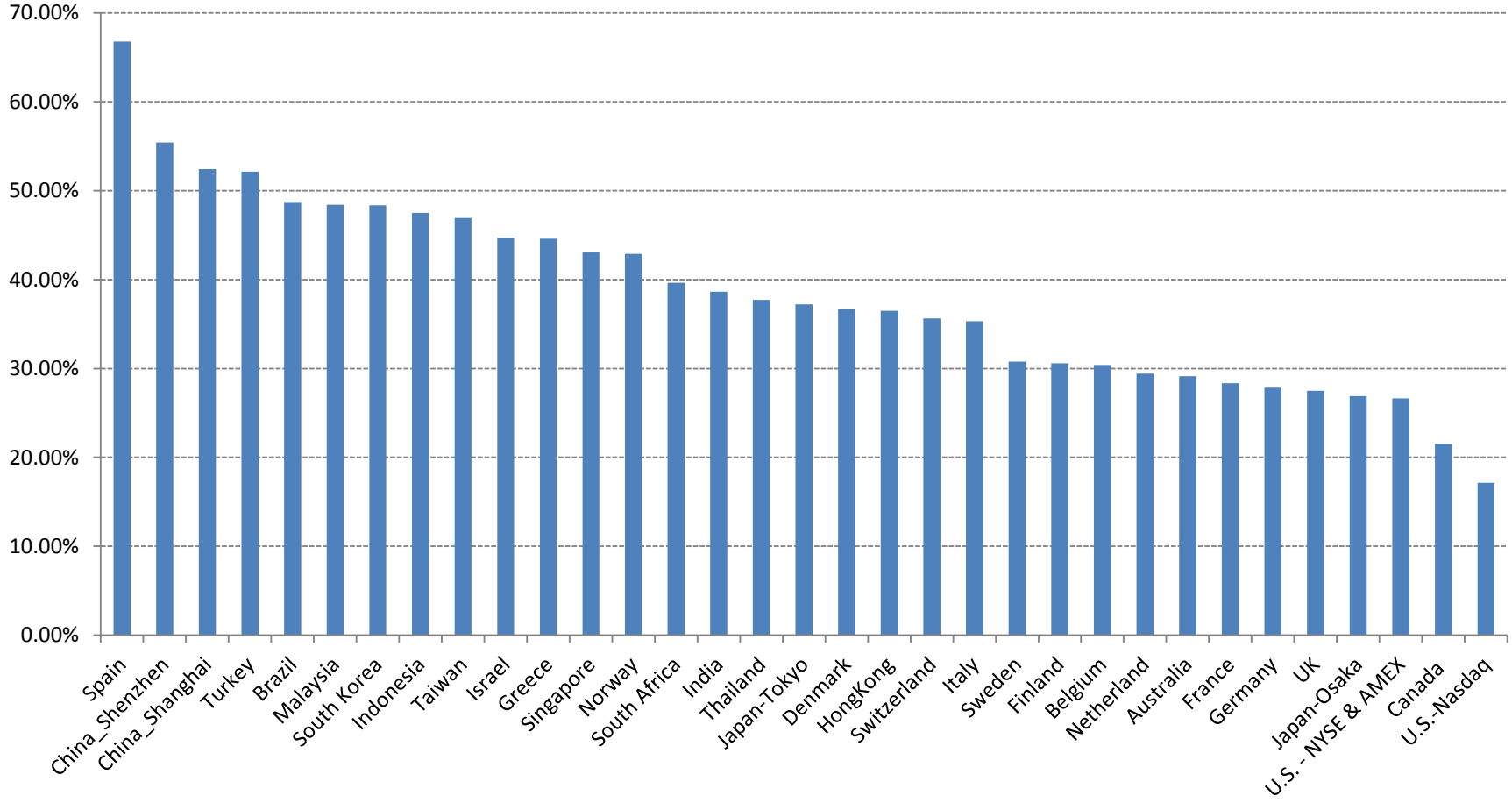


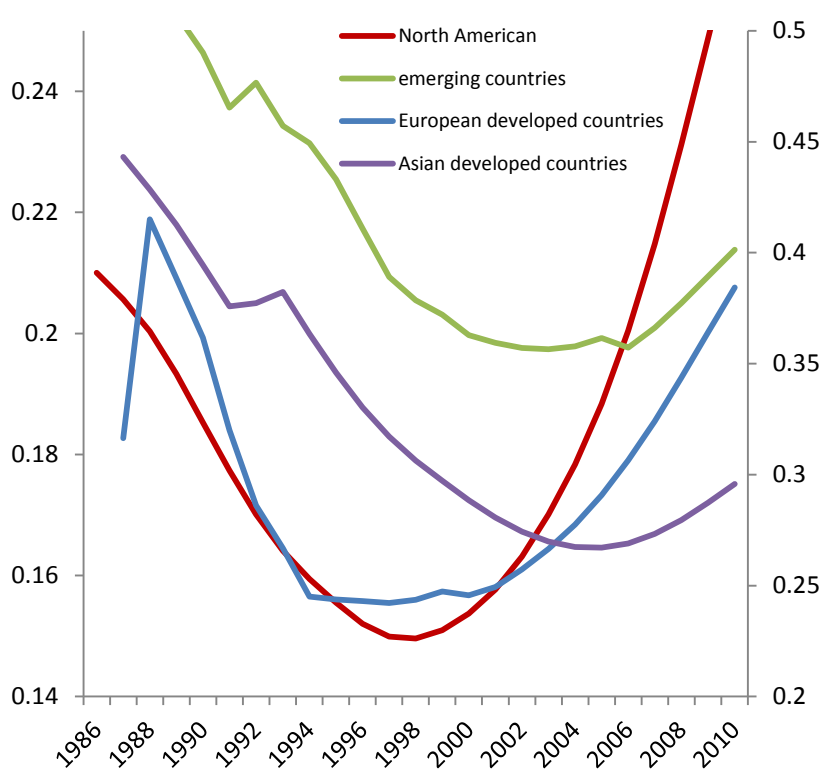
Figure 4.2

The Trends of the Commonalities in Turnover and Excess Return

This figure depicts the trend of the commonality in excess return and turnover using the Hodrick-Prescott filter. Here we consider both the non-overlapping yearly time-series of R^2 (Panel A) and the overlapping weekly time-series of R^2 that are obtained from regressing the past year stock turnover/excess return on the corresponding extracted factors (Panel B for the U.S. NYSE & AMEX). In Panel A, North American uses the major axis and other areas use the secondary axis.

Panel A: Non-overlapping R^2

The Trend of the Commonality in Excess Return



The Trend of the Commonality in Turnover

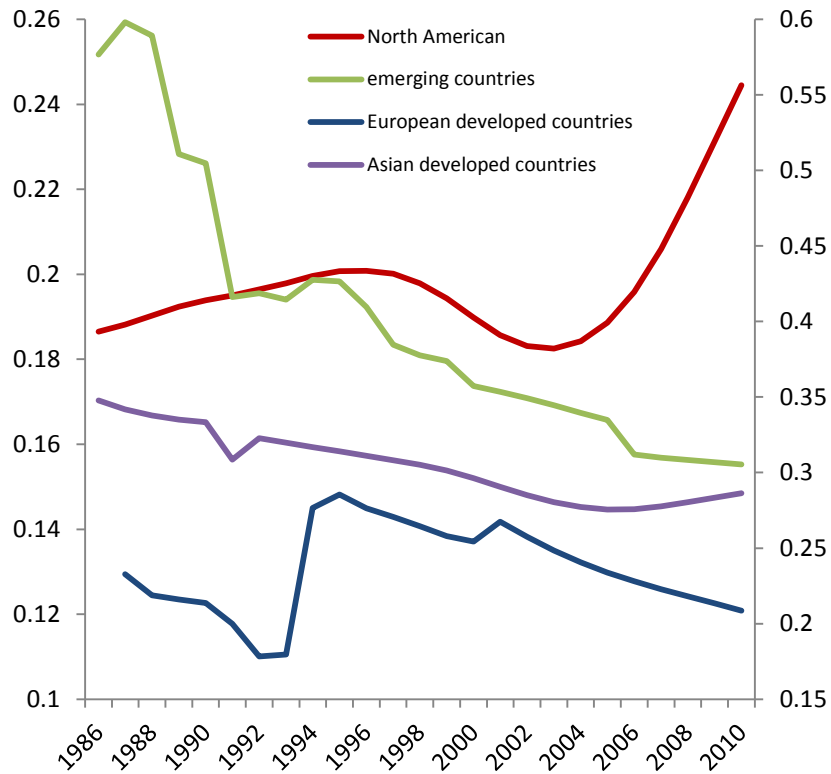


Figure 4.2, continued

Panel B: Over-lapping R^2 for NYSE & AMEX

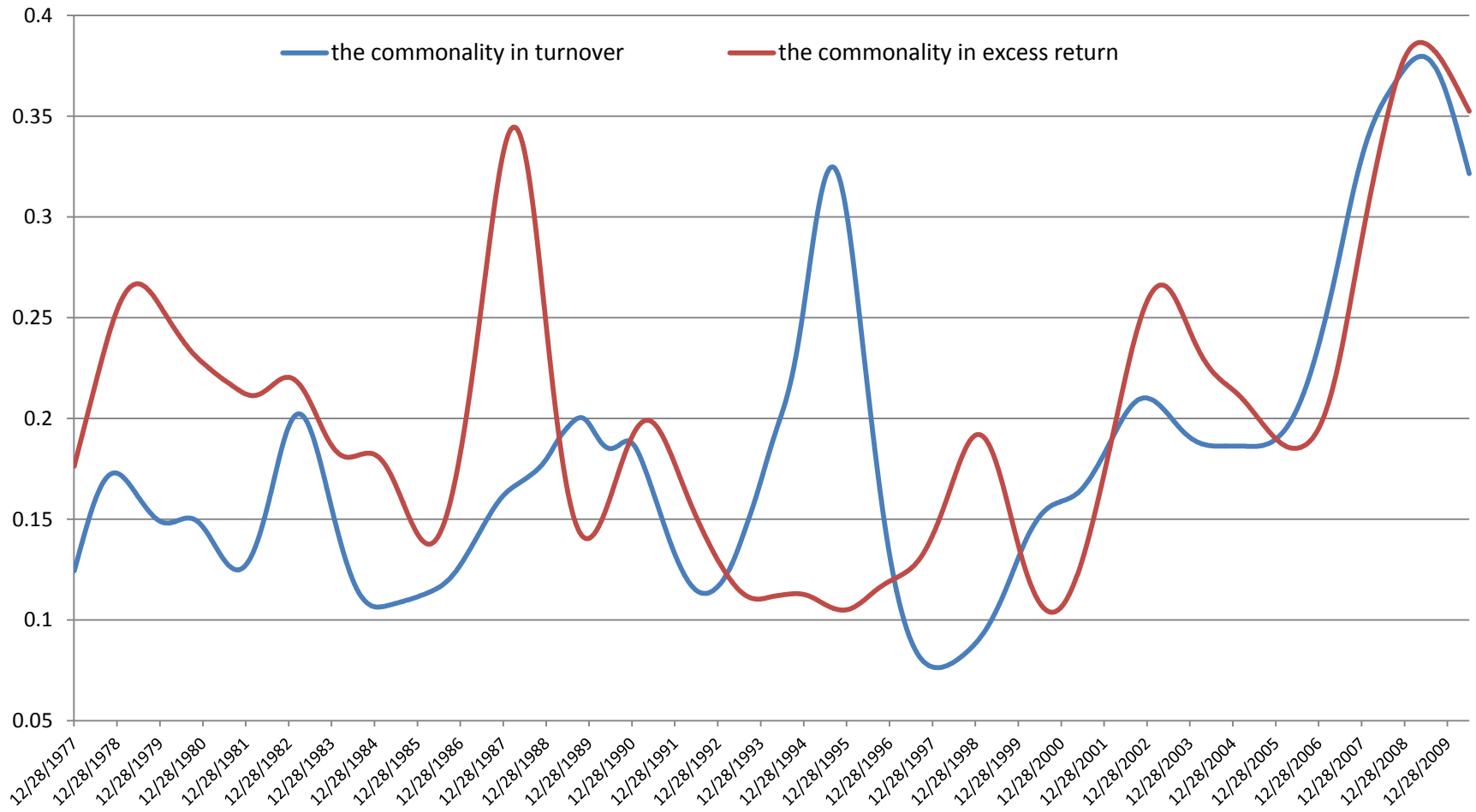


Figure 4.3

The Commonality in Turnover and Excess Return for NYSE & AMEX

This figure depicts the weekly R^2 that are obtained from regressing the past year stock turnover/excess return on the corresponding extracted factors. The blue line represents the commonality in turnover and the red line is for the commonality in excess return.

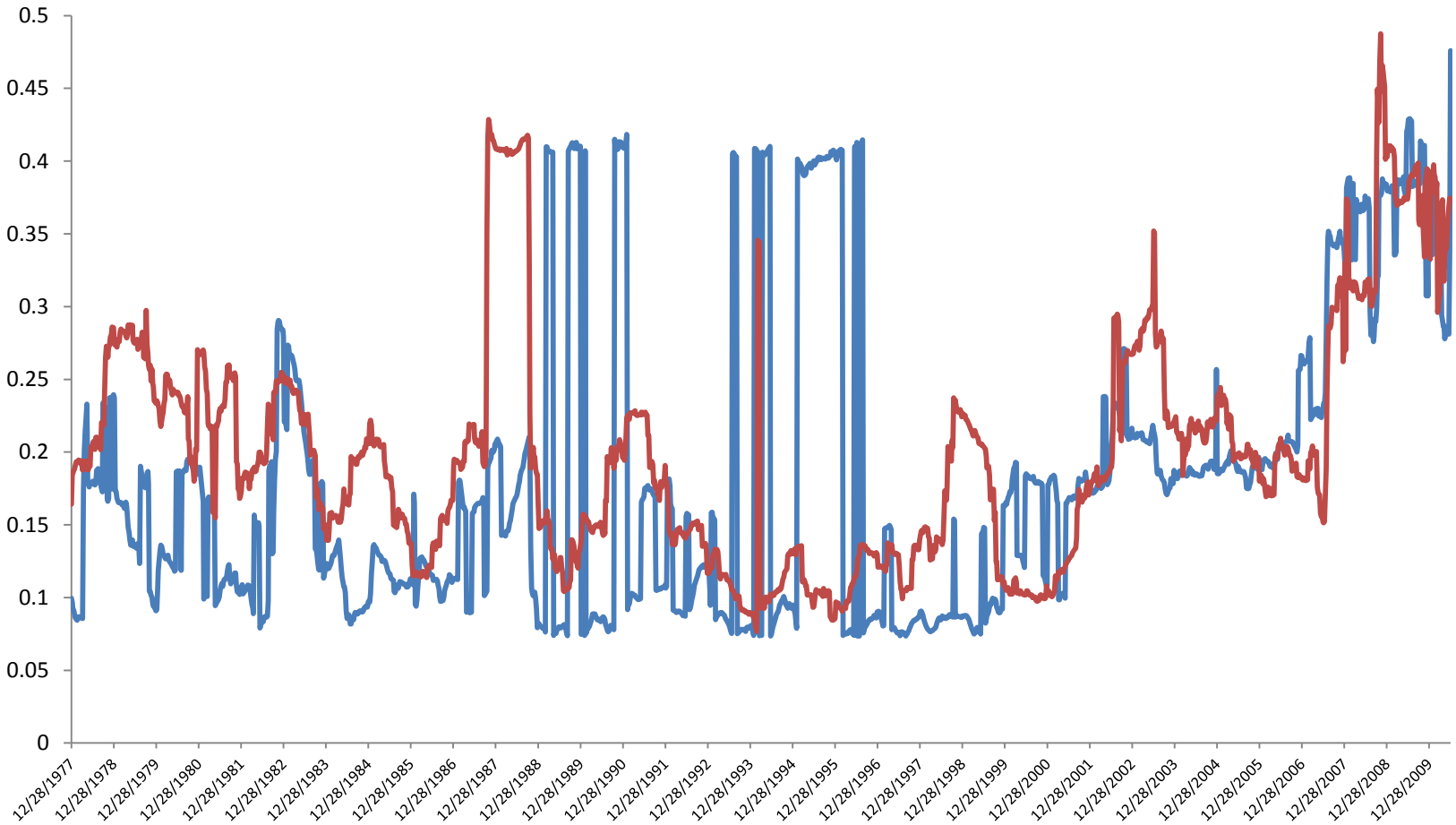


Figure 4.4

Performance Ratios of the Fama-French (1993) Three-factor Model for the Commonality in Turnover and Excess Return

This figure depicts the Fama-French (1993) three-factor model performance ratios for the commonality in turnover (Red bar on the left hand side) and excess return (Blue bar on the right hand side) in 33 countries, respectively, over the period from January 1977 to June 2010. The ratios for turnover are shown in negative number just for the illustration convenience and the real ratios are positive.

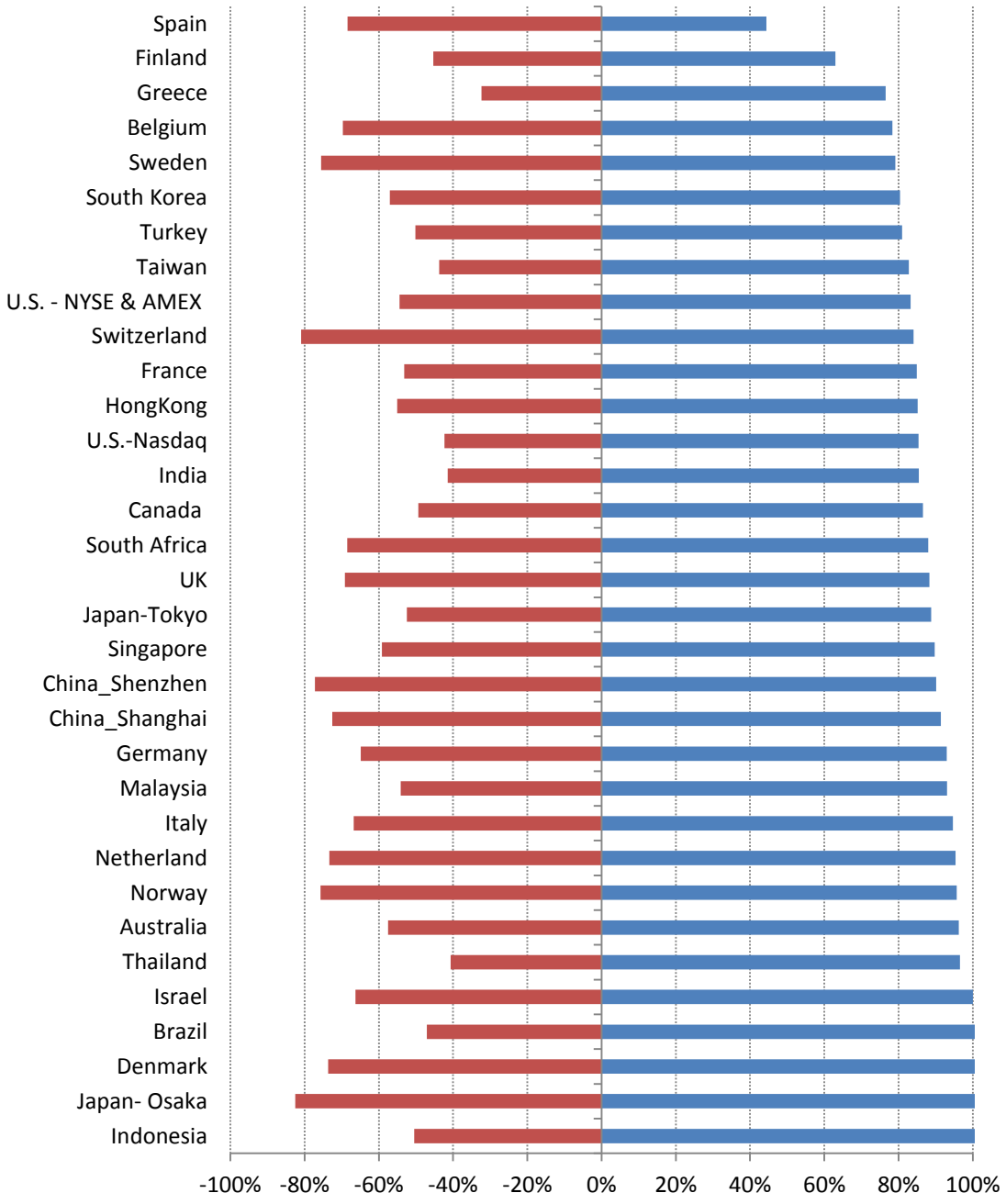


Figure 4.5

Performance Ratios of the Hou-Karolyi-Kho (2011) Three-factor Model for the Commonality in Turnover and Excess Return

This figure depicts the Hou-Karolyi-Kho (2011) three-factor model performance ratios for the commonality in turnover (Red bar on the left hand side) and excess return (Blue bar on the right hand side) in 33 countries, respectively, over the period from January 1977 to June 2010. The ratios for turnover are shown in negative number just for the illustration convenience and the real ratios are positive.

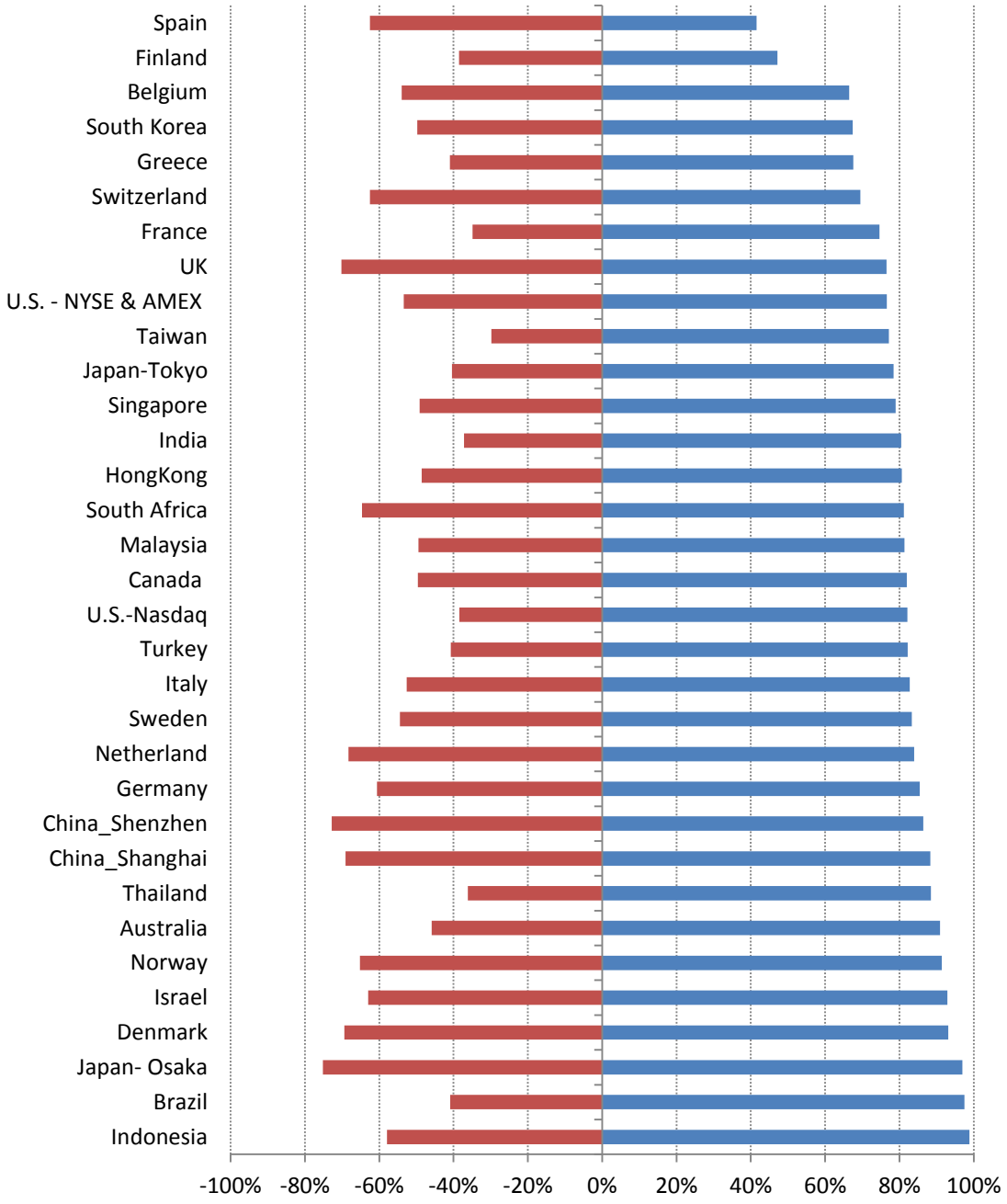


Figure 4.6

Performance Ratios of the Carhart (1997) Four-factor Model for the Commonality in Turnover and Excess Return

This figure depicts the Carhart (1997) four-factor model performance ratios for the commonality in turnover (Red bar on the left hand side) and excess return (Blue bar on the right hand side) in 33 countries, respectively, over the period from January 1977 to June 2010. The ratios for turnover are shown in negative number just for the illustration convenience and the real ratios are positive.

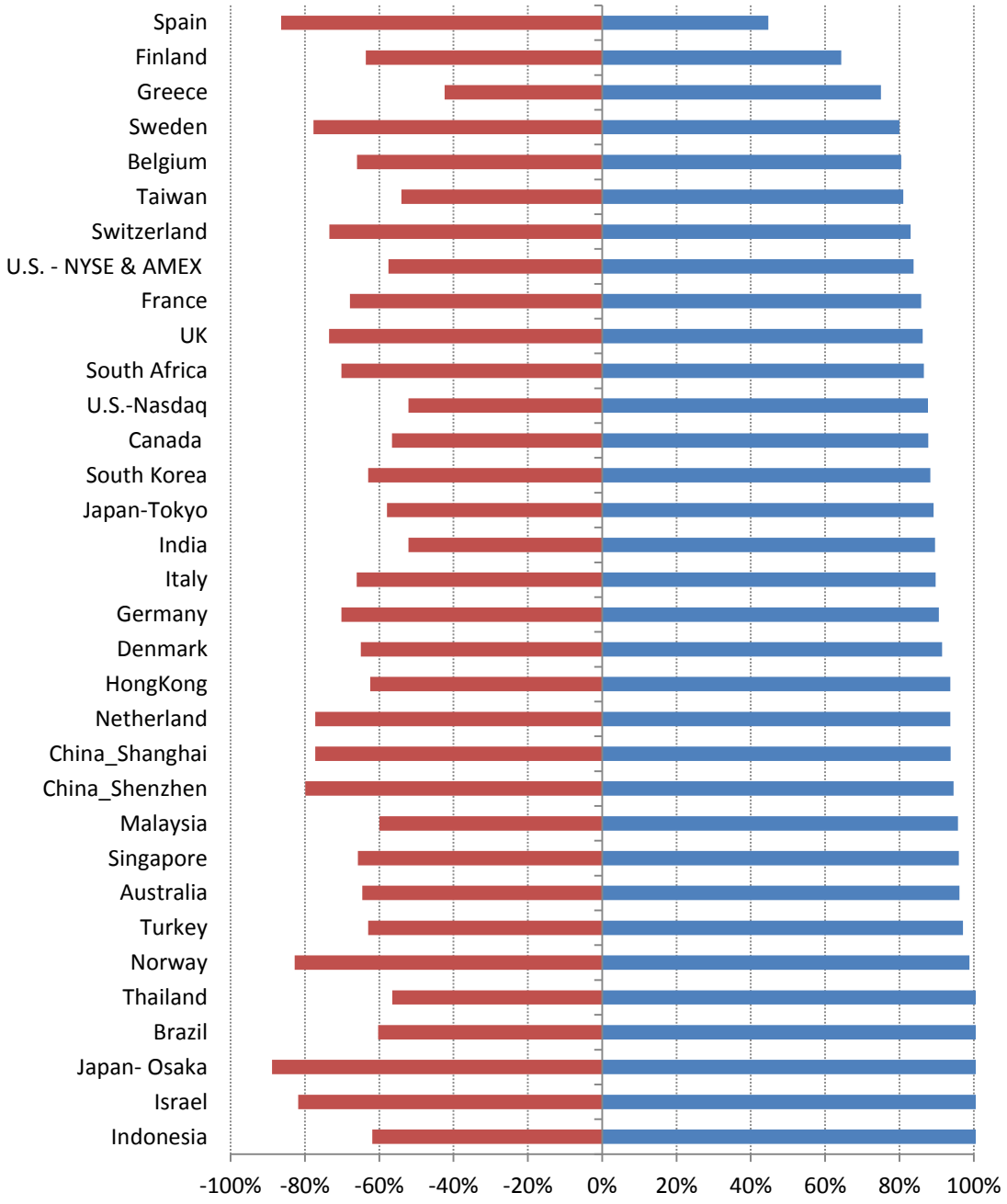


Figure 4.7

Performance Ratios of the MSBC Four-factor Model for the Commonality in Turnover and Excess Return

This figure depicts the MSBC four-factor model performance ratios for the commonality in turnover (Red bar on the left hand side) and excess return (Blue bar on the right hand side) in 33 countries, respectively, over the period from January 1977 to June 2010. The ratios for turnover are shown in negative number just for the illustration convenience and the real ratios are positive.

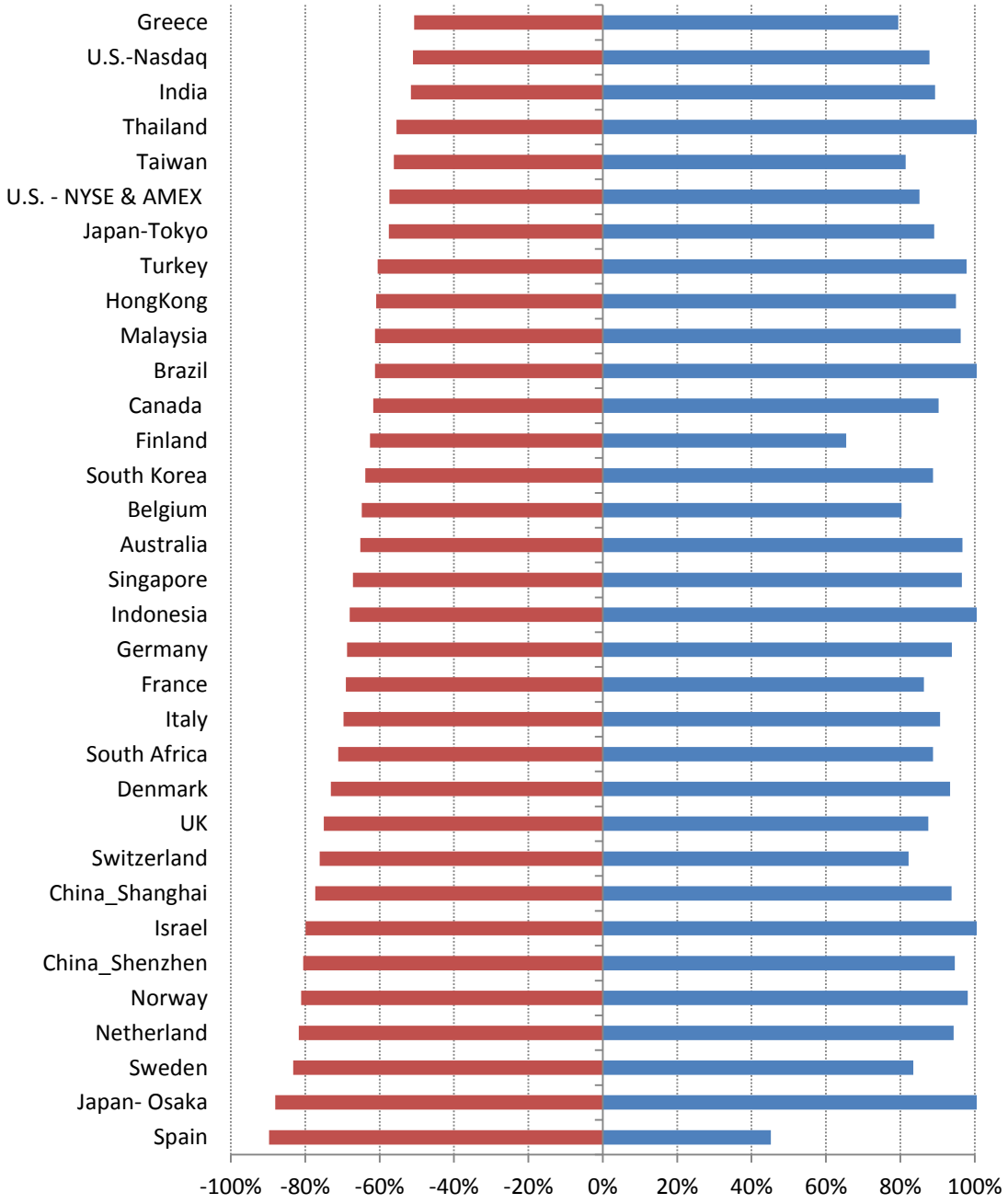


Figure 4.8

Performance Ratios of the Market Specific Four-factor Model for the Commonality in Turnover and Excess Return

This figure depicts the market specific four-factor model performance ratios for the commonality in turnover (Red bar on the left hand side) and excess return (Blue bar on the right hand side) in 33 countries, respectively, over the period from January 1977 to June 2010. The ratios for turnover are shown in negative number just for the illustration convenience and the real ratios are positive.

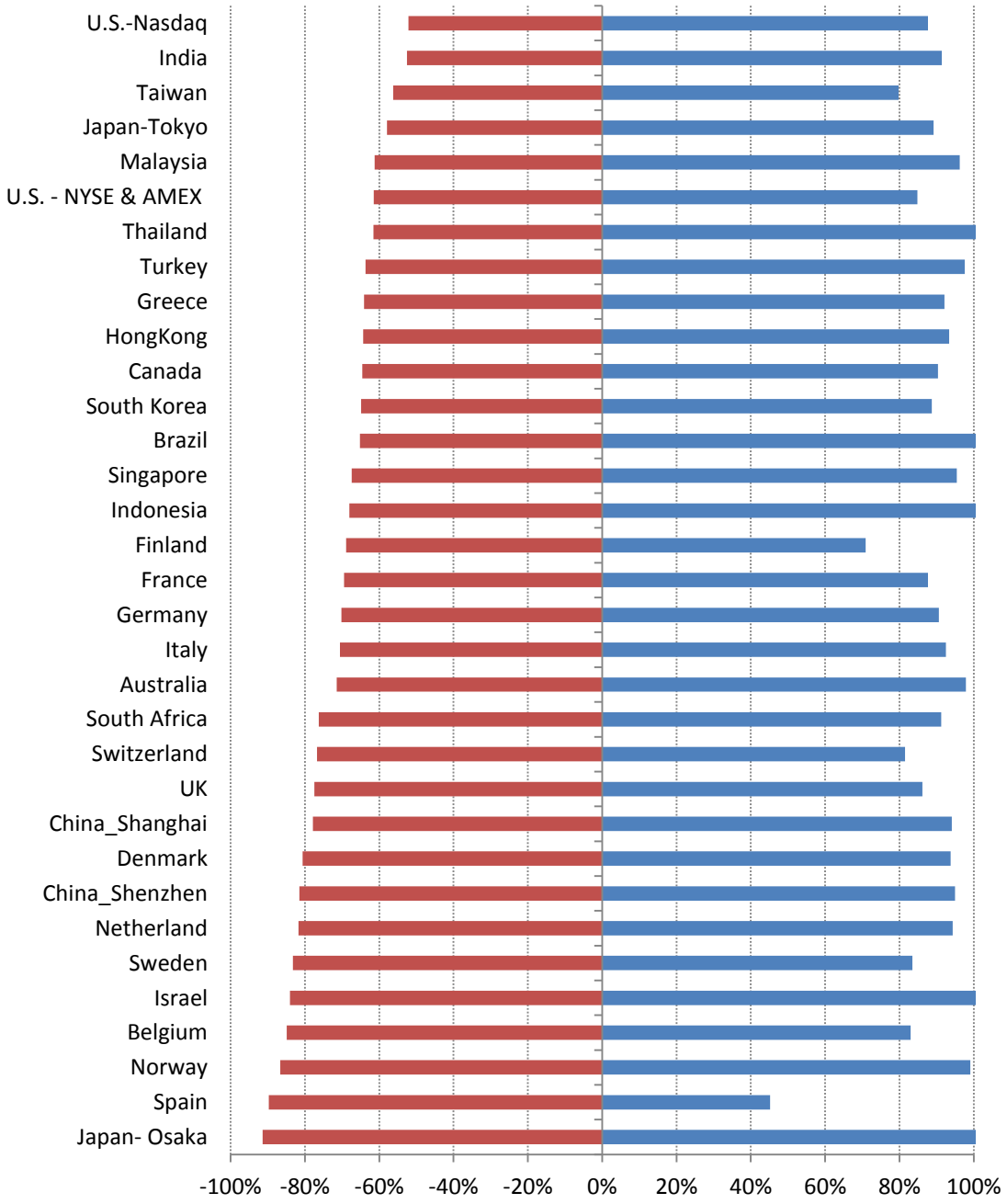


Table 4.1

Summary Statistics (1977-2010)

This table reports summary statistics of weekly data sample from 1976 to 2010. Panel A and C reports the average number of firms for each year and across markets, respectively. And Panel B shows the value-weighted market returns from our sample and their correlations with WSCI index returns.

Panel A: Summary Statistics of the Numbers of Stocks by Year

Year	Stocks with status of DEAD or SUSPENDED	Additional Stocks that are ACTUALLY Dead	Stocks that are Alive until 06/10	Total Available Number of Stocks
1977	18	0	4,069	4,087
1978	18	0	4,125	4,143
1979	18	0	4,200	4,218
1980	18	0	4,329	4,347
1981	18	1	4,489	4,508
1982	20	1	4,651	4,672
1983	20	1	4,983	5,004
1984	20	1	5,463	5,484
1985	20	1	5,862	5,883
1986	21	3	6,537	6,561
1987	26	3	7,337	7,366
1988	69	5	8,898	8,972
1989	184	5	10,483	10,672
1990	295	7	12,434	12,736
1991	376	11	13,327	13,714
1992	497	18	14,253	14,768
1993	640	21	15,259	15,920
1994	766	27	16,919	17,712
1995	972	32	18,249	19,253
1996	1,241	46	19,838	21,125
1997	1,559	78	21,576	23,213
1998	2,108	113	22,912	25,133
1999	2,984	157	23,631	26,772
2000	4,064	195	24,660	28,919
2001	5,164	226	25,256	30,646
2002	6,106	272	25,347	31,725
2003	7,015	315	25,257	32,587
2004	7,902	367	25,615	33,884
2005	8,702	442	26,413	35,557
2006	9,564	514	27,250	37,328
2007	10,653	596	28,005	39,254
2008	11,788	706	28,404	40,898
2009	12,875	868	27,746	41,489
2010	13,673	1,208	27,199	42,080

Table 4.1, continued

Panel B: Correlations with WSCI Index Returns by Market

Country	Data Beginning Date	MSCI Beginning Date	Index Return	Sample Return	Correlation
Developed Markets					
U.K.	01/1977	01/1980	0.17%	0.25%	0.99
Japan	01/1977	01/1980	0.09%	0.10%	0.98
France	01/1977	01/1980	0.19%	0.23%	0.98
Sweden	01/1982	01/1980	0.33%	0.29%	0.97
Netherlands	01/1977	01/1980	0.18%	0.25%	0.97
Australia	01/1977	01/1980	0.17%	0.25%	0.97
Germany	01/1977	01/1980	0.16%	0.17%	0.97
Hong Kong	01/1977	01/1980	0.26%	0.30%	0.96
Ireland	01/1977	01/1988	0.06%	0.15%	0.93
Canada	01/1977	01/1980	0.15%	0.21%	0.94
Finland	01/1987	01/1987	0.25%	0.30%	0.94
Norway	01/1977	01/1980	0.18%	0.24%	0.94
Singapore	01/1980	01/1980	0.15%	0.18%	0.93
New Zealand	01/1986	12/1986	-0.04%	0.13%	0.92
Austria	01/1977	01/1980	0.09%	0.15%	0.89
Denmark	01/1977	01/1980	0.24%[1]	0.24%	0.88
Italy	01/1977	01/1980	0.21%[2]	0.28%	0.88
Belgium	01/1977	01/1980	-1.56%[3]	-2.05%	0.86
Spain	01/1986	01/1980	0.21%[4]	0.16%	0.82
Switzerland	01/1977	01/1980	0.16%[5]	0.19%	0.98
Emerging Markets					
Taiwan	09/1987	01/1988	0.18%	0.19%	0.98
Malaysia	01/1977	01/1988	0.19%	0.20%	0.97
India	01/1990	01/1993	0.30%	0.33%	0.96
Korea, South	04/1980	01/1988	0.22%	0.22%	0.96
Thailand	01/1987	01/1988	0.20%	0.17%	0.96
Hungary	01/1991	01/1995	0.41%	0.35%	0.95
Indonesia	04/1990	01/1988	0.23%	0.26%	0.94
Mexico	01/1988	01/1988	0.56%	0.50%	0.94
Pakistan	07/1992	01/1993	0.22%	0.31%	0.94
Argentina	01/1988	01/1988	1.32%	1.13%	0.93
Colombia	01/1992	01/1993	0.42%	0.39%	0.92
Czech Republic	08/1993	01/1995	0.21%	0.14%	0.92
Russian Federation	09/1995	01/1995	0.55%	0.70%	0.92
Philippines	09/1987	01/1988	0.23%	0.20%	0.91
Greece	01/1988	01/1988	0.22%	0.31%	0.90
South Africa	01/1977	01/1993	0.25%	0.28%	0.90
Sri Lanka	06/1987	01/1993	0.27%	0.26%	0.89
Portugal	01/1988	01/1988	0.05%	0.08%	0.85
Turkey	01/1988	01/1988	0.99%[6]	0.83%	0.83
Poland	04/1991	01/1993	0.43%[7]	0.24%	0.81
Israel	01/1986	01/1993	0.15%[8]	0.20%	0.78
Peru	01/1998	03/2009	1.02%[9]	0.69%	0.73
Brazil	01/1994	01/1992	1.30%[10]	0.37%	0.69
Chile	07/1989	01/1988	0.35%[11]	0.39%	0.64

Note: 1) the correlation is 0.92 if the sample starts from 01/1990;
2) the correlation is 0.90 if the sample starts from 01/1981;

Table 4.1, continued

Panel B: Correlations with WSCI Index Returns by Market (continued)

Note:

3) the correlation is 0.99 if the sample starts from 01/2004;
4) the correlation is 0.91 if the sample starts from 01/1990;
5) the correlation is 0.98 if the sample starts from 01/2004;
6) the correlation is 0.95 if the sample starts from 01/2004;
7) the correlation is 0.97 if the sample starts from 01/2004;
8) the correlation is 0.90 if the sample starts from 01/2004;
9) the correlation is 0.85 if the sample starts from 01/2004;
10) the correlation is 0.96 if the sample starts from 01/1995.
11) the correlation is 0.98 if the sample starts from 01/2004.

Table 4.1, continued

Panel C: Summary Statistics of the Numbers of Stocks by Market

Country	Number of firms	Firms with >50% turnover data and no problem data	Firms with no missing and problem data	Average weekly turnover (%)
Argentina	92	77	4	0.23*
Australia	2,467	2,353	599	0.26
Austria	164	137	45	3.84
Belgium	221	72	26	0.09
Brazil	504	322	154	0.61
Canada	3,306	3,053	811	0.33
Chile	246	168	40	0.11
China-Shanghai	897	739	151	1.49
China-Shenzhen	929	929	443	0.82
Colombia	56	37	9	0.34
Czech Republic	85	74	1	0.004*
Denmark	297	249	46	0.53
Finland	179	158	52	0.55
France	1,453	549	153	0.12
Germany	1,257	844	206	0.16
Greece	381	375	170	0.87
Hong Kong	1,270	1,246	327	0.25
Hungary	53	45	4	1.43*
India	1,224	1,152	372	0.32
Indonesia	480	384	52	0.42
Ireland	223	114	25	0.22
Israel	175	168	54	0.24
Italy	468	366	231	0.43
Japan- Tokyo	2,943	2,800	789	0.65
Japan- Osaka	510	504	172	0.85
Luxembourg	35	13	2	0.07*
Malaysia	1,013	1,012	179	0.44
Mexico	186	140	33	0.7
Netherlands	270	247	91	0.91
New Zealand	193	176	48	0.22
Norway	419	406	143	0.92
Pakistan	142	128	1	1.17*
Peru	150	69	5	0.37*
Philippines	268	203	6	0.49*
Poland	265	204	147	0.56
Portugal	131	50	10	0.47
Russian Federation	302	220	12	0.002
Singapore	801	790	273	0.41
South Africa	1,076	745	156	0.14
South Korea	902	900	209	1.32
Spain	204	160	43	0.66
Sri Lanka	37	30	0	1.19*
Sweden	645	642	298	0.74
Switzerland	353	164	47	0.4
Taiwan	825	800	2	2.29*
Thailand	1,078	1,054	1,054	0.71
Turkey	269	265	42	1.74
U.K.	3,692	2,663	614	0.39

Table 4.1, continued

Panel C: Summary Statistics of the Numbers of Stocks by Market (continued)

Country	Number of firms	Firms with >50% turnover data and no problem data	Firms with no missing and problem data	Average weekly turnover (%)
U.S.-NASDAQ	4,995	4,955	3,109	1.29
U.S.- NYSE &AMEX	3,906	3,814	1,997	2.01
Venezuela	43	18	0	0.16*

Note: *the average weekly turnover is calculated from the firm sample on the second column.

Table 4.2

Summary Statistics of Seven Five-year Sub-periods (1977-2010)

This table shows average weekly turnover (%) and number of firms (#) for each sub-period.

Country	1985-1990 Average weekly turnover (%)	#	1990-1995 Average weekly turnover (%)	#	1995-2000 Average weekly turnover (%)	#	2000-2005 Average weekly turnover (%)	#	2005-2010 Average weekly turnover (%)	#
Argentina					0.56	21	0.58	10	0.48	25
Australia	0.92	65	0.78	100	0.96	202	1.14	334	1.47	474
Austria			3.52	15	4.34	28	1.71	29	1.15	36
Belgium			2.18	13	2.85	21	0.88	66	0.79	74
Brazil					NA	6	2.95	53	2.43	75
Chile			1.18	19	0.4	16	0.32	28	0.57	37
China-Shanghai					5.15	120	2.73	406	10.10	183
China-Shenzhen					6.28	51	2.66	397	9.79	85
Columbia					0.17	2	0.33	3	1.11	11
Czech Public							1.66	4	1.32	6
Denmark					3.06	40	2.05	46	1.79	74
Finland			0.83	4	2.96	17	1.52	60	1.49	92
France			3.00	4	2.68	153	1.31	293	1.26	307
Germany			4.80	9	4.02	2	0.56	324	0.34	229
Greece			2.36	20	4.42	61	1.20	202	1.00	163
Hong Kong			1.12	110	1.55	121	1.19	183	1.35	282
Hungary							2.62	7	2.24	8
India					1.23	227	1.56	373	1.10	688
Indonesia					2.14	26	1.81	43	1.41	54
Ireland							1.04	30	1.22	48
Israel					0.63	15	0.85	53	1.03	90
Italy			0.79	15	1.13	87	1.21	155	1.73	180
Japan-Tokyo			0.65	12	0.75	1,486	1.17	1,546	1.80	1,753
Japan-Osaka			0.60	36	0.69	72	0.78	66	1.32	127
Malaysia	0.98	3	2.08	93	1.54	201	0.86	266	1.25	264
Mexico			2.66	7	2.61	24	1.50	28	1.03	34
Netherland			4.61	56	4.55	73	2.14	106	2.24	84
Norway	4.47	6	3.03	13	3.28	43	2.64	43	2.67	75
New Zealand			0.67	5	0.61	31	0.62	44	0.66	43
Pakistan					2.83	14	4.19	12	NA	0
Peru					1.02	3	1.15	4	0.87	14
Philippine			0.42	8	1.02	29	0.34	25	0.58	40
Poland					2.91	8	1.70	5	1.82	26
Portugal					3.52	12	1.19	32	1.25	30
Russia							0.66	10	0.28	3
Singapore	2.16	33	1.80	73	1.47	104	1.36	133	1.75	152
South Africa			0.43	30	0.83	55	1.04	112	1.01	147
South Korea	3.22	79	3.24	207	5.46	226	4.61	256	3.18	371
Spain			3.21	14	3.07	31	2.11	49	3.72	62
Sweden	5.94	7	4.89	23	3.07	98	2.52	143	1.96	201
Switzerland			5.18	16	3.87	42	2.20	101	1.54	135
Taiwan					4.73	61	4.18	187	4.31	408
Thailand			1.19	2	3.83	16	3.57	23	3.06	115
Turkey			3.25	3	2.92	5	5.91	72	4.57	142
U.K.			2.32	101	1.77	320	2.20	481	2.22	556

Table 4.2, continued

	Country	U.S.- NASDAQ	U.S.- NYSE &AMEX	Canada
1977-1980	Average weekly turnover(%)	2.91	3.30	1.58
	#	*26*	*756*	*60*
1980-1985	Average weekly turnover(%)	3.17	3.60	1.36
	#	*24*	*826*	*47*
1985-1990	Average weekly turnover(%)	3.14	3.29	1.13
	#	*307*	*1,208*	*103*
1990-1995	Average weekly turnover(%)	3.24	2.77	1.06
	#	*609*	*1,339*	*162*
1995-2000	Average weekly turnover(%)	3.26	2.77	1.45
	#	*1,046*	*1,396*	*344*
2000-2005	Average weekly turnover(%)	3.33	3.29	1.27
	#	*1,607*	*1,480*	*488*
2005-2010	Average weekly turnover(%)	3.69	4.90	1.23
	#	*1,666*	*1,460*	*870*

Table 4.3

Test of the Number of Factors in Turnover (Excess Return) Using the Balanced Panel

This table gives the incremental R^2 explained by subsequent ordered eigenvectors, k=1, …, 8 of the covariance matrix of weekly turnover of ordinary common shares in all the available markets for seven(or maximum) sub-periods from January 1977 to June 2010. In addition, this table depicts the number of factors selected by the IC and cross-sectional average R^2 for the selected factor model for each sample period. We also employ Bai and Ng (2004) PANIC test for nonstationarity and denote the stationary factors in red and the nonstationary factor in black.

Panel A: Balanced Turnover

Sub-period	1	2	3	4	5	6	7	8	No. of Factors	R^2 (%)
				China-Shenzhen						***64.53%***
95-00	67.99%	5.09%	3.01%	2.39%					4	78.48%
00-05	30.06%	5.53%	4.14%	2.75%	2.45%	2.37%	1.85%	1.69%	8	50.84%
05-10	42.83%	8.75%	6.15%	3.53%	3.00%				5	64.26%
				China-Shanghai						***58.45%***
95-00	43.96%	7.39%	4.63%	3.56%	2.15%				5	61.69%
00-05	29.31%	6.05%	3.55%	3.12%	2.21%	2.19%	1.93%	1.69%	8	50.05%
05-10	44.28%	8.46%	4.65%	2.48%	2.07%	1.66%			6	63.60%
				Taiwan						***54.41%***
95-00	31.13%	8.65%	4.97%	4.12%	3.99%				5	52.86%
00-05	20.75%	18.48%	7.05%	3.82%	2.87%	2.45%	2.13%	2.05%	8	59.60%
05-10	19.06%	8.51%	6.38%	5.26%	4.15%	3.08%	2.19%	2.13%	8	50.76%
				South Korea						***50.94%***
85-90	29.11%	13.61%	7.48%	4.60%	3.24%				5	58.04%
90-95	26.84%	8.68%	7.47%	3.77%	3.23%	2.54%	2.19%	1.85%	8	56.57%
95-00	37.12%	5.64%	4.12%	3.17%	2.83%	2.59%	1.99%	1.80%	8	59.26%
00-05	22.65%	6.81%	3.74%	3.11%	3.05%	2.40%			6	41.76%
05-10	13.99%	10.06%	4.22%	3.74%	2.45%	2.36%	2.27%		7	39.09%
				Malaysia						***44.68%***
90-95	31.24%	6.37%	4.41%	3.84%					4	45.86%
95-00	18.45%	9.26%	4.91%	4.21%	3.33%	2.82%	2.64%	2.33%	8	47.95%
00-05	18.58%	5.66%	4.51%	3.39%	3.06%	2.58%	2.32%		7	40.10%
05-10	20.87%	5.60%	4.85%	3.22%	3.07%	2.79%	2.32%	2.10%	8	44.82%
				Singapore						***40.72%***
90-95	21.70%	6.40%	5.38%						3	33.48%
95-00	30.76%	10.75%	5.91%	3.59%	3.03%				5	54.04%
00-05	15.00%	6.11%	5.36%	3.85%	3.49%				5	33.81%
05-10	14.93%	8.17%	6.43%	5.41%	3.61%	2.99%			6	41.54%

Table 4.3, continued

Panel A: Balanced Turnover (continued)

Sub-period	1	2	3	4	5	6	7	8	No. of Factors	R^2 (%)
				Turkey						***39.87%***
00-05	24.66%	9.41%	6.67%	4.35%					4	45.09%
05-10	15.18%	10.04%	4.94%	4.49%					4	34.65%
				Germany						***38.61%***
00-05	13.35%	8.33%	3.86%	3.64%	2.69%				5	31.87%
05-10	30.47%	5.15%	4.07%	3.24%	2.41%				5	45.34%
				India						***37.12%***
95-00	18.90%	6.58%	5.41%	3.61%	2.80%				5	37.30%
00-05	18.50%	7.53%	5.41%	3.34%	2.72%	2.25%	2.06%		7	41.81%
05-10	13.94%	5.41%	3.31%	2.94%	2.56%	2.18%	1.92%		7	32.26%
				Japan-Tokyo						***36.55%***
95-00	11.32%	6.66%	3.27%	2.87%	2.40%	2.28%	1.80%	1.70%	8	32.30%
00-05	18.54%	4.36%	3.29%	3.23%	2.31%	1.89%	1.72%	1.62%	8	36.96%
05-10	16.01%	9.93%	4.25%	2.49%	2.36%	1.95%	1.72%	1.69%	8	40.40%
				Brazil						***36.58%***
00-05	15.41%	11.77%	6.70%						3	33.88%
05-10	19.50%	8.49%	6.52%	4.77%					4	39.28%
				Italy						***34.52%***
95-00	34.91%	7.48%	4.97%	4.02%					4	51.38%
00-05	12.37%	8.17%							2	20.54%
05-10	14.99%	8.26%	4.84%	3.55%					4	31.64%
				Hong Kong						***33.04%***
90-95	19.66%	6.78%	4.75%						3	31.19%
95-00	16.24%	9.54%	5.83%	4.44%	3.81%				5	39.86%
00-05	14.72%	7.24%	5.20%	4.21%					4	31.37%
05-10	10.26%	6.56%	5.95%	4.16%	2.79%				5	29.72%
				Thailand						***32.38%***
05-10	12.63%	9.73%	5.22%	4.80%					4	32.38%
				Indonesia						***30.60%***
05-10	15.51%	8.33%	6.76%						3	30.60%
				Spain						***29.59%***
05-10	19.05%	10.54%							2	29.59%

Table 4.3, continued

Panel A: Balanced Turnover (continued)

Sub-period	1	2	3	4	5	6	7	8	No. of Factors	R^2 (%)
				Israel						***29.56%***
00-05	25.68%	7.07%							2	32.75%
05-10	13.94%	7.23%	5.20%						3	26.37%
				Greece						***29.42%***
95-00	18.33%	10.36%	6.01%						3	34.70%
00-05	18.91%	6.54%	4.87%						3	30.32%
05-10	18.28%	4.95%							2	23.23%
				Switzerland						***27.04%***
00-05	18.85%	8.94%							2	27.79%
05-10	14.32%	11.96%							2	26.28%
				U.S. - NYSE & AMEX						***26.33%***
77-80	10.96%	5.89%	4.13%						3	20.98%
80-85	9.51%	7.95%	3.57%	2.50%					4	23.53%
85-90	13.26%	4.22%	2.59%	2.02%					4	22.09%
90-95	8.61%	4.00%	3.54%	2.71%					4	18.86%
95-00	8.77%	4.64%	3.52%	2.64%	2.11%				5	21.68%
00-05	12.15%	6.40%	4.40%	2.89%	2.29%	1.78%			6	29.91%
05-10	26.11%	6.62%	4.33%	3.18%	2.37%	1.70%	1.52%	1.40%	8	47.23%
				U.S.-NASDAQ						***23.49%***
85-90	10.49%	3.46%	3.16%						3	17.11%
90-95	8.56%	4.50%	3.44%	3.03%					4	19.53%
95-00	6.90%	5.73%	3.02%	2.36%					4	18.01%
00-05	9.25%	6.67%	3.82%	3.29%	2.50%	1.98%			6	27.51%
05-10	10.49%	8.32%	4.78%	3.46%	2.58%	2.06%	1.92%	1.69%	8	35.30%
				Netherland						***23.31%***
90-95	12.09%	7.22%							2	19.31%
95-00	16.11%	6.91%							2	23.02%
00-05	18.46%	5.92%							2	24.38%
05-10	14.36%	12.15%							2	26.51%
				Norway						***23.17%***
05-10	16.99%	6.18%							2	23.17%

Table 4.3, continued

Panel A: Balanced Turnover (continued)

Sub-period	1	2	3	4	5	6	7	8	No. of Factors	R^2 (%)
				Belgium						***21.98%***
00-05	13.96%	6.88%							2	20.84%
05-10	13.07%	10.04%							2	23.11%
				Denmark						***21.28%***
05-10	14.37%	6.91%							2	21.28%
				France						***19.89%***
95-00	7.96%	5.99%							2	13.95%
00-05	7.24%	6.42%	4.57%						3	18.23%
05-10	10.88%	9.97%	3.69%	2.95%					4	27.49%
				Sweden						***19.33%***
95-00	13.38%								1	13.38%
00-05	11.56%	6.38%							2	17.94%
05-10	14.08%	5.41%	3.65%	3.53%					4	26.67%
				Canada						***19.18%***
77-80	15.85%								1	15.85%
80-85	13.50%	9.60%	8.89%						3	31.99%
85-90	10.16%	5.93%							2	16.09%
90-95	9.69%	4.81%							2	14.50%
95-00	6.56%	4.59%	3.31%						3	14.46%
00-05	6.88%	4.66%	3.62%	2.74%	2.47%				5	20.37%
05-10	7.35%	4.38%	3.65%	3.27%	2.34%				5	20.99%
				U.K.						***18.52%***
90-95	16.33%	6.00%							2	22.33%
95-00	8.65%	3.92%							2	12.57%
00-05	10.29%	3.20%	2.60%						3	16.09%
05-10	15.34%	5.40%	2.35%						3	23.09%
				South Africa						***18.28%***
95-00	17.48%	7.29%							2	24.77%
00-05	8.77%	5.11%							2	13.88%
05-10	9.70%	6.49%							2	16.19%

Table 4.3, continued

Panel A: Balanced Turnover (continued)

Sub-period	1	2	3	4	5	6	7	8	No. of Factors	R^2 (%)
				Japan-Osaka						***17.46%***
95-00	13.35%								1	13.35%
00-05	13.45%								1	13.45%
05-10	16.86%	4.63%	4.10%						3	25.59%
				Finland						***17.29%***
00-05	10.15%	7.21%							2	17.36%
05-10	10.15%	7.06%							2	17.21%
				Australia						***13.00%***
85-90	9.39%								1	9.39%
90-95	6.37%								1	6.37%
95-00	5.79%	4.39%							2	10.18%
00-05	8.07%	4.27%	3.48%	2.84%					4	18.66%
05-10	8.52%	5.71%	3.55%	2.64%					4	20.42%

Table 4.3, continued

Panel B: Excess Return

Sub-period	1	2	3	4	5	6	7	8	No. of Factors	R^2 (%)
				China-Shenzhen						***55.42%***
95-00	52.05%	5.79%							2	57.84%
00-05	45.32%	3.56%	2.07%	1.59%					4	52.54%
05-10	51.29%	4.60%							2	55.89%
				China-Shanghai						***52.42%***
95-00	45.83%	3.91%	3.32%						3	53.06%
00-05	43.96%	3.23%	1.73%						3	48.92%
05-10	50.83%	2.32%	2.12%						3	55.27%
				Taiwan						***46.93%***
95-00	40.07%	4.93%							2	45.00%
00-05	35.94%	6.30%	2.79%	2.34%					4	47.37%
05-10	37.48%	5.46%	3.59%	1.89%					4	48.42%
				South Korea						***48.35%***
85-90	35.66%	11.68%	4.30%						3	51.64%
90-95	37.72%	7.69%	6.28%	2.44%					4	54.13%
95-00	48.97%	4.39%	3.54%						3	56.90%
00-05	31.21%	2.93%							2	34.14%
05-10	42.89%	2.03%							2	44.92%
				Malaysia						***48.42%***
90-95	43.98%	5.03%							2	49.01%
95-00	59.00%	3.74%	2.02%	1.48%					4	66.24%
00-05	38.44%	2.55%							2	40.99%
05-10	34.23%	3.19%							2	37.42%
				Singapore						***43.04%***
90-95	43.48%	3.90%							2	47.38%
95-00	44.68%	4.91%							2	49.59%
00-05	29.31%	3.53%							2	32.84%
05-10	38.97%	3.36%							2	42.33%
				Turkey						***52.15%***
00-05	53.86%								1	53.86%
05-10	50.44%								1	50.44%

Table 4.3, continued

Panel B: Excess Return (continued)

Sub-period	1	2	3	4	5	6	7	8	No. of Factors	R^2 (%)
				Germany						***27.76%***
00-05	17.45%	4.47%							2	21.92%
05-10	33.60%								1	33.60%
				India						***38.63%***
95-00	29.30%	3.97%	2.84%						3	36.11%
00-05	27.68%	2.93%	2.48%						3	33.09%
05-10	44.17%	2.51%							2	46.68%
				Japan-Tokyo						***37.21%***
95-00	32.47%	3.53%	2.72%	1.64%					4	40.36%
00-05	31.00%	2.46%	1.64%						3	35.10%
05-10	30.00%	4.02%	2.14%						3	36.16%
				Brazil						***48.74%***
00-05	46.42%								1	46.42%
05-10	51.06%								1	51.06%
				Italy						***35.31%***
95-00	26.79%	4.65%							2	32.08%
00-05	26.64%	4.79%							2	31.57%
05-10	42.03%								1	42.28%
				Hong Kong						***36.50%***
90-95	38.59%	4.03%							2	42.62%
95-00	35.23%	4.52%							2	39.75%
00-05	27.52%	3.57%							2	31.09%
05-10	29.39%	3.14%							2	32.53%
				Thailand						***37.73%***
05-10	37.73%								1	37.73%
				Indonesia						***47.49%***
05-10	47.49%								1	47.49%
				Spain						***73.73%***
05-10	57.84%	10.89%	2.76%	2.24%					4	73.73%
				Israel						***44.68%***
00-05	49.49%								1	49.49%
05-10	39.86%								1	39.86%

Table 4.3, continued

Panel B: Excess Return (continued)

Sub-period	1	2	3	4	5	6	7	8	No. of Factors	R^2 (%)
				Greece						***43.74%***
95-00	38.02%	6.86%							2	44.88%
00-05	42.76%	2.95%							2	45.71%
05-10	40.62%								1	40.62%
				Switzerland						***35.65%***
00-05	22.27%	9.17%							2	31.44%
05-10	35.54%	4.32%							2	39.86%
				U.S. - NYSE & AMEX						***26.64%***
77-80	22.32%	3.22%							2	25.54%
80-85	18.60%	3.61%	2.27%						3	24.48%
85-90	24.44%	3.08%							2	27.52%
90-95	15.07%	2.84%							2	17.91%
95-00	14.31%	3.05%	2.38%						3	19.74%
00-05	20.53%	3.52%	2.65%	2.22%					4	28.92%
05-10	32.68%	3.47%	2.69%	2.03%	1.51%				5	42.38%
				U.S.-NASDAQ						***17.14%***
85-90	18.65%								1	18.65%
90-95	9.80%								1	9.80%
95-00	8.67%	2.64%							2	11.31%
00-05	14.94%	2.75%	2.03%						3	19.72%
05-10	21.17%	2.98%	2.07%						3	26.22%
				Netherland						***29.39%***
90-95	31.32%								1	31.32%
95-00	16.59%								1	16.59%
00-05	22.19%	5.66%							2	27.85%
05-10	41.78%								1	41.78%
				Norway						***42.90%***
05-10	42.90%								1	42.90%
				Belgium						***34.58%***
00-05	23.86%	6.84%							2	30.70%
05-10	38.46%								1	38.46%

Table 4.3, continued

Panel B: Excess Return (continued)

Sub-period	1	2	3	4	5	6	7	8	No. of Factors	R^2 (%)
				Denmark						***36.72%***
05-10	36.72%								1	36.72%
				France						***28.16%***
95-00	13.97%	4.45%							2	18.42%
00-05	19.69%	4.87%	3.26%						3	27.82%
05-10	35.55%	2.68%							2	38.23%
				Sweden						***30.76%***
95-00	22.64%								1	22.64%
00-05	27.98%	4.68%							2	32.66%
05-10	36.99%								1	36.99%
				Canada						***21.54%***
77-80	20.99%								1	20.99%
80-85	26.61%								1	26.61%
85-90	22.60%	4.71%							2	27.31%
90-95	12.64%	4.14%							2	16.78%
95-00	9.87%	3.71%							2	13.58%
00-05	12.25%	3.14%							2	15.39%
05-10	25.23%	2.93%	1.97%						3	30.13%
				U.K.						***27.50%***
90-95	35.92%								1	35.92%
95-00	12.13%	3.47%	0.0306						3	18.66%
00-05	14.91%	3.42%	2.65%						3	20.98%
05-10	29.22%	2.78%	2.44%						3	34.44%
				South Africa						***39.64%***
95-00	23.24%	9.40%							2	32.64%
00-05	30.60%	5.86%							2	36.46%
05-10	45.92%	3.89%							2	49.81%
				Japan-Osaka						***26.89%***
95-00	32.86%								1	32.86%
00-05	22.39%								1	22.39%
05-10	25.42%								1	25.42%

Table 4.3, continued

Panel B: Excess Return (continued)

Sub-period	1	2	3	4	5	6	7	8	No. of Factors	R^2 (%)
				Finland						***33.33%***
00-05	21.57%	7.40%							2	28.97%
05-10	37.69%								1	37.69%
				Australia						***29.14%***
85-90	40.99%								1	40.99%
90-95	24.43%	4.48%							2	28.91%
95-00	20.07%								1	20.07%
00-05	20.70%								1	20.70%
05-10	32.60%	2.43%							2	35.03%

Table 4.4

Summary Statistics on the Explanatory Power of Each Principal Component for Individual Turnover and Excess Return

This tables gives the summary statistics, including average level, min and max, on the incremental proportions of the explained variation in turnover and excess return across country and sample period.

Panel A: Absolute Value

Principal Component		1	2	3	4	5	6	7	8	No. of Factors	R^2 (%)
Turnover	Average	17.06%	7.19%	4.67%	3.47%	2.80%	2.31%	2.03%	1.83%	4	30.95%
	Min	5.79%	3.20%	2.35%	2.02%	2.07%	1.66%	1.52%	1.40%	1	6.37%
	Max	67.99%	18.48%	8.89%	5.41%	4.15%	3.08%	2.64%	2.33%	8	78.48%
Excess Return	Average	32.17%	4.34%	2.73%	1.99%	1.51%				2	36.10%
	Min	8.67%	2.03%	1.64%	1.48%	1.51%				1	9.80%
	Max	59.00%	11.68%	6.28%	2.44%	1.51%				5	73.73%

Panel B: Relative Value(over the systematic component)

Principal Component		1	2	3	4	5	6	7	8
Turnover	Average	56.67%	25.55%	14.38%	10.01%	7.20%	5.43%	4.78%	3.90%
	Min	29.72%	10.00%	7.00%	4.00%	3.00%	3.00%	3.00%	3.00%
	Max	100.00%	46.00%	27.79%	15.58%	12.13%	7.20%	6.00%	5.00%
Excess Return	Average	88.52%	13.22%	7.76%	4.50%	4.00%			
	Min	65.00%	4.00%	3.00%	2.00%	4.00%			
	Max	100.00%	29.00%	16.00%	8.00%	4.00%			

Table 4.5

Explaining Stock Turnover by Turnovers on Return Factors

This table displays the average R^2 from time-series regression of individual stock turnover on turnovers of return factors derived from four asset-pricing models: (a) CAPM, (b) Fama and French (1993), (c) Hou, Karolyi and Kho (2011), (d) Lo and Wang (2000). Performance is computed as the average R^2 of the model divided by the average R^2 obtained from regressions stock turnover on extracted turnover factors.

Market/ Sub-period	CAPM		Fama and French		Hou-Karolyi-Kho		Lo and Wang		Factors Average Stock R^2
	Average R^2 (%)	Performance (%)	Average R^2 (%)	Performance (%)	Average R^2 (%)	Performance (%)	Average R^2 (%)	Performance (%)	(%)
China-Shenzhen	**44.4**	**68.8**	**49.8**	**77.2**	**46.9**	**72.7**	**52.1**	**80.8**	**64.5**
95-00	66.3	84.5	67.9	86.5	67.6	86.1	72.4	92.2	78.5
00-05	28.5	56.1	33.0	64.9	30.9	60.7	36.5	71.8	50.8
05-10	38.5	59.8	48.7	75.8	42.4	66.0	47.6	74.0	64.3
China-Shanghai	**36.8**	**63.0**	**42.4**	**72.6**	**40.4**	**69.1**	**47.9**	**82.0**	**58.5**
95-00	40.9	66.3	43.9	71.2	42.8	69.3	54.5	88.4	61.7
00-05	27.6	55.2	32.3	64.5	31.0	61.9	35.6	71.2	50.1
05-10	41.9	65.9	51.1	80.3	47.4	74.5	53.6	84.3	63.6
Taiwan	**9.8**	**18.0**	**23.8**	**43.7**	**16.2**	**29.8**	**31.1**	**57.2**	**54.4**
95-00	12.5	23.7	23.9	45.2	17.9	33.9	32.7	61.9	52.9
00-05	11.9	19.9	26.5	44.4	20.3	34.0	34.8	58.3	59.6
05-10	5.0	9.9	21.1	41.5	10.5	20.8	25.9	51.0	50.8
South Korea	**21.0**	**41.2**	**29.1**	**57.0**	**25.3**	**49.7**	**35.8**	**70.3**	**50.9**
85-90	22.8	39.3	33.7	58.0	31.8	54.8	49.1	84.5	58.0
90-95	21.6	38.2	25.2	44.5	25.5	45.0	44.1	77.9	56.6
95-00	34.3	57.9	39.4	66.4	36.5	61.6	43.6	73.5	59.3
00-05	15.5	37.2	25.1	60.2	17.6	42.2	27.2	65.1	41.8
05-10	10.8	27.6	21.9	56.1	15.3	39.0	15.2	38.9	39.1
Malaysia	**17.3**	**38.8**	**24.2**	**54.1**	**22.1**	**49.4**	**27.9**	**62.5**	**44.7**
90-95	29.2	63.7	32.0	69.7	33.1	72.2	34.1	74.3	45.9
95-00	10.9	22.8	22.9	47.7	18.7	39.0	32.7	68.2	48.0
00-05	11.9	29.6	19.4	48.5	15.4	38.5	21.8	54.3	40.1
05-10	17.3	38.6	22.4	50.1	21.1	47.0	23.2	51.7	44.8
Singapore	**13.8**	**33.8**	**24.1**	**59.2**	**20.0**	**49.1**	**26.3**	**64.6**	**40.7**
90-95	17.9	53.3	25.1	74.8	22.2	66.2	26.1	77.9	33.5
95-00	20.6	38.2	32.7	60.5	25.7	47.6	40.4	74.7	54.0
00-05	7.9	23.2	16.5	48.8	13.7	40.6	18.5	54.6	33.8
05-10	8.8	21.1	22.2	53.3	18.5	44.4	20.4	49.1	41.5

Market/ Sub-period	CAPM		Fama and French		Hou-Karolyi-Kho		Lo and Wang		Factors Average Stock R^2
	Average R^2	Performance	Average R^2	Performance	Average R^2	Performance	Average R^2	Performance	
	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)
Turkey	**11.4**	**28.5**	**20.0**	**50.2**	**16.3**	**40.8**	**18.3**	**45.8**	**39.9**
00-05	14.4	31.8	20.9	46.3	20.9	46.4	22.5	49.9	45.1
05-10	8.4	24.2	19.1	55.2	11.6	33.4	14.0	40.4	34.7
Germany	**18.7**	**48.4**	**25.0**	**64.9**	**23.4**	**60.6**	**23.7**	**61.5**	**38.6**
00-05	10.4	32.6	17.2	54.0	15.6	49.1	17.7	55.7	31.9
05-10	27.0	59.4	32.9	72.5	31.1	68.7	29.7	65.6	45.3
India	**8.5**	**23.0**	**15.4**	**41.4**	**13.8**	**37.2**	**24.2**	**65.3**	**37.1**
95-00	10.1	27.0	16.7	44.8	16.5	44.3	28.2	75.7	37.3
00-05	8.2	19.6	14.6	34.8	14.4	34.5	27.3	65.2	41.8
05-10	7.4	22.8	14.9	46.1	10.5	32.4	17.3	53.5	32.3
Japan-Tokyo	**10.7**	**29.3**	**19.2**	**52.4**	**14.8**	**40.5**	**23.2**	**63.4**	**36.6**
95-00	9.0	27.7	15.6	48.3	11.8	36.4	20.0	62.0	32.3
00-05	12.7	34.3	18.6	50.3	16.4	44.2	23.4	63.4	37.0
05-10	10.5	26.0	23.3	57.6	16.2	40.2	26.0	64.5	40.4
Brazil	**10.9**	**29.9**	**17.2**	**47.0**	**15.0**	**40.9**	**13.9**	**37.9**	**36.6**
00-05	8.0	23.5	13.3	39.2	11.1	32.9	13.2	38.9	33.9
05-10	13.9	35.3	21.1	53.8	18.8	47.8	14.5	37.0	39.3
Italy	**12.7**	**36.7**	**23.1**	**66.8**	**18.2**	**52.6**	**22.8**	**66.1**	**34.5**
95-00	25.0	48.6	35.8	69.6	32.9	64.0	38.9	75.7	51.4
00-05	6.6	31.9	15.3	74.5	8.8	42.8	15.9	77.3	20.5
05-10	6.5	20.6	18.1	57.1	12.8	40.4	13.7	43.1	31.6
Hong Kong	**10.8**	**32.7**	**18.2**	**55.1**	**16.0**	**48.5**	**21.0**	**63.7**	**33.0**
90-95	15.5	49.6	19.6	62.7	17.0	54.4	24.6	78.8	31.2
95-00	12.1	30.2	22.4	56.2	19.9	49.8	24.4	61.1	39.9
00-05	8.9	28.4	16.2	51.6	14.7	46.7	19.6	62.5	31.4
05-10	6.8	22.8	14.7	49.3	12.7	42.7	15.6	52.4	29.7
Thailand	**7.4**	**22.8**	**13.2**	**40.7**	**11.7**	**36.1**	**12.0**	**37.1**	**32.4**
05-10	7.4	**22.8**	13.2	40.7	11.7	36.1	12.0	37.1	32.4
Indonesia	**10.9**	**35.7**	**15.4**	**50.5**	**17.7**	**57.9**	**14.4**	**47.0**	**30.6**
05-10	10.9	**35.7**	15.4	**50.5**	17.7	**57.9**	14.4	**47.0**	30.6
Spain	**8.2**	**27.8**	**20.2**	**68.4**	**18.5**	**62.5**	**27.5**	**93.0**	**29.6**
05-10	8.2	27.8	20.2	68.4	18.5	62.5	27.5	93.0	29.6
Israel	**11.1**	**37.6**	**19.6**	**66.3**	**18.6**	**63.0**	**19.0**	**64.4**	**29.6**
00-05	12.6	38.4	24.2	73.9	23.2	70.8	25.2	76.8	32.8
05-10	9.7	36.7	15.0	56.9	14.1	53.4	12.9	49.1	26.4

Table 4.5, continued

Market/ Sub-period	CAPM		Fama and French		Hou-Karolyi-Kho		Lo and Wang		Factors Average Stock R^2
	Average R^2	Performance	Average R^2	Performance	Average R^2	Performance	Average R^2	Performance	
	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)
Greece	**6.8**	**23.1**	**9.5**	**32.3**	**12.1**	**41.0**	**22.1**	**75.2**	**29.4**
95-00	7.5	21.7	14.0	40.3	15.7	45.2	26.8	77.1	34.7
00-05	7.1	23.4	4.8	16.0	10.9	36.0	21.9	72.3	30.3
05-10	5.8	25.0	9.7	41.8	9.6	41.2	17.7	76.1	23.2
Switzerland	**12.9**	**47.6**	**21.9**	**80.9**	**16.9**	**62.5**	**17.8**	**65.7**	**27.0**
00-05	16.3	58.5	20.8	74.9	18.5	66.6	18.3	65.9	27.8
05-10	9.5	36.0	22.9	87.3	15.3	58.1	17.2	65.4	26.3
U.S. - NYSE & AMEX	**9.1**	**34.4**	**14.3**	**54.5**	**14.1**	**53.4**	**18.1**	**68.6**	**26.3**
77-80	NA	NA	NA	NA	NA	NA	11.6	55.3	21.0
80-85	1.3	5.6	7.7	32.7	9.7	41.3	17.6	74.7	23.5
85-90	10.9	49.5	14.6	66.3	14.1	64.0	14.9	67.4	22.1
90-95	5.6	29.9	9.6	51.0	8.2	43.5	8.8	46.4	18.9
95-00	6.1	28.0	9.0	41.4	8.7	40.1	11.6	53.4	21.7
00-05	5.9	19.7	13.7	45.7	11.9	39.9	18.9	63.1	29.9
05-10	24.4	51.7	31.4	66.5	31.7	67.1	36.6	77.6	47.2
U.S.-NASDAQ	**5.3**	**22.6**	**9.9**	**42.3**	**9.5**	**40.4**	**11.6**	**49.5**	**23.5**
85-90	7.2	41.8	8.7	50.7	9.2	53.5	9.1	53.2	17.1
90-95	4.1	21.1	7.5	38.5	7.5	38.5	6.0	30.8	19.5
95-00	4.1	22.5	8.3	45.9	7.3	40.4	9.4	52.2	18.0
00-05	5.1	18.7	11.2	40.6	9.7	35.2	15.6	56.7	27.5
05-10	6.0	17.1	14.1	39.8	13.8	39.0	18.1	51.1	35.3
Netherland	**10.6**	**45.6**	**17.1**	**73.3**	**15.9**	**68.3**	**14.7**	**62.9**	**23.3**
90-95	8.0	41.5	11.7	60.5	12.1	62.6	11.3	58.7	19.3
95-00	11.3	49.2	16.4	71.2	14.0	60.7	15.2	66.2	23.0
00-05	13.9	56.8	19.1	78.5	17.9	73.4	20.0	82.2	24.4
05-10	9.4	35.3	21.2	79.8	19.7	74.2	12.0	45.3	26.5
Norway	**13.0**	**55.9**	**17.6**	**75.7**	**15.1**	**65.2**	**14.4**	**62.1**	**23.2**
05-10	13.0	55.9	17.6	75.7	15.1	65.2	14.4	62.1	23.2
Belgium	**7.2**	**32.9**	**15.3**	**69.7**	**11.9**	**54.0**	**13.3**	**60.7**	**22.0**
00-05	3.7	17.7	13.8	66.2	7.5	36.0	15.8	75.9	20.8
05-10	10.8	46.6	16.8	72.8	16.2	70.1	10.8	46.9	23.1
Denmark	**8.4**	**39.6**	**15.7**	**73.6**	**14.8**	**69.4**	**11.3**	**53.1**	**21.3**
05-10	8.4	39.6	15.7	73.6	14.8	69.4	11.3	53.1	21.3

Table 4.5, continued

Market/ Sub-period	CAPM		Fama and French		Hou-Karolyi-Kho		Lo and Wang		Factors Average Stock R^2
	Average R^2	Performance	Average R^2	Performance	Average R^2	Performance	Average R^2	Performance	
	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)
France	**2.6**	**13.2**	**10.6**	**53.1**	**6.9**	**34.9**	**13.1**	**66.0**	**19.9**
95-00	5.5	39.1	9.1	65.3	8.4	60.2	8.8	63.4	14.0
00-05	0.9	5.0	7.9	43.1	5.3	29.2	12.0	65.8	18.2
05-10	1.5	5.5	14.7	53.6	7.1	25.8	18.6	67.6	27.5
Sweden	**7.2**	**37.1**	**14.6**	**75.5**	**10.5**	**54.4**	**13.0**	**67.3**	**19.3**
95-00	7.5	56.1	13.1	98.0	10.8	80.8	12.4	92.3	13.4
00-05	6.5	36.0	14.0	78.2	8.5	47.1	14.4	80.2	17.9
05-10	7.6	28.4	16.7	62.5	12.3	46.0	12.3	46.1	26.7
Canada	**5.2**	**26.7**	**9.5**	**48.3**	**9.7**	**49.6**	**10.8**	**60.6**	**19.2**
77-80	NA	NA	NA	NA	NA	NA	14.6	92.3	15.9
80-85	9.7	43.0	16.9	52.7	18.3	57.2	10.9	33.9	32.0
85-90	6.9	47.4	11.3	70.0	12.2	76.0	13.0	80.6	16.1
90-95	6.9	17.8	10.0	69.2	9.1	62.5	11.1	76.4	14.5
95-00	2.6	10.9	3.9	27.0	6.4	44.5	7.7	53.2	14.5
00-05	2.2	14.9	5.1	25.0	5.5	26.9	8.4	41.2	20.4
05-10	3.1	26.0	9.7	46.1	6.4	30.6	9.8	46.9	21.0
U.K.	**10.1**	**54.4**	**12.8**	**69.2**	**13.0**	**70.1**	**14.4**	**77.6**	**18.5**
90-95	13.6	60.7	16.3	73.2	16.9	75.9	15.9	71.2	22.3
95-00	4.9	38.8	7.7	61.1	8.6	68.2	9.4	75.0	12.6
00-05	7.9	49.3	9.7	60.4	11.0	68.2	12.8	79.4	16.1
05-10	13.9	60.2	17.5	75.7	15.5	67.1	19.4	83.9	23.1
South Africa	**9.1**	**49.9**	**12.5**	**68.5**	**11.8**	**64.6**	**14.3**	**78.4**	**18.3**
95-00	14.9	60.0	19.6	79.0	19.8	80.0	22.2	89.8	24.8
00-05	5.0	35.7	7.0	50.5	6.6	47.4	10.3	74.1	13.9
05-10	7.6	46.8	11.0	67.9	9.0	55.8	10.5	64.8	16.2
Japan-Osaka	**9.8**	**56.0**	**14.4**	**82.5**	**13.1**	**75.2**	**13.6**	**77.8**	**17.5**
95-00	8.6	64.3	14.3	106.7	12.7	94.9	12.5	93.9	13.4
00-05	9.0	66.8	14.2	105.7	12.6	94.0	12.6	93.5	13.5
05-10	11.8	45.9	14.8	57.7	14.1	55.0	15.7	61.2	25.6
Finland	**4.5**	**26.0**	**7.8**	**45.3**	**6.7**	**38.5**	**11.9**	**69.0**	**17.3**
00-05	4.2	24.3	7.2	41.2	6.2	35.6	14.0	80.7	17.4
05-10	4.8	27.7	8.5	49.4	7.1	41.4	9.8	57.2	17.2

Table 4.5, continued

Market/ Sub-period	CAPM		Fama and French		Hou-Karolyi-Kho		Lo and Wang		Factors Average Stock R^2
	Average R^2 (%)	Performance (%)	Average R^2 (%)	Performance (%)	Average R^2 (%)	Performance (%)	Average R^2 (%)	Performance (%)	(%)
Australia	**3.9**	**29.7**	**7.5**	**57.5**	**6.0**	**45.8**	**8.1**	**62.1**	**13.0**
85-90	4.4	46.3	9.3	98.8	6.3	66.7	8.5	90.0	9.4
90-95	3.1	48.2	5.6	87.3	5.6	87.6	7.7	121.4	6.4
95-00	3.5	34.0	5.2	50.9	5.2	50.6	5.2	51.5	10.2
00-05	3.7	19.8	6.5	35.0	5.8	30.9	6.8	36.6	18.7
05-10	4.7	23.1	10.9	53.1	7.1	34.5	12.1	59.3	20.4

Table 4.6

Explaining Stock Return by Return Factors

This table presents the average R^2 from time-series regression of individual stock excess return on return factors derived from three asset-pricing models: (a) CAPM, (b) Fama and French (1993), (c) Hou, Karolyi and Kho (2011). Performance is computed as the average R^2 of the model divided by the average R^2 obtained from regressions stock excess return on extracted excess return factors.

Market/ Sub-period	CAPM		Fama and French		Hou, Karolyi and Kho		Factors Average
	Average R^2 (%)	Performance (%)	Average R^2 (%)	Performance (%)	Average R^2 (%)	Performance (%)	Stock R^2 (%)
China-Shenzhen	**46.9**	**84.5**	**50.0**	**90.1**	**47.9**	**86.4**	**55.4**
95-00	50.2	86.8	51.2	88.5	50.3	87.0	57.8
00-05	42.8	81.5	46.3	88.2	44.7	85.1	52.5
05-10	47.5	85.0	52.4	93.7	48.6	87.0	55.9
China-Shanghai	**43.6**	**83.1**	**47.9**	**91.4**	**46.3**	**88.3**	**52.4**
95-00	42.8	80.7	46.2	87.1	44.4	83.6	53.1
00-05	41.6	85.0	45.8	93.5	45.1	92.2	48.9
05-10	46.3	83.8	51.8	93.7	49.5	89.5	55.3
Taiwan	**34.9**	**74.4**	**38.8**	**82.8**	**36.2**	**77.2**	**46.9**
95-00	37.9	84.2	40.0	88.9	40.0	89.0	45.0
00-05	33.3	70.3	39.6	83.6	34.0	71.9	47.4
05-10	33.6	69.4	36.9	76.3	34.6	71.4	48.4
South Korea	**31.0**	**64.1**	**38.9**	**80.4**	**32.6**	**67.4**	**48.3**
85-90	31.0	60.0	39.1	75.8	34.8	67.4	51.6
90-95	25.9	47.8	32.5	60.0	26.9	49.7	54.1
95-00	36.8	64.7	48.5	85.2	37.7	66.3	56.9
00-05	23.8	69.8	31.2	91.5	25.1	73.4	34.1
05-10	37.5	83.5	43.0	95.8	38.5	85.6	44.9
Malaysia	**37.9**	**78.4**	**45.1**	**93.1**	**39.4**	**81.3**	**48.4**
90-95	40.7	83.0	44.6	91.0	42.8	87.4	49.0
95-00	51.6	77.9	60.9	92.0	52.5	79.2	66.2
00-05	29.8	72.7	39.2	95.5	31.0	75.6	41.0
05-10	29.7	79.5	35.6	95.0	31.2	83.4	37.4
Singapore	**31.0**	**72.1**	**38.6**	**89.8**	**34.0**	**79.0**	**43.0**
90-95	39.6	83.7	45.2	95.3	42.5	89.7	47.4
95-00	30.8	62.0	38.7	77.9	35.7	72.1	49.6
00-05	20.5	62.5	30.3	92.3	22.8	69.3	32.8
05-10	33.1	78.2	40.4	95.4	35.0	82.7	42.3
Turkey	**40.1**	**76.9**	**42.2**	**81.0**	**42.9**	**82.2**	**52.2**
00-05	33.8	62.7	37.5	69.6	35.5	65.9	53.9
05-10	46.5	92.1	47.0	93.1	50.3	99.6	50.4

Table 4.6, continued

Market/ Sub-period	CAPM Average R^2 (%)	CAPM Performance (%)	Fama and French Average R^2 (%)	Fama and French Performance (%)	Hou, Karolyi and Kho Average R^2 (%)	Hou, Karolyi and Kho Performance (%)	Factors Average Stock R^2 (%)
Germany	**20.4**	**73.4**	**25.8**	**93.0**	**23.7**	**85.5**	**27.8**
00-05	13.8	62.7	18.5	84.5	17.1	78.0	21.9
05-10	27.0	80.3	33.1	98.6	30.4	90.4	33.6
India	**27.3**	**70.6**	**33.0**	**85.5**	**31.1**	**80.5**	**38.6**
95-00	24.1	66.7	28.2	78.2	29.0	80.3	36.1
00-05	20.2	60.9	26.5	80.1	24.2	73.1	33.1
05-10	37.5	80.4	44.3	95.0	40.1	85.8	46.7
Japan-Tokyo	**25.6**	**68.7**	**33.0**	**88.8**	**29.2**	**78.4**	**37.2**
95-00	24.1	59.7	34.0	84.2	31.8	78.8	40.4
00-05	25.8	73.4	32.8	93.4	27.8	79.3	35.1
05-10	26.9	74.3	32.3	89.4	27.9	77.2	36.2
Brazil	**46.2**	**94.7**	**49.4**	**101.4**	**47.5**	**97.5**	**48.7**
00-05	43.9	94.5	47.0	101.2	46.2	99.5	46.4
05-10	48.5	94.9	51.9	101.6	48.8	95.6	51.1
Italy	**27.7**	**79.4**	**33.1**	**94.6**	**29.0**	**82.8**	**35.0**
95-00	22.8	72.5	28.7	91.4	24.1	76.7	31.4
00-05	22.3	70.9	27.8	88.4	23.5	74.9	31.4
05-10	38.2	90.8	42.7	101.7	39.2	93.2	42.0
Hong Kong	**26.8**	**73.4**	**31.1**	**85.1**	**29.4**	**80.6**	**36.5**
90-95	34.2	80.3	37.8	88.6	36.2	84.9	42.6
95-00	28.9	72.7	37.5	94.3	31.7	79.8	39.8
00-05	21.2	68.3	28.5	91.7	25.5	82.1	31.1
05-10	22.8	70.1	20.5	62.9	24.2	74.5	32.5
Thailand	**31.9**	**84.4**	**36.4**	**96.6**	**33.4**	**88.5**	**37.7**
05-10	31.9	**84.4**	36.4	**96.6**	33.4	**88.5**	37.7
Indonesia	**44.4**	**93.5**	**48.9**	**103.0**	**46.9**	**98.8**	**47.5**
05-10	44.4	93.5	48.9	103.0	46.9	98.8	47.5
Spain	**29.2**	**39.6**	**33.8**	**45.8**	**30.7**	**41.6**	**73.7**
05-10	29.2	39.6	33.8	45.8	30.7	41.6	73.7
Israel	**38.1**	**85.2**	**44.7**	**100.0**	**41.5**	**92.9**	**44.7**
00-05	43.5	87.9	49.8	100.5	47.3	95.6	49.5
05-10	32.6	81.8	39.6	99.4	35.7	89.5	39.9
Greece	**29.1**	**66.4**	**33.5**	**76.5**	**29.6**	**67.6**	**43.7**
95-00	34.4	76.7	38.8	86.5	35.0	77.9	44.9
00-05	21.2	46.3	29.8	65.1	21.6	47.1	45.7
05-10	31.6	77.8	31.8	78.2	32.2	79.1	40.6

Market/ Sub-period	CAPM		Fama and French		Hou, Karolyi and Kho		Factors Average
	Average R^2 (%)	Performance (%)	Average R^2 (%)	Performance (%)	Average R^2 (%)	Performance (%)	Stock R^2 (%)
Switzerland	**23.0**	**64.4**	**30.0**	**84.0**	**24.8**	**69.5**	**35.7**
00-05	15.9	50.5	22.9	72.7	18.5	58.9	31.4
05-10	30.0	75.4	37.1	93.0	31.0	77.7	39.9
U.S. - NYSE & AMEX	**18.6**	**69.9**	**22.2**	**83.3**	**20.4**	**76.6**	**26.6**
77-80	NA	NA	NA	NA	NA	NA	25.5
80-85	17.5	71.5	20.7	84.5	19.0	77.6	24.5
85-90	22.0	79.8	26.0	94.4	22.9	83.2	27.5
90-95	13.2	73.6	16.0	89.5	14.7	82.3	17.9
95-00	11.0	55.7	15.4	77.8	13.0	65.8	19.7
00-05	17.5	60.7	21.4	74.1	20.0	69.1	28.9
05-10	30.6	72.2	33.6	79.2	32.8	77.4	42.4
U.S.-NASDAQ	**12.3**	**71.8**	**14.6**	**85.4**	**14.1**	**82.1**	**17.1**
85-90	17.1	91.4	18.9	101.3	17.7	95.0	18.7
90-95	8.4	85.3	9.7	98.9	9.4	96.1	9.8
95-00	6.3	55.4	8.4	74.0	7.3	64.5	11.3
00-05	11.9	60.2	14.6	74.2	14.8	75.2	19.7
05-10	18.0	68.5	21.6	82.3	21.1	80.6	26.2
Netherland	**22.3**	**76.0**	**28.0**	**95.4**	**24.7**	**84.0**	**29.4**
90-95	24.5	78.1	28.9	92.2	27.6	88.0	31.3
95-00	11.2	67.5	16.8	101.5	13.9	83.7	16.6
00-05	16.6	59.6	23.8	85.5	18.5	66.5	27.9
05-10	37.0	88.7	42.6	101.9	38.7	92.6	41.8
Norway	**38.5**	**89.7**	**41.0**	**95.7**	**39.2**	**91.4**	**42.9**
05-10	38.5	89.7	41.0	95.7	39.2	91.4	42.9
Belgium	**20.9**	**60.4**	**26.9**	**77.9**	**23.0**	**66.5**	**34.6**
00-05	18.5	60.4	24.2	78.9	20.8	67.7	30.7
05-10	23.3	60.5	29.7	77.1	25.2	65.5	38.5
Denmark	**32.8**	**89.3**	**37.2**	**101.4**	**34.2**	**93.1**	**36.7**
05-10	32.8	89.3	37.2	101.4	34.2	93.1	36.7
France	**18.9**	**67.2**	**25.5**	**90.6**	**21.0**	**74.6**	**28.2**
95-00	10.4	56.5	16.8	91.1	12.7	69.2	18.4
00-05	14.9	53.6	22.3	80.2	17.2	61.9	27.8
05-10	31.4	82.2	37.4	97.9	33.1	86.5	38.2
Sweden	**24.1**	**78.4**	**29.7**	**96.5**	**25.6**	**83.3**	**30.8**
95-00	15.4	67.9	22.3	98.3	18.5	81.8	22.6
00-05	23.4	71.6	29.4	90.0	24.3	74.3	32.7
05-10	33.6	90.8	37.4	101.2	34.1	92.2	37.0

Table 4.6, continued

Market/ Sub-period	CAPM Average R^2 (%)	CAPM Performance (%)	Fama and French Average R^2 (%)	Fama and French Performance (%)	Hou, Karolyi and Kho Average R^2 (%)	Hou, Karolyi and Kho Performance (%)	Factors Average Stock R^2 (%)
Canada	**15.9**	**73.6**	**18.6**	**86.5**	**17.7**	**82.0**	**21.5**
77-80	NA	NA	NA	NA	NA	NA	21.0
80-85	24.7	92.8	29.3	110.0	28.1	105.7	26.6
85-90	20.6	75.2	23.4	85.8	22.7	83.1	27.3
90-95	11.1	66.0	13.4	79.6	12.5	74.4	16.8
95-00	6.9	50.5	8.4	62.2	8.8	64.9	13.6
00-05	9.9	64.0	12.1	78.5	11.3	73.6	15.4
05-10	22.1	73.5	25.3	83.8	22.5	74.7	30.1
U.K.	**18.7**	**67.8**	**24.3**	**88.3**	**21.1**	**76.5**	**27.5**
90-95	33.3	92.6	37.4	104.0	35.1	97.6	35.9
95-00	6.0	32.1	13.6	72.6	8.3	44.6	18.7
00-05	10.3	48.9	15.9	75.6	13.5	64.2	21.0
05-10	25.1	72.9	30.4	88.3	27.4	79.4	34.4
South Africa	**29.6**	**74.6**	**34.9**	**88.0**	**32.2**	**81.2**	**39.6**
95-00	20.7	63.3	27.4	83.8	23.8	73.0	32.6
00-05	25.7	70.6	30.4	83.5	28.4	77.8	36.5
05-10	42.3	84.9	46.9	94.1	44.4	89.1	49.8
Japan-Osaka	**24.2**	**90.1**	**27.5**	**102.1**	**26.1**	**96.9**	**26.9**
95-00	31.3	95.2	34.3	104.5	32.8	99.8	32.9
00-05	19.1	85.2	22.8	101.9	21.0	93.7	22.4
05-10	22.3	87.7	25.2	99.3	24.4	96.0	25.4
Finland	**13.7**	**41.1**	**22.9**	**68.7**	**15.7**	**47.1**	**33.3**
00-05	4.1	14.2	16.4	56.6	7.0	24.3	29.0
05-10	23.3	61.8	29.4	78.0	24.4	64.7	37.7
Australia	**25.3**	**86.7**	**28.0**	**96.2**	**26.5**	**90.9**	**29.1**
85-90	38.7	94.5	42.5	103.6	40.2	98.0	41.0
90-95	22.5	77.7	25.7	88.8	24.1	83.3	28.9
95-00	17.2	85.7	19.1	95.0	18.0	89.8	20.1
00-05	18.0	86.8	20.0	96.7	19.1	92.3	20.7
05-10	30.0	85.7	32.9	94.0	31.1	88.7	35.0

Table 4.7

Summary Statistics on the Explanatory Power of Asset-pricing Models for Individual Turnover and Excess Return

	CAPM		Fama and French		Hou-Karolyi-Kho		Lo and Wang		Factors
	Average R^2 (%)	Performance (%)	Average R^2 (%)	Performance (%)	Average R^2 (%)	Performance (%)	Average R^2 (%)	Performance (%)	Average Stock R^2 (%)
					Turnover				
Mean	11.8	36.7	18.5	59.7	16.4	53.0	20.1	64.1	31.2
Min	2.6	13.2	7.5	32.3	6.0	29.8	8.1	37.1	13.0
Max	44.4	68.8	49.8	82.5	46.9	75.2	52.1	93.0	64.5
					Excess Return				
Mean	28.8	74.7	33.8	88.5	30.8	80.4			38.7
Min	12.3	39.6	14.6	45.8	14.1	41.6			17.1
Max	46.9	94.7	50.0	103.0	47.9	98.8			73.7

Table 4.8

Average Standard Deviation of Turnovers on FMPs

This table presents the average standard deviation of turnovers on all FMPs across the sub-periods. The standard deviations of turnovers for each FMP are calculated over selected sub-periods. All the standard deviations from the sub-periods for each market are equally-weighted averaged and offer a way to compare the volatility of turnovers on FMPs within each market. The FMPs are as follow: 1)MKT, value-weighted market portfolio ; 2) SMB, FMP formed on size; 3)HML, FMP formed on book value of common equity relative to market value; 4) CHL, FMP formed on C/P, cash flow to price ratio; 5)DPG, FMP formed on D/P, dividend yield; 6) EPG, FMP formed on E/P, earning to price ratio; 7)LBG, FMP formed on leverage ratio; 8) MTN, momentum FMP; 9) CON, contrarian FMP; 10)MAG, FMP formed by the rule of moving average-oscillator; 11) RB, FMP formed by the rule of trading range break-out; 12) CPI, FMP formed on the growth rate of CPI; 14)IP, FMP formed on the growth rate of industrial production; 15)UE, FMP formed on the change of unemployment rate. And the * denotes the corresponding factor which gives the largest average volatility in turnover.

	Market	Fundamental Factor							Technical Factor				Macroeconomic Factor			
	MKT	*	SMB	HML	CHL	DPG	EPG	LBG	MTN	CON	MAG	RB	*	CPI	IP	UE
China-Shenzhen	3.94	HML	3.20	6.06	2.80	2.67	2.70	3.19	1.49	26.36	3.59	8.56	IP	2.41	2.56	
China-Shanghai	2.64	SMB	3.46	2.36	2.28	2.52	2.93	3.09	1.67	22.40	2.52	7.78	CPI	2.38	2.25	
Taiwan	3.85	CHL	5.00	5.58	6.84	3.39	4.79	2.33	1.56	12.19	1.56	5.33	IP	5.65	8.53	5.93
South Korea	1.22	SMB	2.91	2.04	2.35	2.06	1.90	1.94	0.98	20.21	1.78	6.36	UE	1.38	1.48	1.53
Malaysia	0.62	SMB	2.20	1.23	0.88	0.77	1.06	0.74	0.78	10.42	1.12	4.22	IP	0.65	0.82	
Singapore	0.36	SMB	1.83	0.72	0.97	1.36	1.57	1.76	1.25	8.45	0.95	2.82	CPI	1.10	0.63	
Turkey	2.71	LBG	4.84	4.15	4.38	4.30	7.28	10.41	2.37	16.47	2.54	7.36	UE	1.92		2.79
Germany	0.05	SMB	0.58	0.11	0.11	0.15	0.11	0.10	0.32	5.01	0.21	1.49	IP	0.17	0.31	0.26
India	1.58	EPG	1.99	5.62	3.56	2.75	5.79	1.88	0.69	6.24	0.71	3.66	CPI	4.59		2.53
Japan-Tokyo	0.39	SMB	0.69	0.43	0.37	0.37	0.47	0.27	0.51	3.05	0.35	2.04	CPI	0.47	0.36	0.32
Brazil	1.25	EPG	2.27	2.07	2.84	2.59	3.11	1.56	1.24	8.95	1.44	4.06	IP	1.83	2.58	3.60
Italy	0.86	HML	1.35	1.70	1.27	1.36	1.27	0.92	0.60	5.07	0.56	2.08	CPI	1.61	1.58	1.55
Hong Kong	0.52	SMB	1.11	0.76	0.58	0.79	0.72	0.79	0.78	6.93	0.70	2.24	UE	1.07		1.08
Thailand	2.08	EPG	2.76	5.64	4.37	5.29	6.97	3.34	1.28	8.83	1.71	5.22	CPI	3.60	2.30	2.28
Indonesia	0.53	HML	1.56	2.63	1.85	1.75	1.68	2.23	1.49	10.97	1.19	3.03	IP	1.06	1.45	
Spain	1.88	CHL	2.97	6.39	8.18	3.83	3.49	5.15	2.46	4.85	2.82	4.56	CPI	2.29	2.24	2.08
Israel	0.32	EPG	0.68	0.70	0.74	0.61	0.96	0.51	0.52	2.74	0.43	1.38	CPI	0.59	0.53	
Greece	2.66	CHL	3.10	3.61	5.00	1.31	4.11	4.78	0.91	11.25	1.51	4.45	UE	4.14	4.62	4.87
Switzerland	3.80	CHL	3.86	4.77	5.95	1.72	1.58	5.95	0.88	4.63	0.87	3.81	IP	4.91	5.06	2.47
U.S. - NYSE & AMEX	1.07	HML	1.00	1.63	1.33	0.99	0.96	1.09	0.81	6.53	0.50	1.86	CPI	1.33	1.09	1.13
Netherland	1.77	EPG	2.20	3.61	3.24	3.20	4.15	2.40	1.74	6.62	1.37	4.84	UE	3.00	3.00	3.01
Norway	3.03	LBG	2.58	4.15	2.96	2.61	3.19	9.01	2.30	10.55	1.41	3.48	CPI	3.25	2.41	2.30
U.S.-NASDAQ	1.26	DPG	2.20	1.99	2.78	2.96	1.97	1.65	0.68	7.55	0.59	2.13	IP	2.81	2.35	1.94
Belgium	0.40	EPG	0.53	0.80	0.71	1.07	1.49	0.84	0.73	2.97	0.52	2.25	UE	0.74	0.95	1.22
Denmark	1.12	CHL	2.21	1.02	6.80	1.95	2.92	1.13	0.79	5.50	0.96	4.16	CPI	3.54	3.33	3.36

Table 4.8, continued

	Market	Fundamental Factor							Technical Factor				Macroeconomic Factor			
	MKT	*	SMB	HML	CHL	DPG	EPG	LBG	MTN	CON	MAG	RB	*	CPI	IP	UE
Denmark	1.12	CHL	2.21	1.02	6.80	1.95	2.92	1.13	0.79	5.50	0.96	4.16	CPI	3.54	3.33	3.36
France	0.96	HML	1.14	1.99	1.46	1.76	1.97	1.10	0.66	3.59	0.55	1.95	IP	1.53	1.90	1.71
Sweden	1.40	CHL	1.77	2.80	3.89	2.80	2.83	2.85	0.95	5.37	0.96	3.17	CPI	3.22	2.91	2.31
U.K.	0.68	EPG	0.73	0.75	1.28	1.14	1.43	0.86	0.53	4.32	0.48	2.21	UE	1.22	0.98	1.35
South Africa	0.43	DPG	0.97	0.98	1.05	1.79	1.44	1.52	0.53	3.16	0.44	1.77	UE	0.88		1.04
Japan- Osaka	0.58	CHL	1.17	0.91	1.18	1.01	0.59	0.80	0.92	9.73	0.76	4.16	CPI	1.18	0.87	0.97
Canada	0.63	CHL	0.98	0.95	1.68	1.14	1.65	1.19	0.86	5.24	0.46	1.57	CPI	1.19	1.19	1.37
Finland	0.95	EPG	1.40	1.73	2.71	1.76	3.57	1.54	0.73	3.49	0.60	2.71	CPI	2.81	1.47	4.50
Australia	0.49	DPG	0.74	0.66	0.94	1.17	1.04	0.62	0.49	3.23	0.37	1.60	UE	0.87		0.98
Average	**1.39**	**CHL**	**2.00**	**2.44**	**2.65**	**1.97**	**2.48**	**2.35**	**1.05**	**8.27**	**1.11**	**3.58**	**UE**	**2.10**	**2.13**	**2.17**

Table 4.9

Summary Statistics of the Market Specific Model and Two Universal Models

Market	Three Factors	Market Specific Model Average R^2 (%)	Market Specific Model Performance (%)	Carhart Four-factor Model Average R^2 (%)	Carhart Four-factor Model *Performance (%)*	MKT+SMB+HML+CHL Average R^2 (%)	MKT+SMB+HML+CHL *Performance (%)*	Factors Average Stock R^2 (%)
China-Shenzhen	SMB+HML+EPG	52.6	*81.5*	51.5	*79.9*	52.0	*80.6*	64.5
China-Shanghai	SMB+HML+EPG	45.5	*77.9*	45.1	*77.2*	45.2	*77.3*	58.4
Taiwan	SMB+CHL+EPG	30.6	*56.3*	29.4	*54.0*	30.6	*56.2*	54.4
South Korea	SMB+HML+LBG	33.0	*64.9*	32.1	*63.0*	32.5	*63.8*	50.9
Malaysia	SMB+HML+CHL	27.4	*61.2*	26.8	*59.9*	27.4	*61.2*	44.7
Singapore	SMB+CHL+LBG	27.4	*67.4*	26.8	*65.7*	27.3	*67.1*	40.7
Turkey	SMB+HML+LBG	25.4	*63.7*	25.1	*63.0*	24.1	*60.5*	39.9
Germany	SMB+HML+MTN	27.1	*70.2*	27.1	*70.2*	26.5	*68.8*	38.6
India	SMB+HML+CON	19.5	*52.6*	19.4	*52.2*	19.1	*51.6*	37.1
Japan-Tokyo	SMB+HML+MTN	21.2	*57.9*	21.2	*57.9*	21.0	*57.5*	36.6
Brazil	SMB+HML+DPG	23.8	*65.1*	22.0	*60.3*	22.4	*61.3*	36.6
Italy	SMB+CHL+CON	24.3	*70.5*	22.8	*66.0*	24.1	*69.7*	34.5
Hong Kong	SMB+EPG+CON	21.2	*64.3*	20.6	*62.4*	20.1	*60.9*	33.0
Thailand	SMB+HML+DPG	19.9	*61.6*	18.3	*56.5*	18.0	*55.5*	32.4
Indonesia	SMB+HML+CHL	20.8	*68.0*	18.9	*61.9*	20.8	*68.0*	30.6
Spain	SMB+HML+CHL	26.5	*89.7*	25.6	*86.4*	26.5	*89.7*	29.6
Israel	SMB+HML+LBG	24.8	*84.1*	24.2	*81.8*	23.6	*79.9*	29.6
Greece	CHL+LBG+CON	18.8	*64.1*	12.5	*42.4*	14.9	*50.7*	29.4
Switzerland	SMB+CHL+CON	20.7	*76.7*	19.9	*73.4*	20.6	*76.1*	27.0
U.S. - NYSE & AMEX	SMB+CHL+CON	16.2	*61.5*	15.1	*57.5*	15.1	*57.4*	26.3
Netherland	SMB+HML+CHL	19.0	*81.7*	18.0	*77.2*	19.0	*81.7*	23.3
Norway	SMB+HML+DPG	20.1	*86.6*	19.2	*82.8*	18.8	*81.1*	23.2
U.S.-NASDAQ	SMB+HML+MTN	12.2	*52.1*	12.2	*52.1*	12.0	*51.1*	23.5
Belgium	SMB+HML+LBG	18.7	*84.9*	14.5	*66.0*	14.2	*64.8*	22.0
Denmark	SMB+CHL+DPG	17.2	*80.6*	13.8	*64.9*	15.6	*73.1*	21.3
France	SMB+HML+CON	13.8	*69.5*	13.5	*67.9*	13.7	*69.1*	19.9
Sweden	SMB+HML+CHL	16.1	*83.2*	15.0	*77.7*	16.1	*83.2*	19.3
U.K.	SMB+CHL+EPG	14.3	*77.4*	13.6	*73.5*	13.9	*75.0*	18.5
South Africa	SMB+CHL+DPG	13.9	*76.3*	12.8	*70.2*	13.0	*71.1*	18.3
Japan- Osaka	SMB+HML+LBG	16.0	*91.4*	15.5	*88.9*	15.4	*88.0*	17.5
Canada	SMB+CHL+LBG	12.4	*64.5*	10.8	*56.5*	11.8	*61.7*	19.2
Finland	SMB+HML+LBG	11.9	*68.9*	11.0	*63.6*	10.8	*62.6*	17.3
Australia	SMB+CHL+EPG	9.3	*71.4*	8.4	*64.5*	8.5	*65.2*	13.0
Average		**21.9**	***70.0***	**20.7**	***66.2***	**21.1**	***67.4***	**31.2**

Table 4.10

Cross-country Comparison on the Performances of Empirical Asset Pricing Models

This table provides the performance ratios of the Fama-French (FF in the table, 1993) three-factor model, Hou, Karolyi and Kho (HKK in the table, 2011) three-factor model, Carhart (1997) four-factor model, the MSBC four-factor model and the market-specific four factor model. Panel A presents the results for the Fama-French three-factor model and the Hou-Karolyi-Kho three-factor model, which reliable explain the average returns around the world. Panel B presents the results for the other three factor models which show relatively better power in capturing the common variation in stock turnovers around the world. Performance is computed as the average R^2 of the model divided by the average R^2 obtained from regressions stock return (turnover) on extracted return (turnover) factors. The countries are ranked by the performance ratio on the turnover regressions.

Panel A: Fama-French Three-factor Model and Hou-Karolyi-Kho Three-factor Model

	FF Three-factor Model			HKK Three-factor Model	
Market	Performance on Return (%)	Performance on Turnover (%)	Market	Performance on Return (%)	Performance on Turnover (%)
Japan-Osaka	102.1	82.5	Japan- Osaka	96.9	75.2
Switzerland	84.0	80.9	China_Shenzhen	86.4	72.8
China-Shenzhen	90.1	77.2	U.K.	76.5	70.2
Norway	95.7	75.7	Denmark	93.1	69.4
Sweden	79.1	75.5	China_Shanghai	88.3	69.1
Denmark	101.4	73.6	Netherland	84.0	68.3
Netherland	95.4	73.3	Norway	91.4	65.2
China-Shanghai	91.4	72.6	South Africa	81.2	64.6
Belgium	78.4	69.7	Israel	92.9	63.0
U.K.	88.3	69.2	Spain	41.6	62.5
South Africa	88.0	68.5	Switzerland	69.5	62.5
Spain	44.4	68.4	Germany	85.5	60.6
Italy	94.6	66.8	Indonesia	98.8	57.9
Israel	100.0	66.3	Sweden	83.3	54.4
Germany	93.0	64.9	Belgium	66.5	54.0
Singapore	89.8	59.2	U.S. - NYSE & AMEX	76.6	53.4
Australia	96.2	57.5	Italy	82.8	52.6
South Korea	80.4	57.0	South Korea	67.4	49.7
Hong Kong	85.1	55.1	Canada	82.0	49.6
U.S. - NYSE & AMEX	83.3	54.5	Malaysia	81.3	49.4
Malaysia	93.1	54.1	Singapore	79.0	49.2
France	84.9	53.1	Hong Kong	80.6	48.6

Table 4.10, continued

Panel A: Fama-French Three-factor Model and Hou-Karolyi-Kho Three-factor Model (continued)

	FF Three-factor Model			HKK Three-factor Model	
Market	Performance on Return (%)	Performance on Turnover (%)	Market	Performance on Return (%)	Performance on Turnover (%)
Japan-Tokyo	88.8	52.4	Australia	90.9	45.9
Indonesia	103.0	50.5	Greece	67.6	41.0
Turkey	81.0	50.2	Brazil	97.5	40.9
Canada	86.5	49.4	Turkey	82.2	40.8
Brazil	101.4	47.0	Japan-Tokyo	78.4	40.5
Finland	63.0	45.3	Finland	47.1	38.5
Taiwan	82.8	43.7	U.S.-NASDAQ	82.1	38.5
U.S.-NASDAQ	85.4	42.3	India	80.5	37.2
India	85.5	41.4	Thailand	88.5	36.1
Thailand	96.6	40.7	France	74.6	34.9
Greece	76.5	32.3	Taiwan	77.2	29.9
Average	**87.6**	**59.7**		**80.4**	**52.9**

Panel B: Carhat Four-factor Model, MSBC Four-factor Model, and Market Specific Model

-	Carhart Four-factor Model		-	MSBC Four-factor Model		-	Market Specific Model	
Market	Performance on Return (%)	Performance on Turnover (%)	Market	Performance on Return (%)	Performance on Turnover (%)	Market	Performance on Return (%)	Performance on Turnover (%)
Japan- Osaka	104.0	88.9	Spain	45.2	89.7	Japan- Osaka	105.9	91.4
Spain	44.7	86.4	Japan-Osaka	105.6	88.0	Spain	45.2	89.7
Norway	98.8	82.8	Sweden	83.5	83.2	Norway	99.1	86.6
Israel	104.2	81.8	Netherland	94.3	81.7	Belgium	83.0	84.9
China-Shenzhen	94.6	79.9	Norway	98.2	81.1	Israel	104.7	84.1
Sweden	80.0	77.7	China-Shenzhen	94.6	80.6	Sweden	83.5	83.2
China-Shanghai	93.8	77.2	Israel	103.8	79.9	Netherland	94.3	81.7
Netherland	93.7	77.2	China-Shanghai	93.8	77.3	China-Shenzhen	94.9	81.5
U.K.	86.3	73.5	Switzerland	82.2	76.1	Denmark	93.8	80.6
Switzerland	83.0	73.4	U.K.	87.5	75.0	China-Shanghai	94.0	77.9
Germany	90.6	70.2	Denmark	93.4	73.1	UK	86.2	77.4
South Africa	86.6	70.2	South Africa	88.7	71.1	Switzerland	81.5	76.7
France	85.9	67.9	Italy	90.7	69.7	South Africa	91.2	76.3
Italy	89.7	66.0	France	86.3	69.1	Australia	97.8	71.4
Belgium	80.5	66.0	Germany	93.9	68.8	Italy	92.5	70.5
Singapore	96.0	65.7	Indonesia	106.3	68.0	Germany	90.6	70.2
Denmark	91.5	64.9	Singapore	96.6	67.1	France	87.6	69.5
Australia	96.1	64.5	Australia	96.7	65.2	Finland	70.9	68.9
Finland	64.3	63.6	Belgium	80.4	64.8	Indonesia	106.3	68.0
Turkey	97.1	63.0	South Korea	88.8	63.8	Singapore	95.4	67.4
South Korea	88.3	63.0	Finland	65.4	62.6	Brazil	103.0	65.1
Hong Kong	93.7	62.4	Canada	90.3	61.7	South Korea	88.7	64.9
Indonesia	106.3	61.9	Brazil	101.5	61.3	Canada	90.4	64.5
Brazil	102.2	60.3	Malaysia	96.3	61.2	Hong Kong	93.4	64.3
Malaysia	95.7	59.9	Hong Kong	95.0	60.9	Greece	92.1	64.1
Japan-Tokyo	89.2	57.9	Turkey	97.8	60.5	Turkey	97.6	63.7
U.S. - NYSE & AMEX	83.8	57.5	Japan-Tokyo	89.1	57.5	Thailand	101.1	61.6
Canada	87.7	56.5	U.S. - NYSE & AMEX	85.2	57.4	U.S. - NYSE & AMEX	84.8	61.5
Thailand	101.2	56.5	Taiwan	81.5	56.2	Malaysia	96.3	61.2
Taiwan	81.0	54.0	Thailand	101.7	55.5	Japan-Tokyo	89.2	57.9
India	89.6	52.2	India	89.4	51.6	Taiwan	79.8	56.3
U.S.-NASDAQ	87.7	52.1	U.S.-NASDAQ	87.8	51.1	India	91.4	52.6
Greece	75.0	42.4	Greece	79.5	50.7	U.S.-NASDAQ	87.7	52.1
	89.2	**66.6**		**90.0**	**67.9**		**90.7**	**71.1**

APPENDIX

This appendix briefly discusses the BN (2002, 2004) methodology for decomposing turnover and excess return. As the first step, this article estimate common factors in large panels by the method of asymptotic principal components based on the variance-covariance matrix of turnover over different periods rather than among different stocks. This is because the variance-covariance matrix for turnover among stocks, or portfolios, is not well defined because of time trends in turnover. This article follow the same logic as CM (2007) and get around this problem by taking advantage of the large cross-section of individual stocks and using the variance-covariance matrix of turnover over different time periods.

The number of factors that can be estimated by this nonparametric method is *min{N,T}*, much larger than permitted by estimation of state space models. This article start with an arbitrary number *k max* and estimate the *k* systematic factor and factor loadings by solving the following optimization problem

$$V(k) = \min_{D^k, G^k} T^{-1} N^{-1} \sum_{t=1}^{T} \sum_{j=1}^{N} \left(\tau_{jt} - D_j^k G_t^k\right)^2$$

where G_t^k denotes the *k*-vector of systematic factors and D_j^k denotes *k*-vector of factor loadings for firm *j*.

To determine the number of factors, BN (2002) propose the following selection criterion:

$$\widehat{K} = \mathrm{argmin}_{0<k<kmax} IC(k)$$

where *IC(k)* equals the measure of the goodness of fit *V(k)* plus a second term that serves as an adjustment for the increase in the degrees of freedom that results from increasing *k*:

$$IC(k) = \log\{V(k, \widehat{G}^k\} + k \cdot \left(\frac{N+T}{NT}\right) \ln\left(\frac{NT}{N+T}\right)$$

The selection criterion depends on the trade-off between the goodness of fit and parsimony. The advantage of the *IC(k)* statistic criteria is that it not only takes the sample size in both the cross-section and the time-series dimensions into consideration, but also the fact that the factors are not observed.

BN (2002) show that, $\widehat{K}$, the value of *k* that minimizes the *IC(k)* statistic in selection criterion is a consistent estimate for the number of factors in the factor model. Additionally, there are several advantages of the BN (2002) statistics. First BN (2002) do not impose any restrictions between *N* and *T*, allowing for both large *N* and large *T*. Second, the results hold under heteroscedasticity in both the time and serial dependence and cross-section dependence. In addition, the model selection procedure is easy to implement.

After decomposing the panel data into systematic and idiosyncratic components to stock returns and turnover panels, BN (2004) develop a PANIC (panel analysis of nonstationarity in idiosyncratic and common components) methodology to detect whether there is nonstationarity in either the systematic or idiosyncratic components, or in both. They show that common stochastic trends can be consistently estimated by using the principal components method, regardless of whether the idiosyncratic series contain unit roots. Similarly, their proposed unit root test of the idiosyncratic series is valid whether any of the systematic factors contain a unit root. A great advantage of PANIC is that it directly tests the unobserved components of the data.

CHAPTER 5

CONCLUSION

This dissertation sheds new light on at least three important issues on the fields of empirical asset pricing and international finance. First, I investigate a new dimension of liquidity risk: the likelihood of market liquidity at its extremes, and find that extreme liquidity risk is priced cross-sectionally in the U.S. equity market. This finding underscores the empirical relevance of liquidity risk. Secondarily, we interpret our findings in the Chapter 3 as a step forward in the international asset pricing literature with important implications for practitioners in guiding cost-of-capital calculations and risk control and performance evaluation analysis of global portfolios. Last but not least, Chapter 4 tries to understand the common factors driving trading around the world. It enables us not only to determine how well classic multifactor models perform in developed or emerging markets in terms of capturing the systematic turnover, but also to identify which factors in stock returns are important for explaining the common variation in stock turnover for each country.

In line with prior studies, I next outline some related research projects in the near future. Like Fama and French (1998, 2012), Griffin (2002) and Hou, Karolyi, and Kho (2011) and others, our initial tests in Chapter 2 assume that there is no currency risk. But our framework allows us to further relax this restriction and study the effect of currency risks on the relative performance of global factors and local factors in the new "hybrid" model. Currency risk is certainly a potential problem in global asset pricing. To date, academic studies have had limited success in empirically indentifying significant exposure of nonfinancial firms with regard to unexpected

changes in exchange rates (Bodnar and Wong, 2003; Griffin and Stulz, 2001; He and Ng, 1998; Bartov et al., 1996; Prasad and Rajan, 1995; Bartov and Bodnar, 1994). Our project takes a new look at the exposure puzzle by studying how global investors and local investors trade differently in response to currency fluctuations and its potential impact on firm value. Because what constitutes globally-accessible stocks and purely-local stocks vary for investors by country of domicile, the need to hedge exchange rates varies and currency risks are expected to play different roles in the risk prices of global factors and local factors. To accommodate the extensive practice that exists for foreign currency hedging, we will also push the new "hybrid" structure to incorporate cross-sectional variation in currency forward, commodities and bonds, which comprise a significant portion of global investment activity. Finally, we will extend our unconditional testing framework for the hybrid model to a conditional one allowing for time variation in expected returns, variances and covariances, a potentially important factor for the transitioning emerging markets (Bekaert and Harvey, 1995; Bekaert, Harvey, Lundblad, and Siegel, 2011) for which our hybrid model performs especially well.