Three Essays in Asset Pricing

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Three Essays in Asset Pricing

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Abstract

This dissertation consists of three essays. My first paper re-examines the link between idiosyncratic risk and expected returns for a large sample of firms in both developed and emerging markets. Recent studies using Fama-French three factor models have shown a negative relationship between idiosyncratic volatility and expected returns for developed markets. This relationship has not been studied to date for emerging markets. This study relates the current-month's idiosyncratic volatility to the subsequent month's returns for a sample of both developed and emerging markets expanding benchmark factors by including both a momentum and a systematic liquidity risk component.

My second essay contributes to the important literature on the topic of the small capitalization stocks historical outperformance over large capitalization stocks by investigating the hypothesis that the small firm premium is related to macroeconomic and financial variables and that relationship is driven by the economic cycle in the United States and Canada. More specifically, this study employs recent advances in nonlinear time series models to explore the relationship between the small firm premium, and financial and macroeconomic variables in the Canadian and U.S. economies.

My third paper re-examines the findings of a recent research paper that suggested that market wide liquidity may act as a leading indicator to the economic cycle. Using several liquidity measures

and various macroeconomic variables to proxy for the economic conditions, the paper presents evidence that stock market liquidity could forecast business cycles: A major decrease in the overall level of market liquidity could indicate weak economic growth in the subsequent months. However, the drawback in the analysis is that the relationship is investigated in a linear approach even though it has been proven that most macroeconomic variables follow non-linear dynamics. Employing similar liquidity measures and macroeconomic proxies, and two popular econometrics models that account for non-linear behavior, this study hence re-investigates the relationship between stock market liquidity and business cycles.

Acknowledgments

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CHAPTER 1

Idiosyncratic Volatility, Momentum, Liquidity, and Expected Stock Returns in Developed and Emerging Markets

1.1 Introduction

The seminal papers that introduced the foundations of modern portfolio theory (MPT) (Markowitz (1952); Sharpe (1964); Lintner (1965)) assert that, within the framework of the Capital Asset Pricing Model (CAPM), idiosyncratic risk should not be priced as long as representative agents hold the market portfolio or a well-diversified portfolio. Further theoretical extensions have looked at the effects of risk tolerance, information, and transactions costs in establishing a premium for idiosyncratic volatility (*e.g.* Levy (1978), Merton (1987), (Malkiel and Xu (2006) and Jones and Rhodes-Kropf (2003)).

While the theoretical arguments for an idiosyncratic risk premium are relatively straightforward, the empirical evidence for such a premium is mixed, based on Fama-French type factor models. For example, Fu (2009) provides evidence that high idiosyncratic risk portfolios generate higher returns than low idiosyncratic risk portfolios for the US market. Ang et al. (2006) using monthly data document a negative idiosyncratic effect in US stock markets during the period 1963-2000 while Ang et al. (2009) also find a negative idiosyncratic risk effect in 22 developed markets (1980-2003).

This study contributes to the literature by analyzing the behaviour of idiosyncratic risk for an international sample consisting of both developed markets as well as, for the first time, emerging markets stock markets using a five-factor model that incorporates both momentum and liquidity risk. The latter might be deemed of particular importance for emerging markets since poor liquidity is often mentioned as one of the main reasons that prevent foreign investors from investing in emerging markets.

A positive relationship between idiosyncratic volatility and expected returns could imply that some potential risk factors that are not incorporated in the factor models employed in this study are not or may not be completely diversifiable and may hence generate the pricing of idiosyncratic volatility. The international finance literature distinguishes between three categories of non-diversifiable risk factors inherent to emerging markets.

a) Direct barriers that discriminate against foreign shareholders – which could include ownership restrictions and onerous taxes.

b) Indirect barriers – this would include lack of transparency due to poor accounting standards, low investor protection, high transaction costs, and government expropriation of productive assets. Lack of transparency may also be linked to informational inefficiencies. For example, Bhattacharya et al. (2000) show that in emerging markets, insider trading often occurs well before the release of information to the public. Stock prices in such markets respond before public announcements, which is consistent with information leakage. In addition, the price response of shares traded by foreigners lags the price response of shares traded by locals. Another indirect barrier would be related to higher levels of corruption within emerging markets compared to developed markets (Switzer & Tahaoglu (2014)). Many emerging markets may also be prone to agency problems resulting from multilevel (pyramid) ownership structures that facilitate expropriation of the firm's resources by controlling shareholders (Shleifer and Vishny (1997), Lins

(2003)). Shareholder rights are generally weak and takeovers are seldom used as an external disciplining governance mechanism (La Porta et al. (1998), Denis and McConnell (2003);

c) Barriers that result from emerging market specific risks – Clark and Tunaru (2001) for example provide a model that measures the impact of political risk on portfolio investment. They define political risk as the volatility of the exposure of a portfolio to loss in the case of an explicit political event in a given country. Novel feature of their model is that political risk is multivariate and may be correlated across countries. Bekaert et al. (1997)) suggest that political risk is priced in several emerging markets. Other emerging market specific risks would also include economic policy risk, and currency risk that dissuade foreign investment. Bartram et al. (2012) provide further insight into market specific factors that may be associated with differences in idiosyncratic volatility between emerging markets and developed markets. They distinguish between "good" volatility (e.g. due to patents, firm-level R&D investment) from "bad" volatility (e.g. linked to political risk and poor disclosure). They conclude that emerging markets are more prone to "bad" volatility factors, relative to developed markets.[1]

While Bartram et al. (2012) highlight factors likely associated with good or bad volatility, they do not explore whether or not idiosyncratic volatility per se is priced in the different markets considered. This paper provides new evidence on this score. This analysis uses both the Carhart (1997) 4-factor model as well as a 5-factor model that incorporates the Amihud (2002) liquidity factor in the estimation of idiosyncratic risk. Using a five factor model, the results suggest that idiosyncratic risk does not play a role on stock returns for most of the developed markets analyzed.

[1] They estimate idiosyncratic volatility as the standard deviation of error term from a systematic risk model that explains the return of a stock with the return of its country's market, the world market, and Fama–French size and value factors. Given the high correlation between US and developed market returns and the world market returns, the standard errors of their estimates may be higher than for emerging markets, which could distort the significance of the idiosyncratic volatility factor. This problem is highlighted in Girard and Sinha (2006) who show that unlike developed markets, emerging markets are sensitive to local, but not global risk factors.

In contrast, we show, for the first time, that idiosyncratic risk is positively related to month-ahead expected returns for many emerging markets for this model.

Hence this paper present evidence that the idiosyncratic puzzle found by Ang et al. (2009) in developed markets may be sample period specific. Indeed the negative relationship between expected returns and idiosyncratic volatility, estimated using the Fama-French 3 factor model, discovered by Ang et al. (2009) for the period 1980 to 2003 disappear once the sample period is extended to December 2012. The non-existence of the idiosyncratic puzzle observed in this paper corroborate previous papers that have shown the weak evidence of such relationship. For instance, Wei and Zhang (2005) show that a trading strategy based on idiosyncratic volatility does not generate any significant profits in the US stock market during the period 1962 to 2000. Bali et al. (2005) demonstrate that there is no time series relation between idiosyncratic volatility and following stock returns because this relatiomnship is not robust through time, as they show that neither idiosyncratic volatility nor stock market volatility forecasts stock market returns.

Moreover the positive link between idiosyncratic volatility and subsequent monthly returns observed in emerging markets, which rejects the idea of an idiosyncratic puzzle, would be expected according to Levy (1978) and Merton (1987) who asserts that investors demand a return compensation for bearing idiosyncratic risk caused particularly by factors that may not be diversifiable. Bartram et al. (2102) enumerate several such risk factors inherent to emerging markets e.g. political risk, liquidity risk, lack of transparency due to poor accounting standards and informational inefficiencies and low investor protection.

In order to estimate idiosyncratic volatility, the 4-factor model, which is an extension to the Fama-French 3-factor model by adding a momentum factor, and the 5-factor model, which incorporates a liquidity risk factor to the the previous model, were employed. A liquidity risk factor is included in this study since it is generally recognised that liquidity is important for asset pricing and that systematic variation in liquidity matters for expected returns: Since rational investors require a higher risk premium for holding illiquid securities, these assets and assets with high transaction costs are characterized by low prices relative to their expected cash flows i.e. average liquidity is priced (Amihud and Mendelson (1986); Brennan and Subrahmanyam (1996); Chordia et al. (2001)). For instance Haugen and Baker (1996) document that the liquidity of stocks is one of several common factors in explaining stock returns across global markets. Amihud et al. (1997) show that enhancement in liquidity on the Tel Aviv Stock Exchange is linked to price increases.

This paper examines the issue of liquidity for developed countries but as well as for a set of markets where liquidity ought to be particularly important i.e. emerging markets. Two reasons show that laying emphasis on illiquidity is critical for emerging markets due to their limited access to global capital markets. Firstly returns in emerging countries may be further significantly lessened by the increased illiquidity of trading stocks relative to returns in more developed markets. Secondly Bekaert et al. (2007) show results suggesting that local market liquidity is an important driver, much more so than local market risk, of expected returns (liquidity is a priced factor) in emerging markets and that model specifications that incorporate liquidity risk outperform other models that only consider market risk factors in predicting future returns.

Moreover Bekaert et al. (2007) document that higher political risk and weak law and order conditions could act as segmentation indicators and that liquidity may further affect expected returns in countries with these aspects. The authors explain that liquidity effects are relatively small in a developed country such as the United States since its market is large in the number of traded securities and because it has a very diversified ownership structure i.e. a stock market categorized by both long-horizon investors, less prone to liquidity risk, and short-term investors.

Hence, in the United States clientele effects in portfolio choice alleviate the pricing of liquidity while such variety in securities and ownership is deficient in emerging markets, potentially reinforcing liquidity effects. Lesmond (2005) corroborates Bekaert et al. 's (2007) findings by investigating the impact of legal origin and political institutions on liquidity levels provide evidence that countries with poor political and legal systems and organizations have considerably greater liquidity costs than do countries with solid and strong political and legal institutions. Higher incremental political risk translates into a 1.9% increase in price impact costs employing the Amihud measure.

The remainder of this study is organized as follows. In the next section, a review of the literature is presented. An introduction of the data used in this paper and a description of the research methodology is provided in section 3. The empirical results follow in section 4. The paper concludes with a summary in section 5.

1.2 Literature Review

Idiosyncratic volatility has been a topic of considerable interest in the literature since the seminal contributions of Levy (1978) and Merton (1987) and the empirical results of Campbell et al. (2001) that show a secular increase in idiosyncratic volatility over a long horizon. Merton (1987) argues that to the extent that investors cannot create portfolios that contain only systematic risk they demand a return compensation for bearing idiosyncratic risk: the less diversified the portfolios, the higher the proportion of idiosyncratic risk impounded into expected returns making high idiosyncratic stocks earn more than low idiosyncratic stocks – *i.e.* idiosyncratic risk should be positively related to stock returns. However, no consensus has emerged on the actual effects of idiosyncratic volatility on the cross-sectional variation in stock returns. Some studies have found a positive relationship, consistent with Merton (1987). Others have shown either no relationship or even a negative relationship between idiosyncratic risk and stock returns.

1.2.1 Positive Relationship between Idiosyncratic Volatility and Stock Returns

Malkiel and Xu (1997) form portfolios of US stocks based on idiosyncratic volatility and show a positive relationship between idiosyncratic volatility and the cross-section of monthly future stock returns. Goyal and Santa-Clara (2003) also find that average stock idiosyncratic volatility is positively related to value-weighted market returns. Similar results are shown by Wei and Zhang (2005), and Pukthuanthong-Le and Visaltanachoti (2009). Fu (2009) shows that forecasts of idiosyncratic volatility based on exponential generalized autoregressive conditional heteroskedasticity (EGARCH) models are positively related to returns from 1963 to 2006, Bainbridge and Galagedera (2009) show evidence of a positive relationship between idiosyncratic volatility and expected stock returns for Australian stocks. Ben-David et al. (2010) present evidence that hedge finds generate higher returns from trading high idiosyncratic risk stocks rather than low idiosyncratic risk stocks. Nartea, Ward, and Yao (2011) show a positive relationship between idiosyncractic volatility and expected stock returns in four Southeast Asian stock markets (i.e. Singapore, Malaysian, Indonesia, and Thailand) during the period from the early 1990s to the end of 2007. More recently, Brooks, Li and Miffre (2013) show that cross-sectional returns are positively related to differences in the unsystematic risk of portfolio returns. Their finding is that idiosyncratic risk is priced. In sum, these papers are in line with the notion that agents who fail to fully diversify their portfolios demand higher average returns to compensate them for bearing higher levels of firm-specific risk (Merton (1987),

1.2.2 Negative Relationship between Idiosyncratic Volatility and Stock Returns

Ang et al. (2006) provide empirical evidence suggesting that U.S. stocks with higher lagged idiosyncratic volatility have abnormally lower equally-weighted returns, a phenomenon which they call “the idiosyncratic risk puzzle.” The authors report that the average return differential between the lowest and highest quintile portfolios formed on one-month lagged idiosyncratic volatilities is about -1.06% per month for the period 1963-2000. In their paper, idiosyncratic volatility is measured as the standard deviation of the residuals of the daily three-factor Fama and French (1993) model over the prior month. Guo and Savickas (2006) show that value-weighted idiosyncratic volatility is negatively and significantly related to subsequent quarterly excess stock market returns, for G7 countries using quarterly data over the period 1963 to 2002, Chang and Dong (2006) document a negative relationship between idiosyncratic volatility and expected stock returns in the Japanese stock market from 1975 to 2002. Koch (2010) finds that low idiosyncratic volatility stocks generate higher returns than high idiosyncratic volatility stocks in the German stock market from 1974 to 2006; the differential return between the low idiosyncratic volatility and high idiosyncratic volatility stocks portfolios.

2.3 No Relationship between Idiosyncratic Volatility and Stock Returns

Wei and Zhang (2005) demonstrate that a trading strategy based on idiosyncratic volatility does not yield any significant economic gains using US stock market data over the period 1962 to 2000. Bali et al. (2005) argue that the findings of Goyal and Santa-Clara (2003) that the average idiosyncratic risk is positively related to future returns are not robust through time. They conclude that there is no time series relation between diversifiable risk and subsequent stock returns, as they show that neither idiosyncratic volatility nor stock market volatility forecasts stock market returns in an extended sample ending in 2001. Bali and Cakici (2008) state that the relationship between idiosyncratic volatility and the cross-section of stock returns largely depends on the data frequency used to compute asset-specific volatility. Nartea and Ward (2009) report that there is no association between diversifiable volatility and expected stock portfolio returns in the Philippine stock market.

Huang, Liu, Rhee and Zhang (2010) suggest that the disparate results for Bali and Cakici (2008) and Ang et al. (2009) can be explained by short term monthly return reversals – which could confound the results of conventional three or four factor models of expected returns. On balance, they suggest that no relationship between idiosyncratic return and risk should be observed once return reversals are accounted for.

In sum, the evidence to date concerning the relationship between idiosyncratic volatility and stock returns remains ambiguous. Furthermore, most existing empirical research focuses on

US stock markets, and is based on simple applications of basic factor models (e.g. the one factor model or the three factor Fama-French (1993) model), or time series approaches (such as GARCH) that are not directly linked to asset pricing models. This paper looks to extend our understanding of the role of idiosyncratic risk and volatility by a) providing more recent evidence from other developed and emerging stock markets; and b) using further extensions to the Fama-French (1993) model that may improve the measurement of idiosyncratic risk.

1.3 Data and Methodology

This study uses stock market daily returns on firms from 23 developed and 15 emerging markets: Argentina, Australia, Austria, Belgium, Brazil, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Malaysia, Mexico, the Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Singapore, South Africa, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, the UK and the US. Non US firm returns are collected from the Thompson Financial Datastream for the sample period January 1980 to December 2012. US stock returns are obtained from CRSP. We consider the returns from local investor or currency hedged foreign investor perspectives by studying local-currency denominated returns for the analyses, with excess returns are computed using each country 1-month or 3-month T-Bill rates.[2] As per Ang et. al. (2009), in all non-U.S. countries, we exclude very small firms by eliminating the 5% of firms with the lowest market capitalizations. The number of stocks included and the coverage period for each country are shown in Table I. A set of illustrative stocks in various countries used in the analyses is provided in Appendix 1.[3]

[2] For nations in which the 1-month or 3-month T-Bill rates are not available the 1 month U.S. T-Bill rate was used as per Ang et. al. (2009). Note also that for countries in which the 1-month or 3-month T-Bill rates were obtainable, idiosyncratic volatilities were computed twice using both local rates and the 1-month U.S. T-Bill rate giving similar results for each country.

[3] A complete listing of stocks for all countries used in the analyses is available on request.

Table 1.1 Description of Sample This table presents data coverage of the G7 countries, 16 developed markets and 15 emerging markets. *N*(start) and *N*(end) show the number of stocks at the starting and ending sample period.

Country	Start	*N*(Start)	End	*N*(End)
G7 Countries				
Canada	Jan 1980	32	Dec 2012	233
France	Jan 1980	34	Dec 2012	233
Germany	Jan 1980	47	Dec 2012	233
Italy	June 1986	35	Dec 2012	149
Japan	Jan 1980	319	Dec 2012	916
United Kingdom	Jan 1980	388	Dec 2012	911
United States	Jan 1980	1978	Dec 2012	3788
Developed Markets				
Australia	Jan 1984	30	Dec 2012	152
Austria	Jun 1999	30	Dec 2012	46
Belgium	Jun 1986	30	Dec 2012	83
Denmark	Jun 1992	30	Dec 2012	42
Finland	Jul 1994	30	Dec 2012	46
Greece	Jul 1998	30	Dec 2012	47
Hong Kong	Jun 1988	35	Dec 2012	122
Ireland	Dec 2007	30	Dec 2012	30
Netherlands	Jan 1980	34	Dec 2012	105
New Zealand	Sep 1999	30	Dec 2012	45
Norway	Jun 2001	30	Dec 2012	47
Portugal	Jun 1998	30	Dec 2012	46
Singapore	Feb 1989	30	Dec 2012	93
Spain	Jun 1999	30	Dec 2012	46
Sweden	Aug 1991	30	Dec 2012	66
Switzerland	Jul 1980	30	Dec 2012	133
Emerging Markets				
Argentina	Jan 1995	30	Dec 2012	50
Brazil	Oct 1994	30	Dec 2012	97
India	Nov 1994	93	Dec 2012	198
Indonesia	Jun 1998	30	Dec 2012	50
Israel	June 1996	30	Dec 2012	50
Korea	May 1987	31	Dec 2012	97
Malaysia	Jan 1986	30	Dec 2012	89
Mexico	Mar 1993	30	Dec 2012	84
Philippines	Nov 1994	30	Dec 2012	50
Poland	Apr 2005	30	Dec 2012	50
Russia	Jan 2007	30	Dec 2012	47
South Africa	Jan 1990	34	Dec 2012	70
Taiwan	Nov 1994	30	Dec 2012	70
Thailand	Aug 1994	30	Dec 2012	50
Turkey	Apr 1997	30	Dec 2012	49

1.3.1 Estimating Idiosyncratic Volatilities

This paper uses an intertemporal approach in which lagged monthly idiosyncratic volatility is related to monthly returns. Ang et al. (2006, 2009) measure idiosyncratic risk by realized idiosyncratic volatility using a local version of the Fama and French (1993) three-factor model (Equation 1.1).The idiosyncratic volatility of a stock in each month is the standard deviation of the regression residuals ε_i in Equation (1.1):

$$r_i = \alpha_i + \beta_i MKT + s_i SMB + h_i HML + \varepsilon_i \tag{1.1}$$

where r_i is the daily excess returns of stock i, α_i is the Fama–French adjusted alpha, MKT is the excess return on the market portfolio in each country defined as the value-weighted average of all stocks; SMB (small minus big market capitalization) and HML (high minus low book-to-market) are return differences between the top 33.33 per cent and bottom 33.33 per cent ranked stocks in each country respectively; β_i , s_i and h_i are the estimated factor exposures. Griffin (2002) provides evidence that the Fama and French factors are country specific and concludes that the three-local factor Fama-French model provides a better explanation of time-series variation in stock returns for international stocks than a global factor model.

This study extends the three-factor model by adding two additional factors to estimate idiosyncratic volatilities: a momentum factor and an illiquidity factor. We perform the analyses using both the Carhart (1997) model (Equation 1.2) that incorporates momentum, as well as a five-factor model (Equation 1.3) that includes an an illiquidity premium as well:

$$r_i = \alpha_i + \beta_i MKT + s_i SMB + h_i HML + m_i MOM + \varepsilon_i \tag{1.2}$$

$$r_i = \alpha_i + \beta_i MKT + s_i SMB + h_i HML + m_i MOM + l_i IML + \varepsilon_i \tag{1.3}$$

Analogous to the size (SMB), and the book-to-market (HML) return proxies, the momentum factor (*MOM*) is constructed as the equal-weighted average of firms with the highest 30 percent eleven-month returns lagged one month minus the equal-weighted average of firms with the lowest 30 percent eleven-month returns lagged one month (Carhart (1997)).

The illiquidity premium denoted IML (illiquid-minus-liquid portfolio return) is the difference between the average excess return on high-illiquidity stocks (30% percent highest) and low-illiquidity stocks (30% percent lowest). In this study the proxy used for illiquidity is the "price impact"illiquidity measure proposed by Amihud (2002). This measure captures the response associated with one dollar of trading volume. More specifically, the illiquidity factor is computed as the daily ratio of absolute stock return to dollar volume:

$$Illiq_i = \frac{|r_i|}{DVOL_i} \tag{1.4}$$

where r_i is a daily stock return of stock i, and $DVOL_i$ is daily dollar volume.

We use the illiquidity measure proposed by Amihud (2002) since it is one of the most widely used in the finance literature. This popularity is due to two advantages it has over many other liquidity measures. First, the measure can be easily constructed using daily stock data. Second, the measure shows a strong positive relationship with a high-frequency price impact measure and expected stock return (*e.g.* Amihud (2002), and Chordia et al. (2009)).

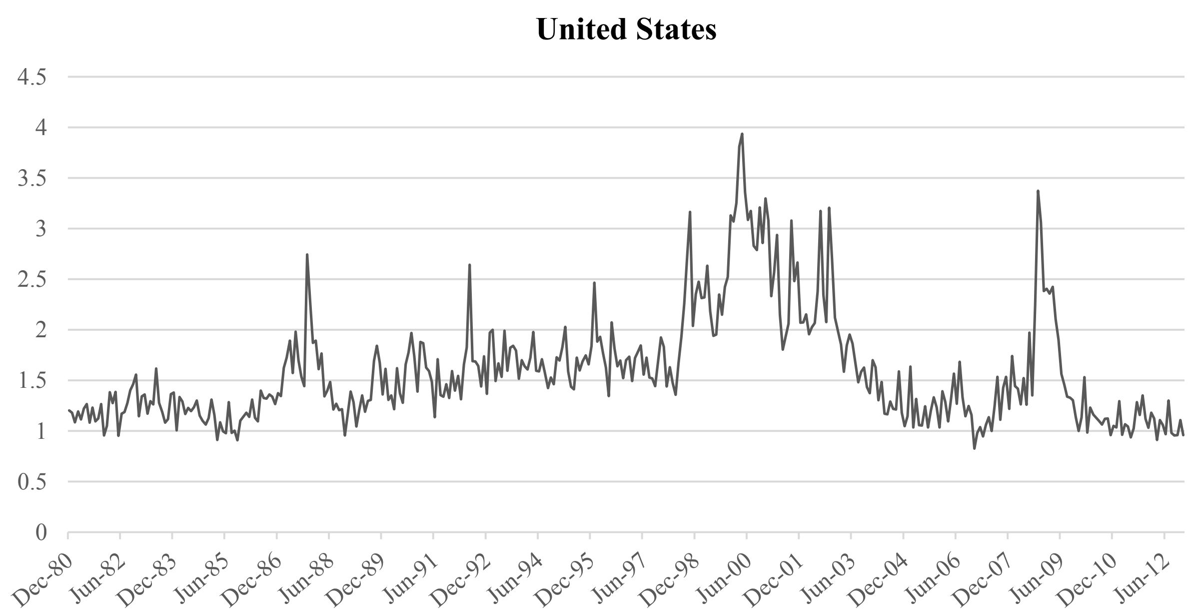
The trading strategy based on idiosyncratic volatility corresponds involves portfolio formation based on an estimation period of L months, a waiting period of M months, and a holding period of N months. The $L/M/N$ strategy is defined as follows. At month t, idiosyncratic volatilities from regressions (3) and (4) on daily data over an L-month period from month $\mathrm{t} - L - M$ to month $t - M$ are measured. At time t, portfolios based on these idiosyncratic volatilities are formed and held for N months. In this study, the analysis focuses on the 1/0/1 strategy, in which stocks are sorted into quintile portfolios based on their level of idiosyncratic volatility estimated using daily returns over the previous month, and held for 1 month. The portfolios are reformed at the beginning of each month.

1.4. Empirical Results

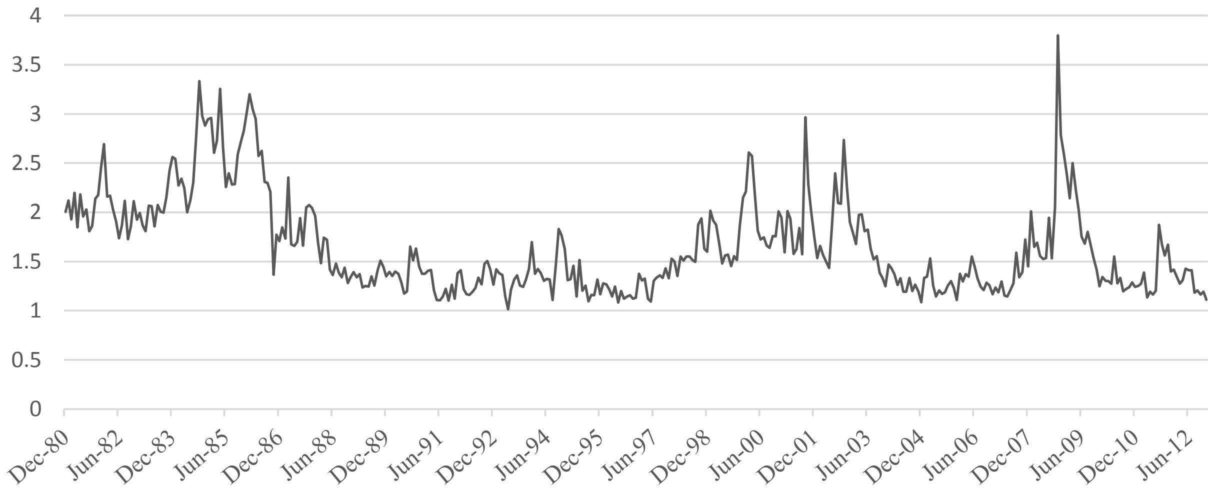
Figure 1.1 provides graphs of the time variation of aggregate idiosyncratic volatility for the United States, G7 countries (except Italy), developed markets and emerging markets all depict no significant positive trend over the full sample period.

Figure 1.1

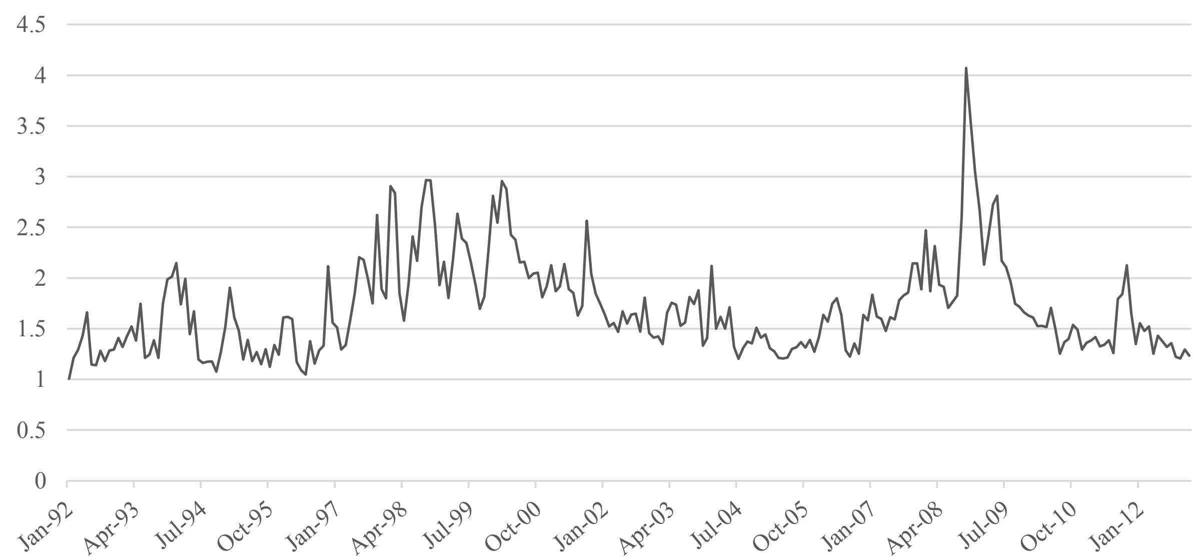
Time Series Plots of Aggregate Monthly Idiosyncratic Volatility (%) – based on 4 factor model



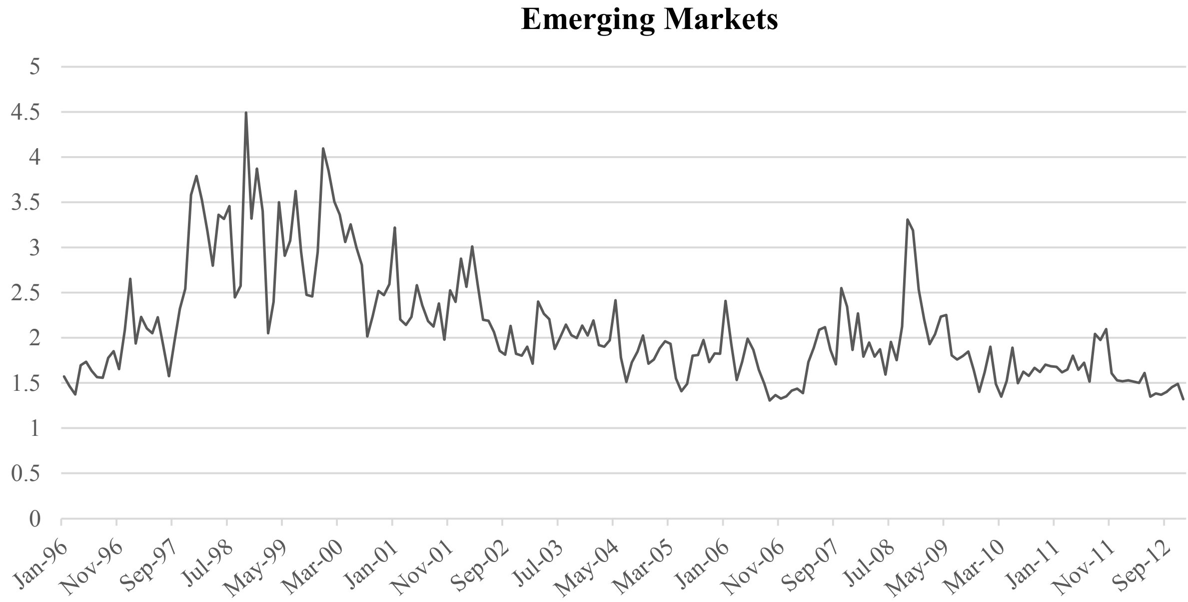
G7 Countries except Italy



Developed Markets



Developed Markets: Australia, Belgium, Denmark, Hong Kong, Netherlands, Singapore, Sweden and Switzerland.



Emerging Markets: Argentina, Brazil, India, Korea, Malaysia, Mexico, Philippines, South Africa, Taiwan and Thailand.

The positive trend in idiosyncratic volatility observed by Campbell et al. (2001) for the period ending 1997 continues until June 2000, but is not clearly evident thereafter. It is also noteworthy that for the US, three out of the seven peaks in the aggregate levels of idiosyncratic volatility occur during the October 1987 crash, the March 2000 technology bubble burst, and the Fall 2008 global financial crisis. Spikes in idiosyncratic volatility are also observed for other G-7 and developed markets as well as for emerging markets during March 2000 and Fall 2008.

Table 1.2 reports summary statistics for three different average volatility measures of stock returns across countries: idiosyncratic volatilities measured based on the 4-factor model, the 5-factor model, and total volatility which is computed as the volatility of daily raw returns over the previous month; the volatility measures are all annualized by multiplying by $\sqrt{250}$.

New Zealand has the lowest idiosyncratic volatility (20.50% per annum based on the 4-factor model and 19.08% using the 5-factor model) while Ireland shows the highest idiosyncratic volatility (42.87% per annum measured on the 4-factor model and 39.99% measured on the 5-factor model). The average idiosyncratic volatilities for G7 Countries are 29.26% and 28.05% based on the 4-factor and 5-factor models respectively. The estimates of idiosyncratic volatility are lower for developed markets (27.97% and 26.63%) but higher for emerging markets (30.45% and 28.45%), perhaps reflecting the direct and indirect barriers to foreign investors, as well as country specific risks that are of greater significance for emerging markets.

Table 1.2 Descriptive Statistics

This table summarizes the time-series statistics of individual stock idiosyncratic volatilities. N(end) denotes the number of stocks at the ending sample period. The column "Number of months" reports the number of monthly observations for each country. The column "Total Volatility" is the mean of the standard deviation of daily returns. The columns "Idiosyncratic Volatility 4 Factor Model" and "Idiosyncratic Volatility 5 Factor Model" reports the mean of idiosyncratic volatilities computed in reference to the 4 factor and 5 factor model respectively. Average time series of volatilities in each country are expressed in annualized terms by multiplying by $\sqrt{250}$.

Country	N(End)	Number of Months	Total Volatility (%)	Idiosyncratic Volatility (%) 4 Factor Model	Idiosyncratic Volatility (%) 5 Factor Model
A. *G7 Countries*					
Canada	233	396	59.28	37.67	35.95
France	233	396	43.92	28.80	27.54
Germany	233	396	39.15	31.90	30.81
Italy	149	319	36.98	25.06	23.95
Japan	916	396	38.08	28.55	27.36
United Kingdom	911	396	31.55	24.25	23.11
United States	3788	396	40.08	28.60	27.53
B. *Developed Markets*					
Australia	152	348	37.48	26.92	25.78
Austria	46	163	32.78	22.50	21.31
Belgium	83	319	32.85	24.24	22.98
Denmark	42	247	39.94	23.02	21.76
Finland	46	222	37.56	26.08	24.51
Greece	47	174	45.97	28.49	26.44
Hong Kong	122	295	55.08	28.85	30.36
Ireland	30	61	85.16	42.87	39.99
Netherlands	105	396	45.18	30.41	28.84
New Zealand	45	160	30.00	20.50	19.08
Norway	47	139	43.52	28.66	26.96
Portugal	46	175	69.23	35.90	33.69
Singapore	93	287	38.42	32.33	31.15
Spain	46	163	41.10	29.60	28.15
Sweden	66	257	35.91	23.43	22.32
Switzerland	133	390	30.92	23.82	22.77
C. *Emerging Markets*					
Argentina	50	216	70.62	32.80	28.48
Brazil	97	219	67.36	33.18	31.17
India	198	218	59.89	36.60	35.32
Indonesia	50	175	77.30	39.14	36.20
Israel	50	199	41.28	27.63	25.81
Korea	97	308	53.27	33.65	31.43
Malaysia	89	324	41.37	26.21	24.82
Mexico	84	238	55.05	26.10	24.47
Philippines	50	218	47.65	34.58	31.70
Poland	50	93	49.50	27.76	26.29
Russia	47	72	73.35	31.49	28.78
South Africa	70	276	42.48	26.43	25.20
Taiwan	70	218	40.78	23.56	22.58
Thailand	50	221	60.94	31.30	29.52
Turkey	49	189	45.12	26.29	25.01

Tables 1.3 and 1.4 (Tables 1.5 and 1.6) show the results for the returns of equal-weighted (value-weighted) portfolios sorted on past 1-month idiosyncratic volatility for all countries measured based on the five-factor and 4-factor models respectively; Portfolio 1 (5) is the portfolio of stocks with the lowest (highest) volatilities.

A negative relationship between idiosyncratic volatility and portfolio future returns in each of the non-U.S. G7 countries (Panel A) is observed, using both equal- and value-weighted portfolios, consistent with Ang et al. (2009) for the full period from January 1980 to December 2012 (except for Italy which starts in June 1986). However, the US (equally-weighted) and the United Kingdom (value-weighted) are the only G7 countries that exhibit a positive relationship between asset-specific risk and expected monthly returns which contrasts with Ang et al. (2006, 2009).

However, two critical facts in these figures deserve attention. First none of the G7 countries display a monotonic idiosyncratic volatility – returns relationship across portfolios ranked from the lowest idiosyncratic risk portfolio (Quintile 1) to the highest (Quintile 5). Average returns decline from quintile 1 to quintile 2 for Canada, France, Germany, Italy and Japan and then increase as we move from portfolio 2 to portfolio 5, as is shown in Appendix 2. Using equal-weighted portfolios, the difference of returns between quintile 1 and quintile 5 is significant for only three countries: France, Germany and Japan, amounting to 1.57, 1.06 and 1.24 percent per month respectively based on the five-factor model.[4]

For value-weighted portfolios, the results are even more attenuated: the relationships between idiosyncratic volatility and expected returns are weaker and only two countries: Canada and Germany show a statistically significant relationship when idiosyncratic volatility is measured

[4] The estimates are 1.60, 1.04 and 1.24 percent per month when diversifiable risk is estimated using the four-factor model), and are statistically significant at conventional levels.

based on the five-factor model. Germany appears to be the country with the most significant results amongst the G7 countries, and shows a monotonic (negative) relationship between idiosyncratic volatility and stock market return performance. The results in this paper are consistent with Koch (2010) who also shows that the idiosyncratic volatility puzzle in Germany cannot be explained by return reversals (as per Huang et al. (2010)). Germany has long been known as having one of the most bank-based financial systems relative to other countries in the G-7. The relatively "thinner" equity market of German firms may in part explain the idiosyncratic volatility puzzle for Germany. Providing a more thorough rational explanation of this result remains a matter for future research, however.

Panels B of Tables 1.3 to 1.4 display results for developed markets and provide mixed evidence on the relationship between idiosyncratic risk and monthly expected returns. Indeed, for equal-weighted portfolios, 5 (11) developed markets show a negative (positive) relationship between idiosyncratic volatility and monthly expected returns but none of the differences in mean are statistically significant. For value-weighted portfolios, the results remain almost identical: 2 (14) developed markets (when idiosyncratic volatility is estimated in respect to the 5-factor model) and 5 (11) developed markets (when idiosyncratic volatility is estimated in respect to the 4-factor model) suggest a negative (positive) relationship between idiosyncratic volatility and monthly expected returns. Moreover, as per the results regarding G7 countries, a monotonic relationship from quintile 1 to quintile 5 is not observed for any of the developed countries in the sample.

Table 1.3 Countries Idiosyncratic Volatility in Reference to the 5-Factor Model Equal-weighted quintile portfolios are formed every month by sorting stocks based on idiosyncratic volatility relative to the 5 factor model. Portfolios are formed every month, based on volatility computed using daily data over the previous month. Portfolio 1 (5) is the portfolio of stocks with the lowest (highest) volatilities. The column "Q1-Q5" reports the difference in monthly returns between portfolio 1 and portfolio 5. ** denotes significance at 5% level. *** denotes significance at 1% level.

Country	Q1	Q2	Q3	Q4	Q5	Q1 – Q5
A. ***G7 Countries***						
Canada	2.90	1.33	1.22	1.32	2.29	0.61
France	2.67	0.67	0.86	0.93	1.11	1.57**
Germany	2.04	0.88	1.03	0.89	0.98	1.06**
Italy	2.17	0.14	0.83	0.37	0.62	1.55
Japan	1.64	0.17	0.09	0.26	0.39	1.24***
United Kingdom	1.21	1.03	0.92	1.09	1.05	0.16
United States	1.62	1.45	1.25	1.22	1.68	- 0.06
B. ***Developed Markets***						
Australia	2.31	1.44	0.89	1.35	1.61	0.69
Austria	0.89	0.65	0.75	0.89	1.02	0.13
Belgium	1.21	1.01	0.79	0.71	0.60	0.61
Denmark	1.07	0.79	0.94	1.25	1.61	- 0.55
Finland	0.37	0.83	0.62	1.09	1.46	- 1.08
Greece	0.83	2.45	1.37	1.35	2.12	- 1.29
Hong Kong	2.26	2.25	1.50	1.83	2.17	0.09
Ireland	1.36	1.01	1.02	1.33	1.13	0.23
Netherlands	1.30	0.61	0.61	0.82	0.29	1.01
New Zealand	1.29	0.69	0.87	0.99	0.91	0.38
Norway	1.39	2.07	1.79	2.00	1.23	0.17
Portugal	-1.25	-0.57	0.44	0.94	0.98	- 2.23
Singapore	3.18	1.12	1.19	1.13	1.33	1.85
Spain	-0.0119	0.0003	-0.0015	-0.0003	0.0193	- 0.0312
Sweden	2.04	1.20	0.87	1.24	1.58	0.45
Switzerland	1.24	0.93	0.73	0.76	0.93	0.31
C. ***Emerging Markets***						
Argentina	0.31	0.24	0.31	1.45	4.58	- 4.27***
Brazil	0.11	1.84	2.19	2.06	2.59	- 2.48***
India	1.63	2.50	2.00	2.22	2.56	- 0.93
Indonesia	-0.48	0.45	0.56	2.16	6.75	- 7.23***
Israel	1.15	1.09	10.02	1.78	2.34	1.19
Korea	0.15	1.47	1.67	1.65	2.21	- 2.06***
Malaysia	0.78	0.84	0.84	1.70	2.15	- 1.36
Mexico	1.04	0.88	2.24	2.73	2.69	- 1.66
Philippines	2.20	2.33	1.82	1.89	3.91	- 1.71
Poland	1.82	1.44	1.68	1.31	1.71	0.11
Russia	1.18	2.57	1.35	2.43	3.62	- 2.44***
South Africa	1.77	1.75	1.60	1.74	2.15	- 0.38
Taiwan	0.82	0.37	0.72	1.23	1.79	- 0.97
Thailand	1.41	0.43	1.72	1.85	2.40	- 0.99
Turkey	2.18	2.12	2.06	1.78	1.45	0.73

Table 1.4 Countries Idiosyncratic Volatility in Reference to the 4-Factor Model

Equal-weighted quintile portfolios are formed every month by sorting stocks based on idiosyncratic volatility relative to the 4 factor model. Portfolios are formed every month, based on volatility computed using daily data over the previous month. Portfolio 1 (5) is the portfolio of stocks with the lowest (highest) volatilities. The column "Q1-Q5" reports the difference in monthly returns between portfolio 1 and portfolio 5. ** denotes significance at 5% level. *** denotes significance at 1% level.

Country	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
A. ***G7 Countries***						
Canada	2.96	1.34	1.23	1.25	2.33	0.63
France	2.68	0.65	0.86	0.95	1.09	1.60**
Germany	2.02	0.82	1.04	0.92	0.98	1.04**
Italy	2.22	0.11	0.82	0.38	0.61	1.61
Japan	1.63	0.18	0.11	0.23	0.39	1.24***
United Kingdom	1.22	1.04	0.92	1.08	1.05	0.17
United States	1.76	1.78	1.25	1.42	1.73	0.03
B. ***Developed Markets***						
Australia	2.13	1.47	0.85	1.38	1.62	0.51
Austria	0.84	0.56	0.91	0.86	0.98	- 0.15
Belgium	1.07	1.09	0.80	0.62	0.65	0.43
Denmark	1.24	0.99	0.91	1.19	1.65	- 0.41
Finland	0.34	0.75	0.56	1.15	1.51	- 1.17
Greece	0.82	2.39	0.95	1.81	2.04	- 1.22
Hong Kong	2.31	2.20	1.54	1.80	2.18	0.13
Ireland	1.56	1.11	0.36	1.65	1.16	0.40
Netherlands	1.20	0.68	0.56	0.87	0.27	0.93
New Zealand	1.46	0.84	0.88	0.97	0.86	0.59
Norway	1.37	2.14	1.81	1.90	1.30	0.07
Portugal	-1.34	-0.40	0.46	0.87	1.02	- 2.36
Singapore	3.23	1.05	1.26	1.14	1.34	1.89
Spain	-0.011	0.0018	0.0021	0.0003	0.0019	- 0.0313
Sweden	2.09	1.11	1.01	1.24	1.54	0.55
Switzerland	1.23	0.94	0.70	0.81	0.92	0.32
C. ***Emerging Markets***						
Argentina	0.15	0.36	0.21	1.37	4.65	- 4.51***
Brazil	-0.04	1.75	2.22	2.19	2.49	- 2.54***
India	1.63	2.50	2.00	2.22	2.56	- 0.93
Indonesia	-0.53	0.41	0.36	2.19	6.90	- 7.43***
Israel	1.21	1.05	1.49	7.70	2.31	- 1.10
Korea	0.15	1.47	1.67	1.65	2.21	- 2.06***
Malaysia	0.61	0.90	0.93	1.77	2.05	- 1.44
Mexico	1.20	0.81	1.80	3.01	2.70	- 1.50*
Philippines	1.98	2.93	1.45	1.97	4.09	- 2.11***
Poland	1.67	1.62	1.82	1.21	1.71	- 0.04
Russia	1.28	2.19	2.21	2.36	3.28	- 2.00***
South Africa	1.87	1.46	1.78	1.65	2.19	- 0.33
Taiwan	0.92	0.29	0.93	1.13	1.78	- 0.86
Thailand	1.40	0.38	1.50	2.02	2.42	- 1.02
Turkey	1.99	2.05	2.01	1.93	1.52	0.47

Table 1.5 Countries Idiosyncratic Volatility in Reference to the 5-Factor Model

Value-weighted quintile portfolios are formed every month by sorting stocks based on idiosyncratic volatility relative to the 5 factor model. Portfolios are formed every month, based on volatility computed using daily data over the previous month. Portfolio 1 (5) is the portfolio of stocks with the lowest (highest) volatilities. The column "Q1-Q5" reports the difference in monthly returns between portfolio 1 and portfolio 5. ** denotes significance at 5% level. *** denotes significance at 1% level.

Country	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
A. *G7 Countries*						
Canada	1.78	0.41	0.99	0.92	0.30	1.48**
France	0.48	- 0.12	0.47	0.01	- 0.13	0.61
Germany	2.82	1.83	0.79	0.03	1.13	1.69**
Italia	1.41	0.18	0.58	0.59	1.23	0.18
Japan	1.50	0.61	0.67	0.75	1.23	0.27
United Kingdom	0.43	0.24	0.40	0.70	0.60	- 0.16
United States	1.34	0.53	0.64	1.00	1.45	- 0.11
B. *Developed Markets*						
Australia	1.92	1.42	- 1.79	2.74	2.05	- 0.13
Austria	-0.01	0.55	0.55	1.29	1.46	- 1.47
Belgium	1.14	-0.10	0.03	1.30	1.34	- 0.20
Denmark	1.28	1.00	1.36	0.57	0.79	0.49
Finland	0.04	2.13	1.50	1.33	1.10	- 1.06
Greece	0.32	1.00	1.28	1.59	2.16	- 1.84
Hong Kong	2.28	1.37	1.17	2.23	2.85	- 0.67
Ireland	1.63	1.21	1.21	1.96	2.11	- 0.48
Netherlands	1.67	0.42	0.90	1.52	1.87	- 0.20
New Zealand	1.19	0.90	0.68	-0.33	0.89	0.30
Norway	0.21	1.93	1.44	2.03	1.63	1.42
Portugal	-1.12	0.01	1.23	0.79	1.30	- 2.42
Singapore	2.59	1.17	0.98	1.06	1.69	- 0.90
Spain	- 0.008	0.009	0.011	0.010	0.008	- 0.016
Sweden	1.51	1.09	1.10	1.29	2.37	- 0.86
Switzerland	0.91	0.91	0.73	1.09	1.35	- 0.44
C. *Emerging Markets*						
Argentina	-0.34	1.04	1.28	2.19	4.15	- 4.49***
Brazil	-0.27	1.91	2.17	2.65	2.53	- 2.80***
India	1.89	1.24	2.23	1.88	1.80	- 0.09
Indonesia	1.51	2.55	2.18	3.10	3.76	- 2.25***
Israel	0.32	0.97	1.72	2.10	2.46	2.14
Korea	-0.37	0.19	1.83	2.79	5.71	- 6.08***
Malaysia	1.45	0.65	1.61	2.02	2.82	- 1.37
Mexico	0.56	0.98	1.48	1.90	2.16	- 1.50
Philippines	1.96	2.99	2.27	2.75	5.23	- 3.27***
Poland	1.85	1.52	2.29	0.62	1.47	0.38
Russia	1.02	2.06	0.64	0.98	2.92	- 1.88
South Africa	1.60	1.17	0.99	1.22	1.61	- 0.01
Taiwan	0.92	0.48	0.96	1.76	2.17	- 1.25
Thailand	0.61	1.00	0.51	1.30	1.65	- 1.04
Turkey	1.78	1.94	1.88	2.197	2.42	- 0.64

Table 1.6 Countries Idiosyncratic Volatility in Reference to the 4-Factor Model

Value-weighted quintile portfolios are formed every month by sorting stocks based on idiosyncratic volatility relative to the 4 factor model. Portfolios are formed every month, based on volatility computed using daily data over the previous month. Portfolio 1 (5) is the portfolio of stocks with the lowest (highest) volatilities. The column "Q1-Q5" reports the difference in monthly returns between portfolio 1 and portfolio 5. ** denotes significance at 5% level. *** denotes significance at 1% level.

Country	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
A. *G7 Countries*						
Canada	1.87	0.14	1.39	0.30	1.26	0.63
France	0.45	-0.07	0.56	0.16	- 0.05	0.50
Germany	2.90	1.72	0.88	0.43	0.30	2.60***
Italia	1.44	0.13	1.04	0.71	1.38	0.06
Japan	1.53	0.65	0.60	0.66	1.32	0.21
United Kingdom	0.30	0.12	0.40	0.74	0.62	- 0.32
United States	1.39	0.78	0.74	1.26	1.65	- 0.16
B. *Developed Markets*						
Australia	0.03	3.44	-3.89	- 0.88	0.87	- 0.90
Austria	0.03	0.41	0.90	1.44	1.16	- 1.19
Belgium	1.03	0.21	0.39	1.18	1.64	- 0.61
Denmark	1.06	1.32	1.48	0.42	0.81	0.25
Finland	-0.24	2.23	1.94	0.93	1.28	- 1.52
Greece	0.99	0.86	1.93	1.88	2.29	- 1.30
Hong Kong	2.49	1.58	1.07	2.01	2.91	- 0.52
Ireland	1.13	1.19	1.12	1.90	1.94	- 0.81
Netherlands	1.72	0.47	0.78	1.47	1.51	0.21
New Zealand	1.28	0.65	0.11	-0.03	0.64	0.64
Norway	0.08	2.05	2.23	1.82	1.89	1.81
Portugal	-1.04	-0.02	1.35	0.50	1.51	- 2.55
Singapore	2.73	1.16	1.07	1.05	1.74	0.99
Spain	- 0.010	0.009	0.013	0.011	0.009	- 0.019
Sweden	1.58	0.81	2.17	1.48	2.37	- 0.79
Switzerland	0.94	0.90	0.82	0.99	1.34	- 0.40
C. *Emerging Markets*						
Argentina	-0.26	1.23	1.82	2.27	3.97	- 4.23***
Brazil	0.09	1.58	2.55	2.52	2.58	- 2.49***
India	1.89	1.24	2.28	1.88	1.80	- 0.09
Indonesia	1.36	2.72	2.52	3.20	4.20	- 2.84***
Israel	0.46	0.83	2.19	2.26	2.35	- 1.89
Korea	-0.29	0.05	1.87	2.89	5.76	- 6.05***
Malaysia	0.71	1.14	1.82	2.32	2.60	- 1.89
Mexico	0.81	1.03	1.45	2.76	2.04	- 1.23
Philippines	1.73	3.61	2.59	3.26	4.94	- 3.21***
Poland	1.46	1.04	2.99	1.14	1.37	0.09
Russia	1.02	1.72	0.97	0.87	2.21	- 1.19
South Africa	1.86	0.92	1.08	0.96	1.85	0.01
Taiwan	1.11	0.44	1.00	1.77	2.07	- 0.96
Thailand	0.88	0.74	0.65	1.54	1.75	- 0.87
Turkey	1.85	2.08	1.56	1.64	2.61	- 0.76

The results for emerging countries are shown in Panel C of Tables 1.3 to 1.6, contrast with those of the G-7 and developed countries. While most of the G7 countries show a negative association between diversifiable risk and expected returns, emerging countries exhibit an opposite relation: 12 out of these 15 countries suggest a positive link between idiosyncratic risk and expected returns. Furthermore, contrary to both developed and G7 countries, with the exception of Israel, Russia, and Thailand, the relationship between returns and IV appears to be fairly linear. Using for both equal- and value- weighted portfolios, 5 out of the 15 emerging countries indicate a strong and statistically significant difference in means between quintiles 1 to quintiles 5: Argentina, Brazil, Indonesia, Korea and Russia for equal-weighted portfolios and the same countries for value-weighted portfolios except that Russia is replaced by The Philippines.

One possible reason that the results differ between G7 countries and emerging markets could be because of differences in the level of portfolio diversification attained by investors. Indeed, the results for emerging countries corroborate theories assuming investor under-diversification caused by market frictions that prevent investing in fully diversified portfolios (Levy (1978), Merton (1987)); in such an environment investors request compensation for bearing idiosyncratic risk generating a positive relationship between idiosyncratic volatility and returns.

Other factors that could have affected differences between G7 countries and emerging markets results comprise differences in terms of degrees of financial liberalization (Umutlu et al. (2010)), financial market development (Brown and Kapadia (2007)), and the degree of investor protection (Lemmon and Lins (2003); Cheng and Shiu (2007)).

Tables 1.7 and 1.8 report comparative results for portfolio returns when idiosyncratic volatility is computed using 3-factor model for equal- and value-weighted portfolios respectively.

Again an overall similar pattern is observed when comparing these results with the ones derived from the 4 and 5-factor model. Only 3 (equal-weighted) and 2 (value-weighted) out the G7 countries suggest a strong negative relationship between specific volatility and expected returns.

For developed markets, we also obtain similar general results when idiosyncratic volatility is estimated using the 3, 4 and 5 factor models: no statistically significant relationship is observed except for Australia (value-weighted portfolios). However it is interesting to notice that 9 out of the 16 countries show a negative relationship for the value-weighted portfolios but only 4 out of these same countries suggest the same direction of relationship for equal-weighted portfolios. Note that in their paper, Ang et al. (2009) employ the 3 factor model as well as value-weighted portfolios to obtain a negative association between idiosyncratic volatility and expected returns for G7 and developed countries.

In panel C of Tables 1.7 and 1.8, the results when idiosyncratic volatility is estimated in respect to the 3-factor model remain again similar to the ones exhibited in Tables 1.3 to 1.6: Most of the emerging markets provide evidence of a positive relationship (11 and 13 for equal- and value-weighted portfolios respectively) and 5 out of these 15 countries imply a statistically strong association.

Table 1.7 Countries Idiosyncratic Volatility in Reference to the 3-Factor Model

Equally-weighted quintile portfolios are formed every month by sorting stocks based on idiosyncratic volatility relative to the 3 factor model. Portfolios are formed every month, based on volatility computed using daily data over the previous month. Portfolio 1 (5) is the portfolio of stocks with the lowest (highest) volatilities. The column "Q1-Q5" reports the difference in monthly returns between portfolio 1 and portfolio 5. ** denotes significance at 5% level. *** denotes significance at 1% level.

Country	Q1	Q2	Q3	Q4	Q5	Q1 – Q5
A. *G7 Countries*						
Canada	2.93	1.33	1.18	1.39	0.46	2.47***
France	2.67	0.68	0.90	1.11	1.26	1.41***
Germany	1.97	0.81	0.99	0.957	1.12	0.85
Italia	2.27	0.07	0.79	0.58	0.89	1.38***
Japan	1.57	0.33	0.29	0.35	0.56	1.01
United Kingdom	1.22	1.04	0.86	0.97	1.03	0.19
United States	1.59	1.60	1.01	0.92	1.38	0.21
B. *Developed Markets*						
Australia	2.08	1.42	0.81	1.08	0.82	1.26
Austria	0.65	0.57	0.88	0.87	0.95	- 0.30
Belgium	1.07	1.01	0.94	0.52	0.66	0.41
Denmark	0.95	1.09	0.98	1.34	1.77	- 0.82
Finland	0.40	0.76	0.67	1.24	1.57	- 1.17
Greece	0.72	2.49	1.17	1.04	1.70	- 0.98
Hong Kong	2.37	2.21	1.64	1.53	2.45	- 0.08
Ireland	1.63	1.21	0.40	1.438	1.28	0.35
Netherlands	1.20	0.67	0.73	0.69	0.16	1.04
New Zealand	1.28	0.77	0.74	0.65	0.71	0.57
Norway	1.16	2.35	2.12	1.55	1.05	0.11
Portugal	-1.32	-0.41	0.65	0.78	1.20	- 2.52
Singapore	3.04	1.10	1.23	1.08	1.30	1.74
Spain	-0.01	0.004	-0.003	-0.003	0.025	- 0.026
Sweden	2.06	1.10	1.14	1.26	1.60	0.46
Switzerland	1.23	0.80	0.78	0.91	1.12	0.11
C. *Emerging Markets*						
Argentina	0.10	0.08	0.39	1.39	5.11	- 5.01***
Brazil	-0.07	1.57	2.15	2.37	2.55	- 2.62***
India	2.00	2.21	2.22	2.59	2.87	- 0.87
Indonesia	-0.58	0.32	0.51	2.22	5.26	- 5.64***
Israel	0.24	1.11	1.50	1.67	2.35	2.11
Korea	0.38	1.48	2.00	1.96	3.43	- 3.05***
Malaysia	1.39	0.66	1.00	1.34	1.78	- 0.39
Mexico	1.10	0.86	1.53	2.76	3.06	- 1.96
Philippines	1.15	3.37	1.45	1.84	4.34	- 3.19***
Poland	1.65	1.78	1.31	1.46	1.51	0.38
Russia	1.20	2.24	1.94	2.17	2.52	0.14
South Africa	1.82	1.63	1.47	1.70	2.10	- 0.18
Taiwan	0.55	0.54	0.96	1.30	1.89	- 1.34
Thailand	1.38	0.36	1.21	2.06	2.46	- 1.08
Turkey	1.93	2.23	1.84	2.10	1.40	0.53

Table 1.8 Countries Idiosyncratic Volatility in Reference to the 3-Factor Model

Value-weighted quintile portfolios are formed every month by sorting stocks based on idiosyncratic volatility relative to the 3 factor model. Portfolios are formed every month, based on volatility computed using daily data over the previous month. Portfolio 1 (5) is the portfolio of stocks with the lowest (highest) volatilities. The column "Q1-Q5" reports the difference in monthly returns between portfolio 1 and portfolio 5. ** denotes significance at 5% level. *** denotes significance at 1% level.

Country	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
A. *G7 Countries*						
Canada	1.79	-0.29	1.98	0.05	-0.94	2.73***
France	0.45	-0.05	0.27	0.21	-0.10	0.55
Germany	2.48	2.06	0.91	-0.24	0.07	2.41***
Italia	1.48	0.09	0.64	0.77	1.43	0.05
Japan	1.46	0.63	0.76	0.61	0.27	1.19
United Kingdom	1.38	0.03	0.50	0.71	0.69	0.69
United States	1.52	1.29	1.18	1.26	1.42	0.10
B. *Developed Markets*						
Australia	1.17	5.46	0.86	-2.70	-1.64	2.74**
Austria	-0.22	0.34	0.76	1.33	1.49	- 1.71
Belgium	1.06	0.08	0.18	0.93	1.82	- 0.76
Denmark	1.06	1.01	1.11	1.00	0.77	0.29
Finland	-0.30	2.28	1.06	1.28	1.38	- 1.52
Greece	0.09	1.15	0.91	1.15	1.76	- 1.67
Hong Kong	-0.39	1.63	1.26	2.06	1.83	- 2.22
Ireland	0.19	1.36	0.63	1.59	1.84	- 1.65
Netherlands	0.81	0.49	1.03	1.21	1.80	- 0.99
New Zealand	1.24	0.53	0.51	0.35	0.52	0.72
Norway	0.08	2.70	1.82	1.80	1.75	- 0.67
Portugal	-1.16	-0.02	1.22	0.35	1.67	- 2.73
Singapore	2.55	1.14	1.08	1.10	1.70	0.85
Spain	-0.010	0.008	0.011	0.010	0.008	- 0.018
Sweden	1.46	1.01	1.22	1.46	2.35	- 0.89
Switzerland	0.76	0.91	0.79	1.01	1.34	- 0.58
C. *Emerging Markets*						
Argentina	-0.58	1.11	1.15	2.40	4.27	- 4.85***
Brazil	0.04	1.57	2.08	2.72	2.45	- 2.41***
India	1.05	-0.20	1.55	1.383	1.80	- 0.75
Indonesia	2.00	2.67	2.21	2.74	4.37	- 2.37***
Israel	0.84	0.72	1.64	2.31	2.60	- 1.76
Korea	-0.38	0.35	1.56	2.93	6.07	- 6.45***
Malaysia	1.45	0.65	1.61	2.02	2.82	- 1.37
Mexico	0.53	1.27	1.27	2.29	2.64	- 2.11
Philippines	1.10	4.27	2.16	3.74	4.43	- 3.33***
Poland	1.62	0.96	2.53	1.04	1.41	0.21
Russia	1.51	1.70	0.79	0.99	2.47	- 0.96
South Africa	1.80	1.19	0.89	1.33	1.55	0.25
Taiwan	0.72	0.33	1.14	1.64	2.24	- 1.52
Thailand	-0.16	1.11	0.18	1.56	2.04	- 2.20
Turkey	1.80	2.16	2.04	1.82	2.58	- 0.78

In summary, we observe mixed evidence on the relation between idiosyncratic risk and expected returns when idiosyncratic volatility is estimated using the 5 and 4 factor models. For equal-weighted portfolios, a strong and negative relationship is observed for 3 of the G7 countries: France, Germany and Japan, an idiosyncratic volatility trading strategy of going long on low idiosyncratic volatility stocks and short on high idiosyncratic stocks can generate economically and statistically significant trading profits. For value-weighted portfolios, this same trading strategy would be profitable for Canada and Germany only.

While developed markets present insignificant mixed results, some emerging markets (5 out of 16 countries) provide evidence of a strong positive relation between expected returns and past idiosyncratic. For these countries, an investment strategy of buying high idiosyncratic volatility stocks and shorting low idiosyncratic could result in significant trading profits.

The majority of the countries analyzed in this paper (2, 3 or 4 of the G7 countries depending on the weighting, all developed countries and 11 of the 16 emerging markets) present no evidence of a relationship between diversifiable risk and expected returns. These findings are in contrast to the ones observed by Ang et al. (2009) in which all countries in their study show a negative correspondence between idiosyncratic volatility and expected returns.

1.5 Conclusion

This study examines the role of idiosyncratic risk in an international context motivated by the study of Ang et al. (2006) that reveals the presence of an abnormal negative relationship between realized idiosyncratic volatility and subsequent 1-month stock returns. This negative relationship has been successively denoted to in the literature as the 'idiosyncratic volatility puzzle' with the possibility that this anomaly might be international following evidence reported by Ang et al. (2009) in the US and 22 other developed markets. We expand the Ang et al. (2006) framework to estimate the impact of idiosyncratic risk in international stock markets using two additional asset pricing models to estimate diversifiable risk i.e. the Carhart 4-factor model and the as well as the 5-factor model (4-factor model plus the Amihud liquidity factor).

The results obtained suggest that idiosyncratic risk does not play a role on stock returns for the 16 developed markets analyzed. While some evidence of a negative link between idiosyncratic risk is shown, the relation is statistically significant for only a few of the G-7 countries in the analysis. Indeed, only Germany shows a monotonic negative relationship between idiosyncratic volatility and stock market returns, consistent with Koch (2010). It may be the case that this is due to the fact that equity markets are still not well developed in Germany, which persists as one of the most bank-based financial systems relative to other countries in the G-7. The relatively "thinner" equity market of German firms may in part explain the idiosyncratic volatility puzzle for Germany. Providing a more thorough and rational explanation of this result remains a matter for future research. We do note, on the other hand, idiosyncratic volatility is positively related to future expected returns for 5 out of 15 emerging market countries.

These findings related to emerging countries are consistent with investor under-diversification (e.g., Levy (1978); and Merton (1987)) wherein investors request a premium for taking idiosyncratic risk. This under diversification may be due to informational efficiencies, although liquidity risk per se does not seem to be a driving factor in explaining the divergent results between developed and emerging markets.

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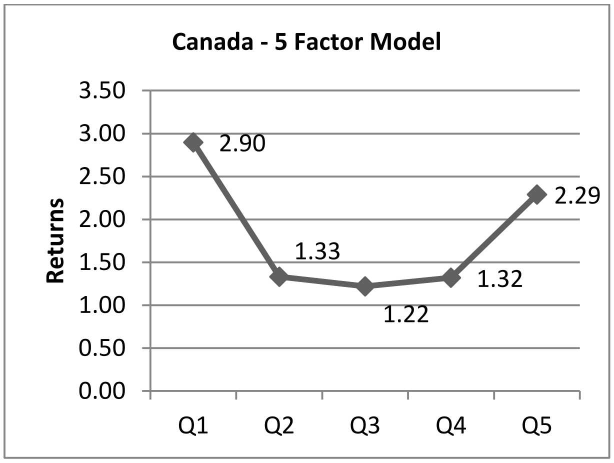
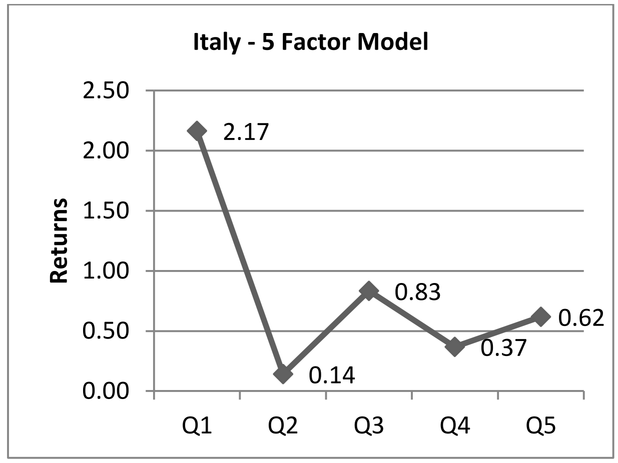
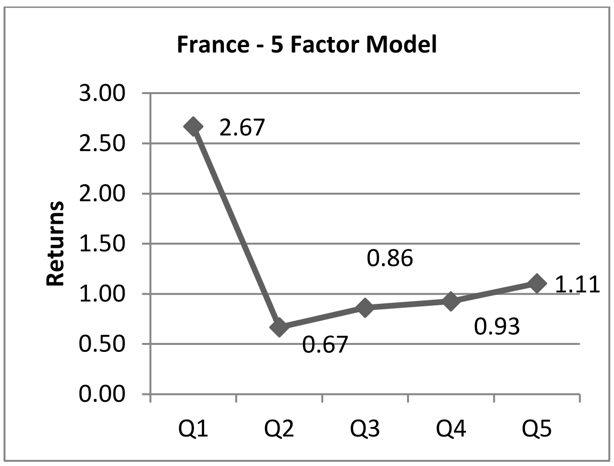
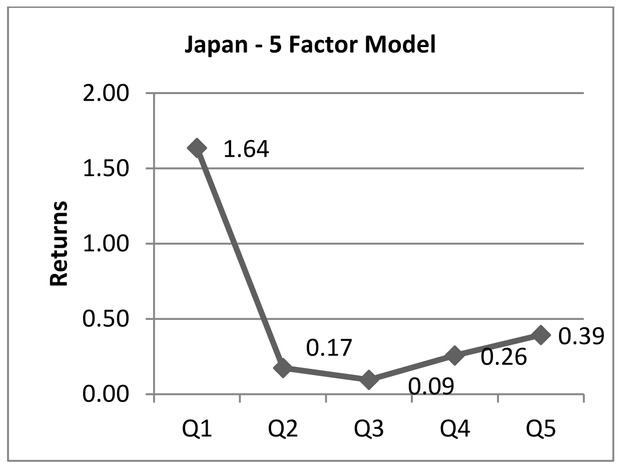
Appendix 1. Equal-Weighted Portfolio Returns Sorted According to Idiosyncratic Volatilities

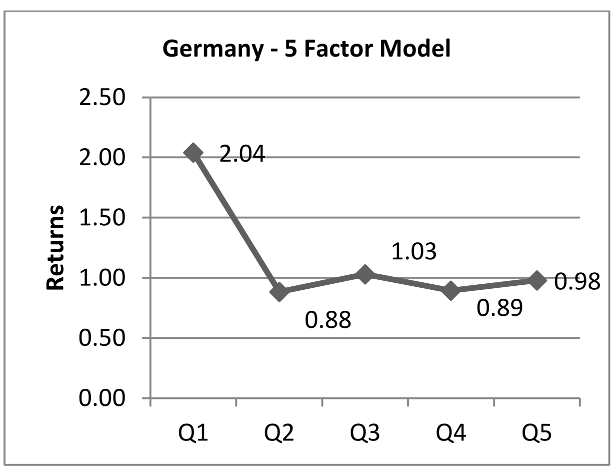
A. G7 Countries

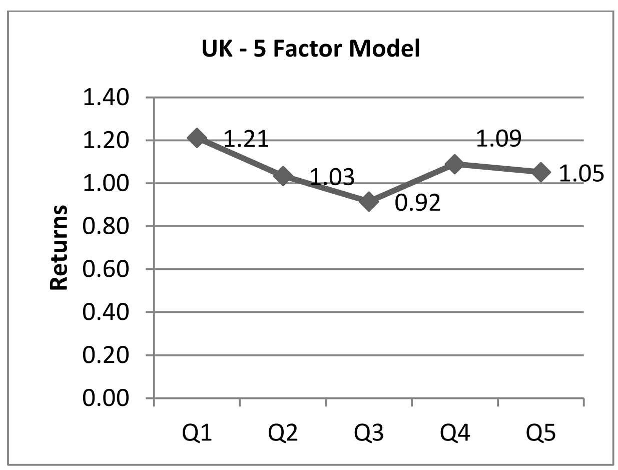


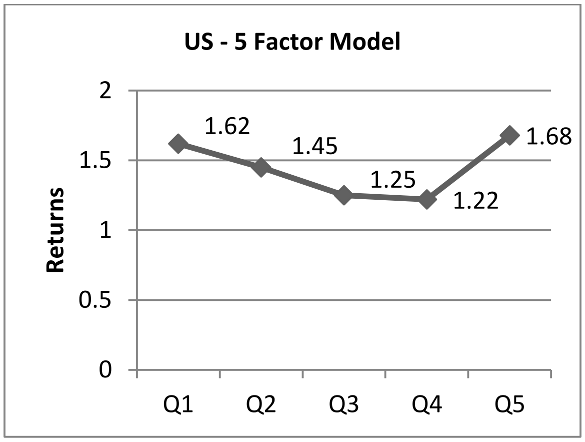




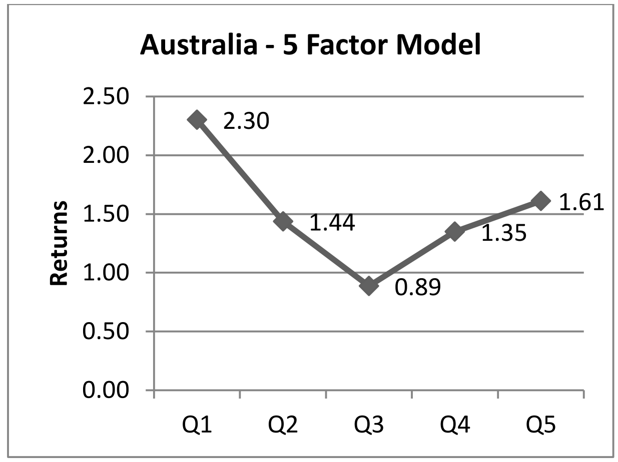


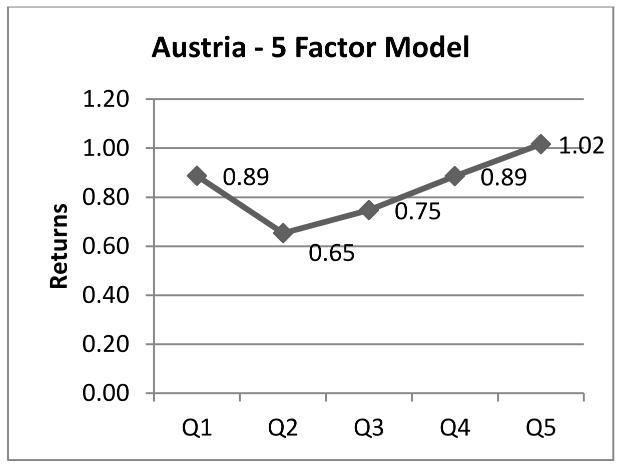


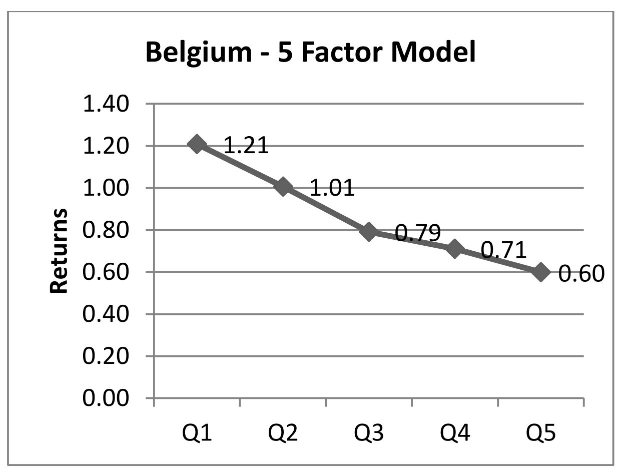


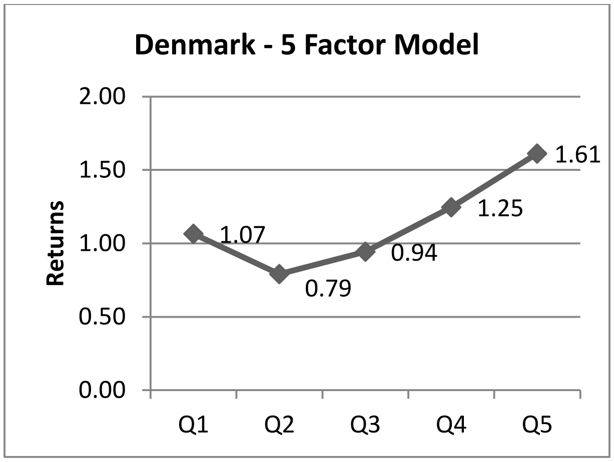


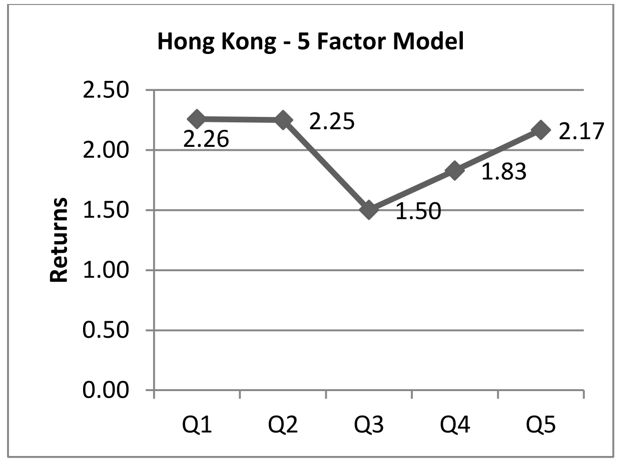
B. Developed Countries

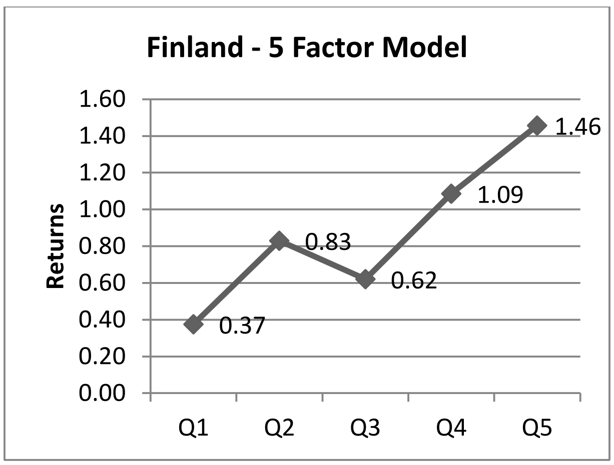


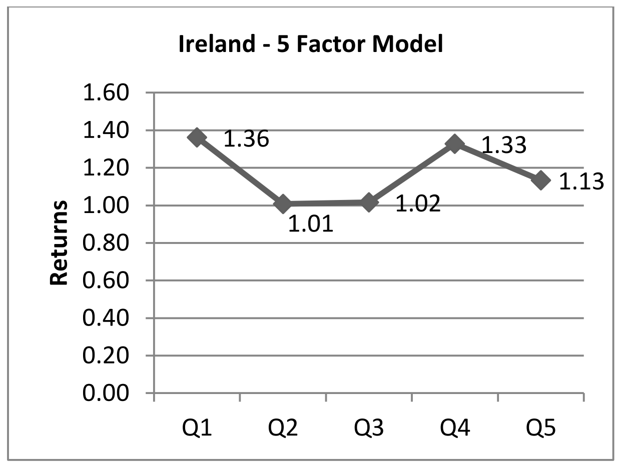


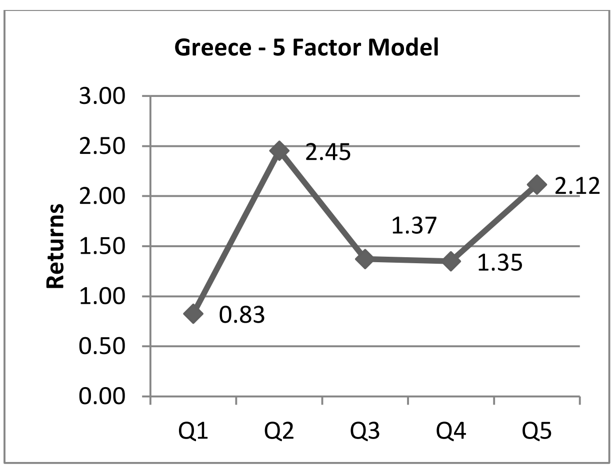


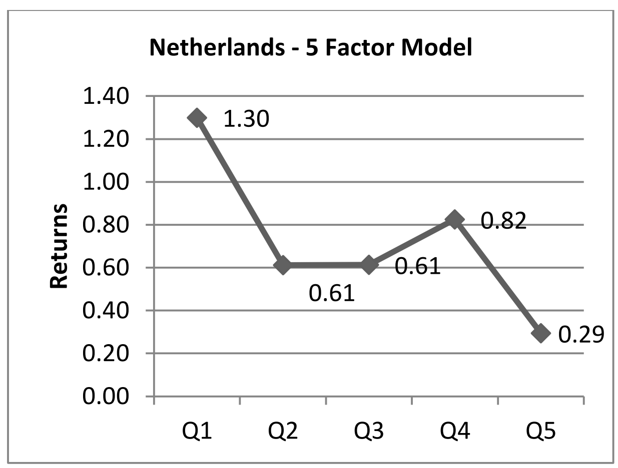

Denmark - 5 Factor Model
Returns
2.00
1.50
1.00
0.50
0.00
1.07
0.79
0.94
1.25
1.61
Q1
Q2
Q3
Q4
Q5

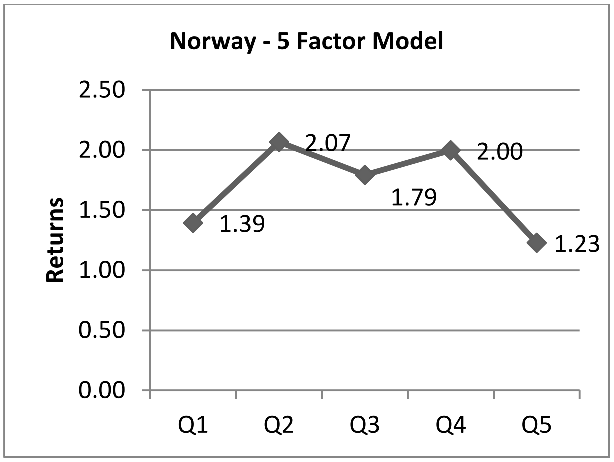

Hong Kong - 5 Factor Model
Returns
2.50
2.00
1.50
1.00
0.50
0.00
2.26
2.25
1.50
1.83
2.17
Q1
Q2
Q3
Q4
Q5

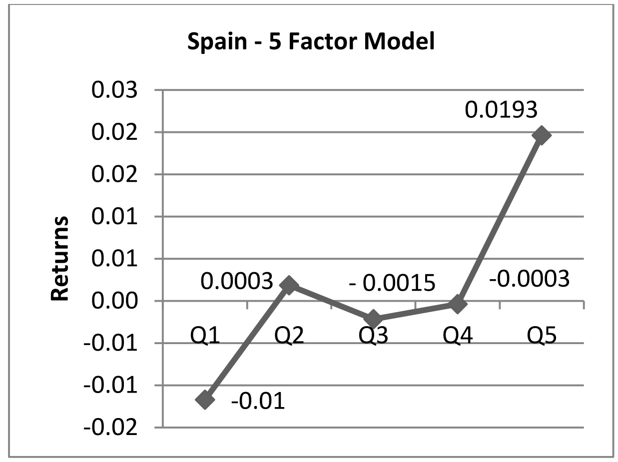

Finland - 5 Factor Model
Returns
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
0.37
0.83
0.62
1.09
1.46
Q1
Q2
Q3
Q4
Q5

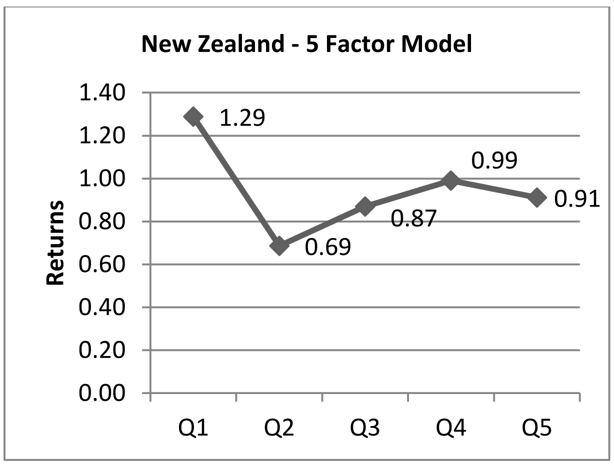

Ireland - 5 Factor Model
Returns
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
1.36
1.01
1.02
1.33
1.13
Q1
Q2
Q3
Q4
Q5

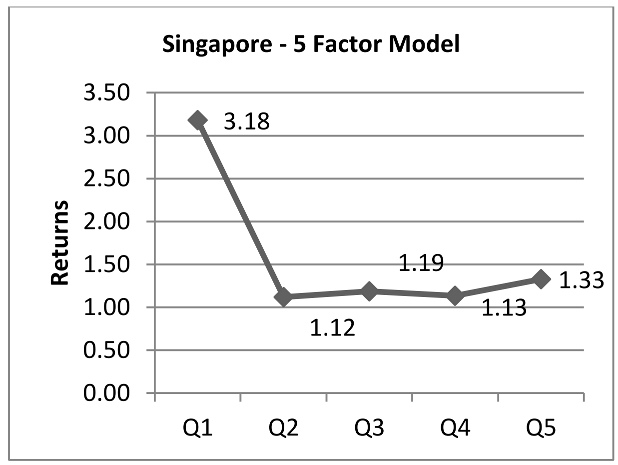

Greece - 5 Factor Model
Returns
3.00
2.50
2.00
1.50
1.00
0.50
0.00
0.83
2.45
1.37
1.35
2.12
Q1
Q2
Q3
Q4
Q5

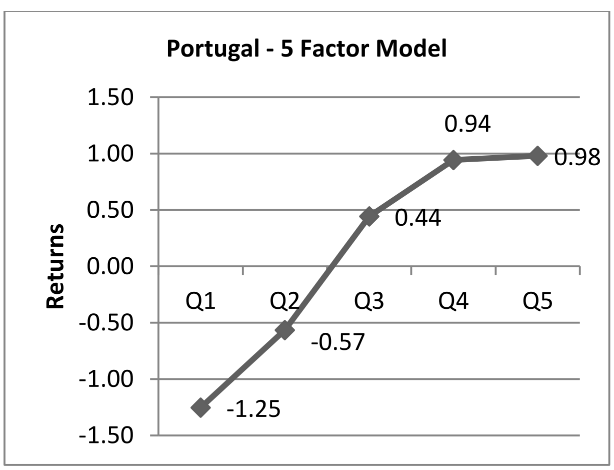

Netherlands - 5 Factor Model
Returns
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
1.30
0.61
0.61
0.82
0.29
Q1
Q2
Q3
Q4
Q5

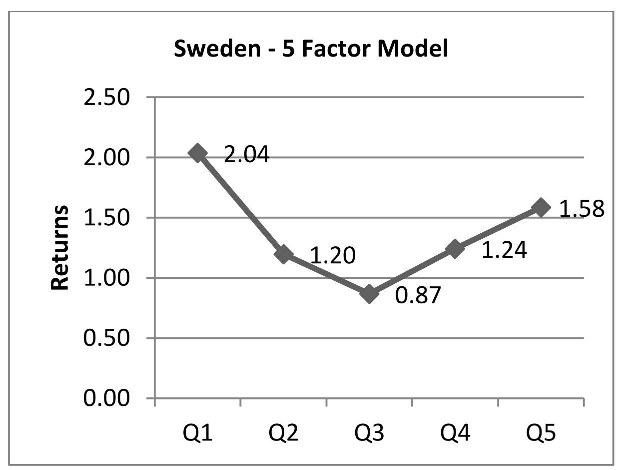

Norway - 5 Factor Model
Returns
2.50
2.00
1.50
1.00
0.50
0.00
Q1
Q2
Q3
Q4
Q5
1.39
2.07
1.79
2.00
1.23

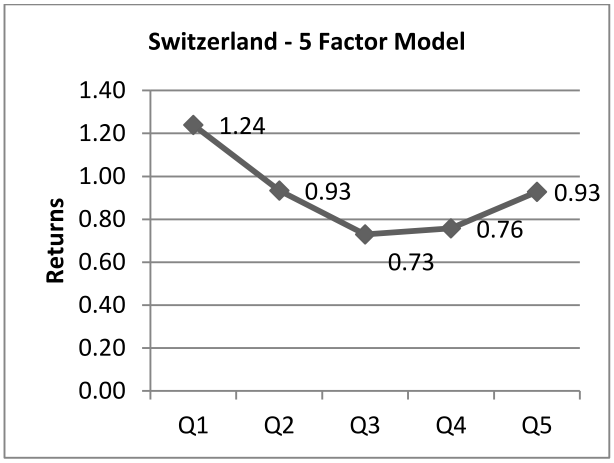

Spain - 5 Factor Model
Returns
0.03
0.02
0.02
0.01
0.01
0.00
-0.01
-0.01
-0.02
Q1
Q2
Q3
Q4
Q5
-0.01
0.0003
- 0.0015
-0.0003
0.0193


New Zealand - 5 Factor Model
Returns
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
Q1
Q2
Q3
Q4
Q5
1.29
0.69
0.87
0.99
0.91

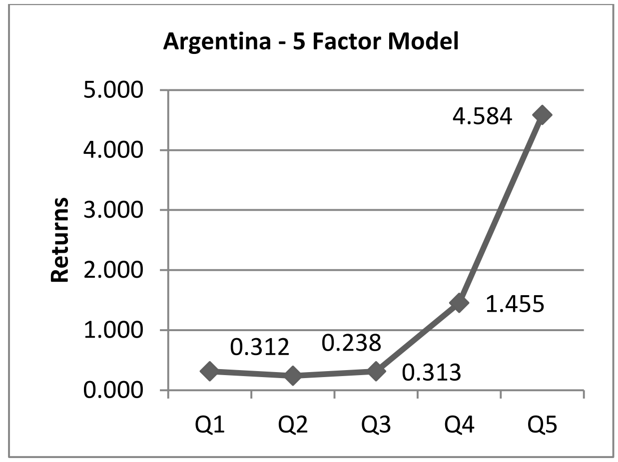

Singapore - 5 Factor Model
Returns
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
Q1
Q2
Q3
Q4
Q5
3.18
1.12
1.19
1.13
1.33

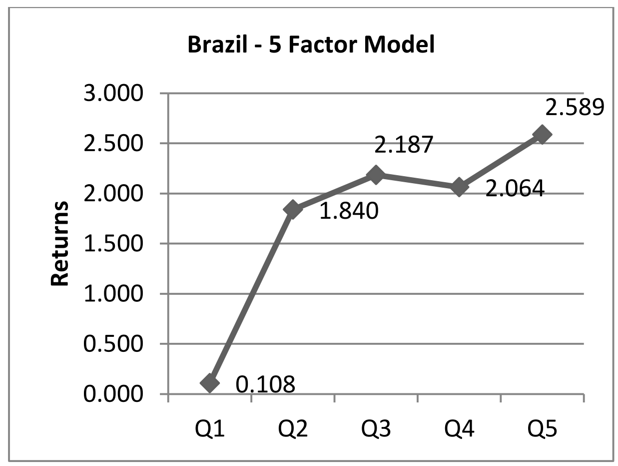

Portugal - 5 Factor Model
Returns
1.50
1.00
0.50
0.00
-0.50
-1.00
-1.50
Q1
Q2
Q3
Q4
Q5
-1.25
-0.57
0.44
0.94
0.98

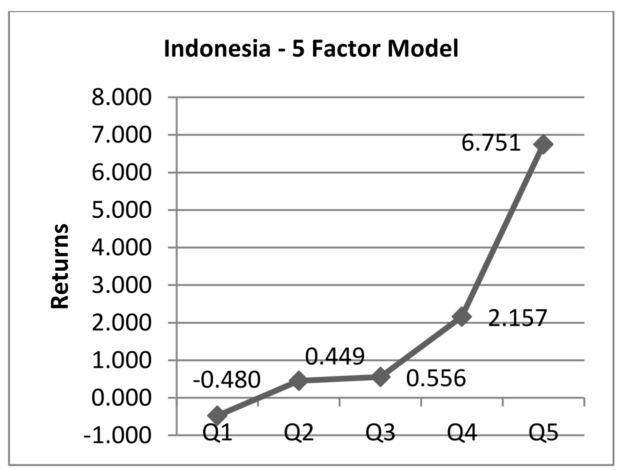

Sweden - 5 Factor Model
Returns
2.50
2.00
1.50
1.00
0.50
0.00
Q1
Q2
Q3
Q4
Q5
2.04
1.20
0.87
1.24
1.58

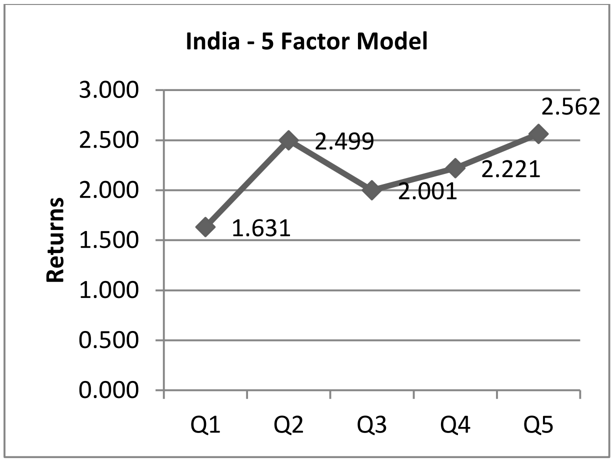


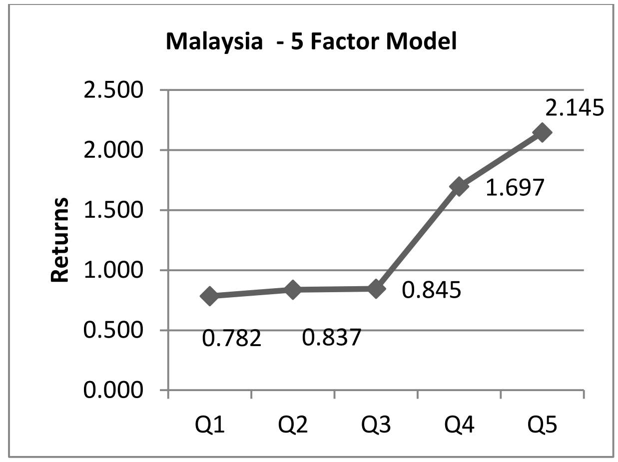
C. Emerging Countries

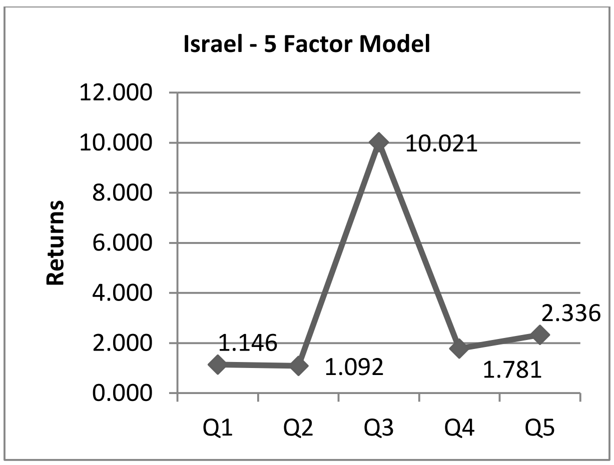


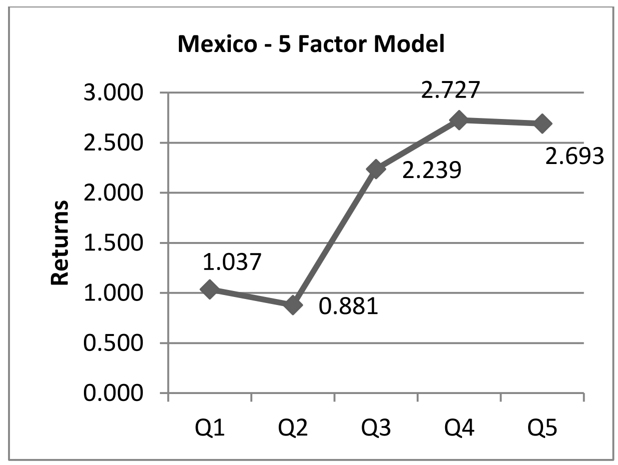


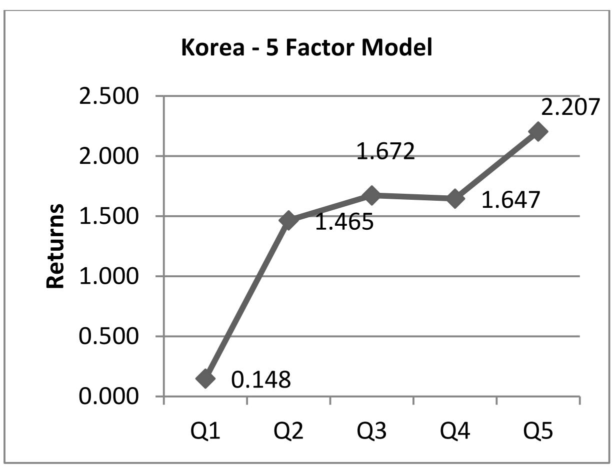


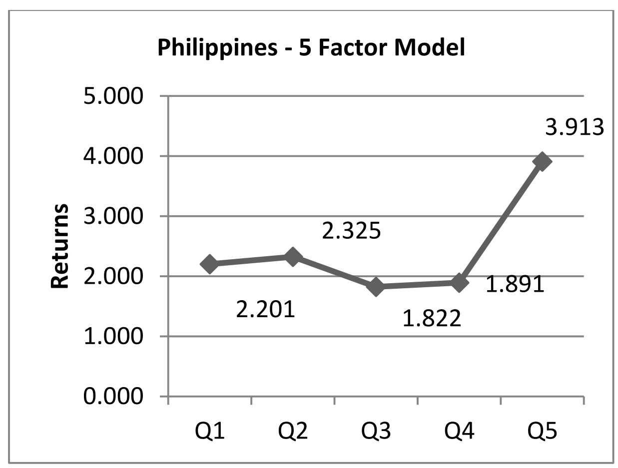

India - 5 Factor Model
Returns
3.000
2.500
2.000
1.500
1.000
0.500
0.000
1.631
2.499
2.001
2.221
2.562
Q1
Q2
Q3
Q4
Q5

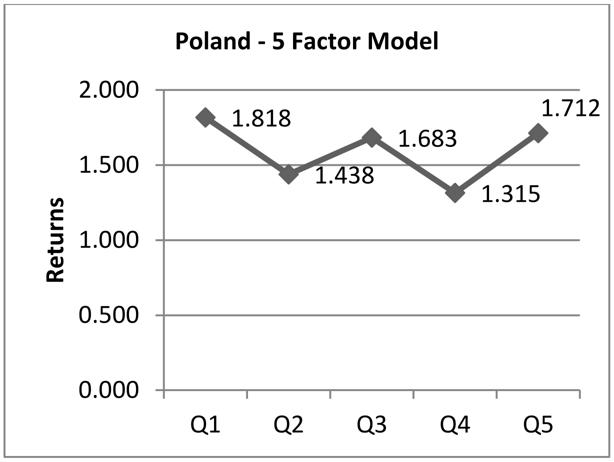

Malaysia - 5 Factor Model
Returns
2.500
2.000
1.500
1.000
0.500
0.000
0.782
0.837
0.845
1.697
2.145
Q1
Q2
Q3
Q4
Q5

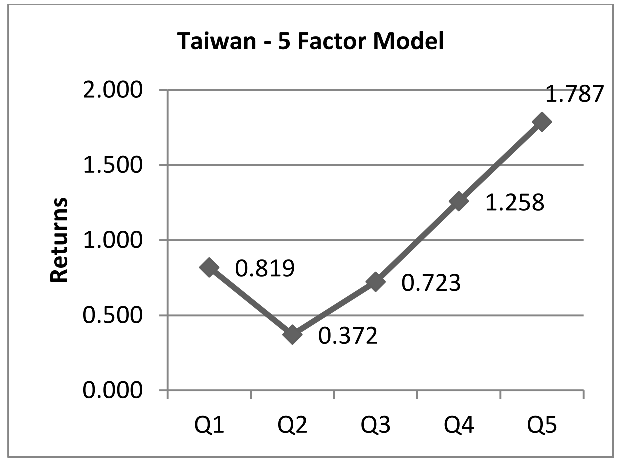

Israel - 5 Factor Model
Returns
12.000
10.000
8.000
6.000
4.000
2.000
0.000
1.146
1.092
10.021
1.781
2.336
Q1
Q2
Q3
Q4
Q5

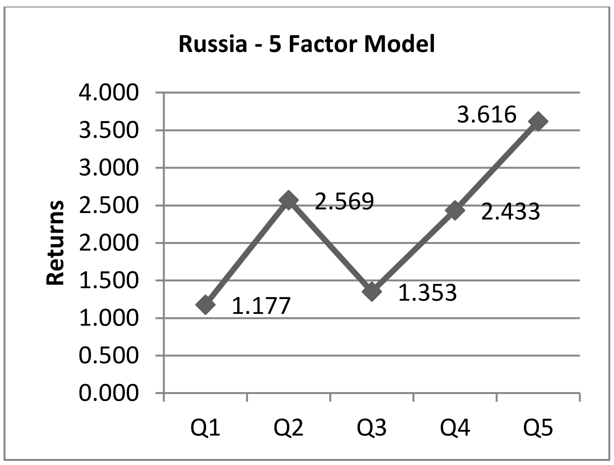

Mexico - 5 Factor Model
Returns
3.000
2.500
2.000
1.500
1.000
0.500
0.000
1.037
0.881
2.239
2.727
2.693
Q1
Q2
Q3
Q4
Q5

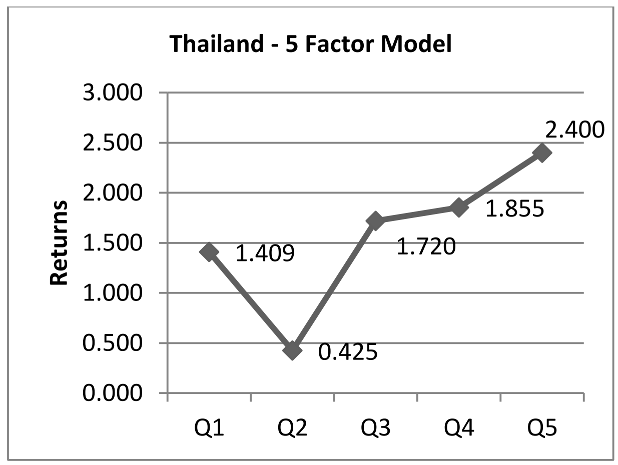

Korea - 5 Factor Model
Returns
2.500
2.000
1.500
1.000
0.500
0.000
0.148
1.465
1.672
1.647
2.207
Q1
Q2
Q3
Q4
Q5

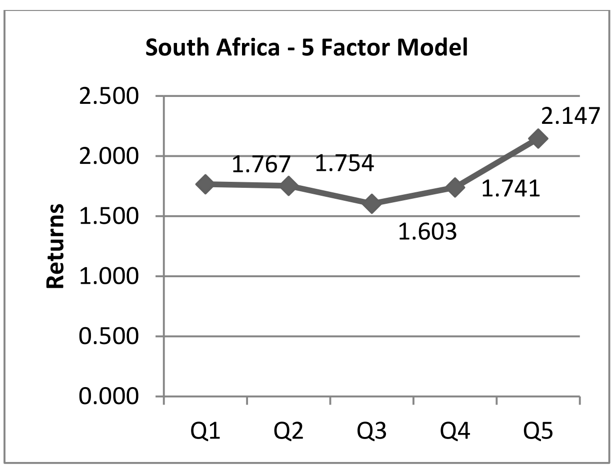

Philippines - 5 Factor Model
Returns
5.000
4.000
3.000
2.000
1.000
0.000
2.201
2.325
1.822
1.891
3.913
Q1
Q2
Q3
Q4
Q5

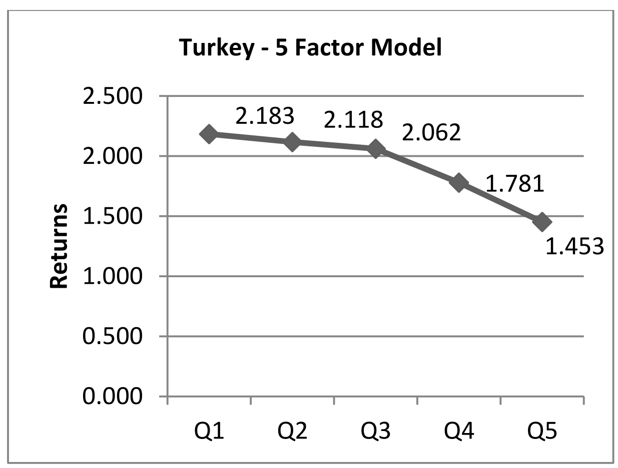

Poland - 5 Factor Model
Returns
2.000
1.500
1.000
0.500
0.000
1.818
1.438
1.683
1.315
1.712
Q1
Q2
Q3
Q4
Q5


Taiwan - 5 Factor Model
Returns
2.000
1.500
1.000
0.500
0.000
0.819
0.372
0.723
1.258
1.787
Q1
Q2
Q3
Q4
Q5


Russia - 5 Factor Model
Returns
4.000
3.500
3.000
2.500
2.000
1.500
1.000
0.500
0.000
1.177
2.569
1.353
2.433
3.616
Q1
Q2
Q3
Q4
Q5


Thailand - 5 Factor Model
Returns
3.000
2.500
2.000
1.500
1.000
0.500
0.000
1.409
0.425
1.720
1.855
2.400
Q1
Q2
Q3
Q4
Q5


South Africa - 5 Factor Model
Returns
2.500
2.000
1.500
1.000
0.500
0.000
1.767
1.754
1.603
1.741
2.147
Q1
Q2
Q3
Q4
Q5


Turkey - 5 Factor Model
Returns
2.500
2.000
1.500
1.000
0.500
0.000
2.183
2.118
2.062
1.781
1.453
Q1
Q2
Q3
Q4
Q5

CHAPTER 2

The Cyclical Behaviour of the Small Cap Premium: Empirical Evidence for the United States and Canada

2.1 Introduction

The small-firm effect refers to the empirical observation that risk-adjusted returns of small-capitalisation stocks tend to outperform on average those of larger capitalisation stocks over the long run and that this outperformance cannot be attributed solely to differences in market risk. Indeed, in the United States, a dollar invested in 1926 in the smallest ten percent of US stocks by market capitalisation (small-cap stocks) generated a return, at the end of 2006, that is almost 14 times larger than the return on a dollar invested in the largest ten percent (large-cap) of stocks. International small-cap stocks also tend to outperform global large-cap stocks over long time horizons. Early research often referred to the small-firm effect as a market anomaly because the excess returns on small-cap stocks could not be explained by the single-factor capital asset pricing model (CAPM), in which the asset's covariance with the market portfolio is the only relevant measure of risk.

The small-firm effect first came to prominence in the US, where Banz (1981) showed that the smallest companies listed on the New York Stock Exchange (NYSE) earned higher average returns than would be predicted by the Sharpe (1964) – Lintner (1965) capital asset-pricing model (CAPM). Using stock return data from 1936 to 1975 Banz (1981) finds statistically significant abnormal returns of five percent per annum for the smallest 20 percent of stocks by market capitalisation. The result is robust to the choice of market portfolio proxy, including value- and equally-weighted equity indices. Moreover, stocks of the smallest firms in the sample are found to outperform the largest ones by 19.8 percent per annum over the long term. Banz concludes that firm size is likely an important pricing factor for equities, but does not offer any theoretical explanations whether the factor is size per se or some other factor that is correlated with size.

A number of academic papers in the 1980s confirmed Banz's (1981) result using alternate data samples. Based on data for 566 NYSE and AMEX stocks between 1963 and 1977, Reinganum (1981) reports that for U.S. stock market data prior to 1980 small-cap stocks had significantly higher returns versus returns for large-cap stocks. Indeed, the author finds that stocks in the lowest decile by market capitalisation outperform the largest decile of stocks by 23.4 percent per annum. Subsequent academic papers that seek to shed additional light on this anomaly include Barry and Brown (1984), Brown et al. (1983), Keim (1983, 1989), Schultz (1983) and Stoll and Whaley (1983).

The small firm phenomenon is not unique to the US equity market, but has been shown for global equity markets as well. For instance, Annaert et al. (2004) provide evidence of a significant small firm premium of 1.5 percent per month in a sample of 2,866 European stocks for the period 1974-2000. Analyzing data for 1,420 quoted shares on the London Stock Exchange, Leledakis et al. (2004) discover a statistically significant small firm effect in the UK market. Rouwenhorst (1999) investigate emerging-market stocks between 1975 and 1997 and uncover a large and economically significant small-cap premium.

2.1.1 The Variation through Time of the Small Cap Premium

However, another group of recent academic papers assert that the small-firm effect has changed dramatically over the past 30 years and that it even may have disappeared since the original publication of the studies that discovered it. Indeed, these studies' empirical results present evidence that the anomaly did not persist, that the outperformance of smaller companies vanished, and that the out-of-sample small-firm premium turned negative. In the United States, the size effect in the nineties is manifested in a negative average size premium. These results echo many empirical irregularities in stock market returns where once an apparent anomaly is revealed only too often it vanishes or goes into reverse.

One of the first recognitions of this phenomenon is presented by Reinganum (1992) who notices that while the S&P 500 surge by 77.46% between November 1985 and October 1990, the DFA Small Company Fund increased only 1.15%. Corroborating Reinganum's paper (1992), Ibbotson and Sinquefeld (1995) show that, in general, small firm returns were significantly higher between 1971 and 1980 than between 1981 and 1990. Dichev (1998) demonstrates that the small firm premium was essentially non-existent in US equity markets during the period 1981 to 1998. Small-cap portfolios monthly returns underperform large-cap stock portfolios for both samples of stocks quoted on the NYSE/AMEX and stocks quoted on NASDAQ.

Similarly, Chan, Karceski and Lakonishok (2000) observe no significant small firm effect in US equity returns for the period 1984-1998. In an extensive study, Horowitz et al. (2000) observe no consistent link between size and realised returns over the period 1980-1996 using three alternative methodologies. Analyzing a comprehensive sample of NYSE, AMEX and NASDAQ stock exchanges firms from 1980 to 1996, the authors report that the lowest decile of stocks by market capitalisation earned 1.18 percent less on average than the largest decile of stocks.

Dimson and Marsh (1999) also contend that the small firm effect in the UK may have disappeared and that it even may have gone into a reverse trend after the early 1980s: the authors show that large-cap firms earned larger returns than small cap firms. The authors compare the performance of the smallest decile of UK firms by market capitalisation (HGSC index) with that of an all-share equity portfolio between 1955 and 1997. The average return for the HGSC index was 24.5 percent over the period 1955-1986, compared to 18.3 percent for the all-share portfolio, implying a statistically significant average small firm premium of 6.2 percent per annum. However during the subsequent decade, the HGSC generated an average return of less than 10.6 percent versus 17.1 percent for the all-share portfolio implying a statistically significant small firm discount of 6.5%.

Hence, studies written in the late 1990s and early 2000s present evidence that small-cap stocks fared poorly relative to large-cap stocks during the 1980s and the 1990s, instigating a number of researchers and market observers to declare the small firm premium dead.

Yet, another group of researchers, such as van Dijk (2011), contend that declaring the small firm premium dead may be a premature conclusion since the small firm effect had gone through long periods of underperformance even before 1980. While admitting that the small firm effect seems to have lessened through the eighties and nineties, van Dijk (2011) reports that the average small-cap premium was 11.3 percent per year over the period 2001-2010, revealing a possible reversal in the small firm effect trend from the previous ten years.

Brown et al. (1983) show that the excess return related to size is highly unstable over time. Analyzing NYSE and AMEX listed stocks, the academics present evidence that excess risk-adjusted for small-cap firms are higher than large-cap firms over the period 1967-79, but that the magnitude and sign of the relationship are not stable: an annualised small-firm excess return of -7.0 percent and 37.3 percent are measured for the periods 1967-1975 and 1976-1979 respectively. The results of the researchers' econometric tests reject the hypothesis that the small firm premium is constant over time, indicating that estimates of the small firm effect are greatly sensitive to the time period considered.

In the United States, while small-cap stocks outperformed large-cap stocks by 3.0 percent per year between 1927 and 2013, the degree of outperformance fluctuated considerably from period to period. The small firm premium was large prior to 1974, particularly large between 1975 and 1980, but diminished considerably after 1980.

All these empirical observations led to the assumption that the small firm effect may perform particularly better during periods of economic expansion and inversely underperform during periods of economic downturn. During the period 1926-2011, the small firm effect averaged -0.4 percent during economic recessions and 3.8 percent during economic growths. The standard explanation for this premium is that small-cap stocks are inherently riskier. The idea is that small-cap stocks are more volatile and more sensitive to overall market movements; they are also more exposed to systematic default risk and business cycle risk.

2.1.2 Research Objective and Research Contribution

This paper investigates the hypothesis that the small firm premium is related to macroeconomic and financial variables and that relationship is driven by the economic cycle in the United States and Canada. More specifically, this study employs recent advances in nonlinear time series models to explore the relationship between the small firm premium, and financial and macroeconomic variables in the Canadian and U.S. economies using novel and popular approaches to modeling macroeconomic and financial data i.e. the Hamilton's (1989) regime switching framework and the smooth-transition regression model (STAR).

The main research objective of this paper is to furthermore investigate the small cap premium by providing an in-depth analysis of the effect of financial and macroeconomic risk exposures on the small cap effect.

Hence, the current study contributes to the literature by providing further insights on the causes of the behaviour of the small cap premium; the current empirical literature reveals that only few studies, for instance, Switzer (2010, 2013) and Chan et al. (1985) examine the effect of economic and financial risk factors, and economic cycles on the level of the small cap premium.

The organization of the paper is as follows. Section 2 reviews the empirical evidence and theoretical explanations concerning the small-firm effect. Section 3 presents the literature review related to the relationship between the small firm effect and, macroeconomic and financial variables and the influence of the economic cycle on this relationship. Section 4 explains this study's objective and describes the data. Section 5 reviews the Hamilton's Markov switching regime and the smooth-transition regression models. Section 6 presents the empirical results and section 7 concludes.

2.2 Explanations for the Small Firm Effect

In this section, the main theoretical explanations concerning the small-firm effect which have been abundantly featured in the academic literature for the past decades are briefly explained.

The various studies that have attempted to explain the small cap premium and that have advocated factors that may account for the observed variation in the small-firm effect over time and its strong seasonality can be classified into three main groups: (1) studies that search for an explanation in the computation and statistical estimation errors; (2) studies that convey an economic or risk-based explanation for the small-firm effect; and (3) studies that suggest other several other explanations for the small cap effect.

2.2.1 The Small Firm Effect as a Statistical Outcome

Several researchers assert that the small-firm effect may be nothing more than a statistical artefact caused by measurement errors, data mining and various methodological biases. A potentially severe data snooping problem arises when many researchers employ the identical dataset to reveal pricing anomalies (Lo and MacKinlay (1990); Black (1993)). Academics in search of interesting research explore numerous diverse hypotheses but only expose and reveal the most appealing and surprising results. The statistical implication of these outcomes is debatable because it is subject to the number of tests conducted to derive the particular result. Every once in a while an interesting pattern is destined to arise simply by chance. The uncovered anomaly, however, will disappear out of sample. Black (1993) contends that the small cap premium suits this description because it largely weakened after its detection in 1981.

Several academics have tried to explain the small-firm effect by pointing out that: (1) measures of the riskiness of small-cap stocks are biased downward, and (2) measures of the average returns of small-cap stocks are biased upward. Roll (1981) claims that the riskiness of small-cap firms is devaluated due to serial correlation in small-cap returns. Consequently, risk measures computed from short-interval return data such as daily returns considerably understate the true systematic risk (beta) of small-stock portfolios. In Roll's viewpoint, the detected significant small-firm effect reflects the true greater systematic riskiness of small stocks rather than a significant economic or empirical anomaly. Reinganum (1982) acknowledges Roll's argument that security betas for small-cap firms may be to some extent biased downward, but demonstrates that the size of the bias is too trivial to explain the small-firm effect.

In summary, numerous studies assert that the small-firm effect may be nothing more than a statistical artefact. However, because the small-firm premium has been documented in several international stock markets the assumption for the statistical artefact remains questionable. While the scale of the small-firm effect may be influenced by a number of statistical issues, none of the studies has been able to completely explain the significant evidence for the small-firm premium over the long-term.

2.2.2 Macroeconomic Factors

Firm market capitalization may be a proxy for some undisclosed macroeconomic or other specific risk factor that influences the dynamic of expected asset returns. Since small-cap stocks carry relatively greater exposure to this size-related systematic risk factor than large capitalization firm stocks, they generate superior returns in equilibrium. If so, the observed small-firm premium reflects investors' compensation for the exposure to risk rather than an anomalous pattern.

Fama and French (1992, 1993, 1996) are advocates of this risk-based approach. To demonstrate their argument the authors first build an equally weighted long-short portfolio mimicking the small-cap premium (called "small minus big", or SMB) that is constructed by going long the smallest 30 percent of firm stocks and going short the largest 30 percent of firm stocks. In the same vein the authors construct an equally weighted long-short portfolio mimicking the value (book-to-market) premium (called "high minus low", or HML) that is constructed by going long the 30 percent of firm stocks with the highest book-to-market ratio and going short the 30 percent of firm stocks with the lowest book-to-market ratio.
They then show that a three-factor model, which contains factors reflecting a company's size (SMB) and equity valuation (HML) in addition to the CAPM market factor, has greater explanatory power for equity returns than the CAPM alone. Using US stock return data from 1963 to 1991, Fama and French (1992) present robust empirical evidence that the SMB and HML factors represent the most significant common return factors besides market risk, for describing the dynamic behavior of realised stock returns. Their investigation aims towards an economic risk explanation for the small firm effect and the related value anomaly.

Numerous researchers assert that the SMB portfolio may be a proxy for several macroeconomic risk factors linked to consumption and investment. Liew and Vassalou (2000) investigate whether the dynamics of the Fama-French factors, as well as Carhart's momentum factor, can be attributed to the future GDP growth. Analyzing ten countries between 1978 and 1996, the authors show that the SMB carries significant information about future GDP growth non-related to the information included in the market factor.

Zhang et al. (2009) also discover a positive link between the SMB factor and future GDP growth and a negative relationship between SMB and unexpected inflation. Small-cap stocks are also found to generate greater returns than large-cap stocks when the short term rates are low and the term spread is high.

Several additional state variables have been related to the SMB factor. Petkova (2006) asserts that the SMB portfolios may be linked to shocks in state variables that forecast excess market returns. In her paper the author present a model that relates average stock returns to variations in aggregate dividend yield, default spread and short-term treasury rates; this approach allows explaining the cross-sectional variation in equity returns better than the Fama-French model. When loadings on the shocks in the predictive variables are incorporated in the model, loadings on SMB lose their explanatory power, implying a strong correlation between the SMB portfolio and the default spread.

2.2.3 Other Explanations

2.2.3.1 The Small Firm Effect as a CAPM Anomaly

The outperformance of small-capitalization stocks cannot be explained uniquely by market risk. The CAPM’s failure to justify the small-firm effect has prompted an enduring debate regarding the nature of this stock market pattern.

Similar to other stock return anomalies, the small-firm premium was uncovered from assessing empirically the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965) and Black

(1972). The CAPM asserts that the market portfolio of invested wealth is mean-variance efficient, involving a linear relationship between the expected return on a stock and his covariance with the market portfolio. In equilibrium and according to this model, the asset's beta is the only factor that matters for pricing assets because it is the only important measure of risk and an appropriate variable to explain the cross-sectional variation in expected returns. From the CAPM equation, the abnormal return on a portfolio of small-cap firm stocks is measured by Jensen's (1968) alpha:

$$\alpha_i : R_{it} - R_{it} - \beta_i \ (RM_{it} - RF_{it}) \tag{2.1}$$

where: R_{it} is the return on a portfolio of small-cap stocks R_{it} = the risk-free rate, typically the yield on Treasury bills and RM_{it} is the return on the market portfolio, typically proxied by a major equity index.

2.2.3.2 Conditional Models

Numerous researchers have tried to explain the small firm effect by including time variation in the covariance of asset returns with the market return (conditional CAPM) or with consumption growth (conditional consumption CAPM). In these models, the asset's beta is not constant as in the traditional CAPM but fluctuates to reflect variations in a pre-defined conditioning variable. The economic reasoning behind a conditional model for the small firm effect is that small and large-cap stocks may have different sensitivities to systematic risk in good and bad times. Lettau and Ludvigson (2001) use the log–consumption-to-wealth ratio as a conditioning variable to demonstrate that conditional specifications perform superiorly than unconditional models and comparably to the Fama-French three-factor model in describing the cross-section of average returns. Once the conditioning information conveyed by the log-consumption-to-wealth ratio is incorporated in the specification, no residual small firm effect persists in the data.

Likewise, Santos and Varonesi (2006) demonstrate that using the fraction of total income produced by wages as a conditioning variable in the CAPM describes the cross-section of 25 Fama-French portfolios formed on value and size. Small firm stocks display evidence to be riskier in bad times, exhibiting higher betas in market downturns.

Campbell and Vuolteenaho (2004) present strong empirical evidence that small stocks' outperformance is caused by higher cash flow risk. The authors rationalise the small firm effect via an economically induced two-beta model in which they split the CAPM beta of a stock into two elements: one that reflects news about the company's future cash flows, and one that reflects news about the discount rate. Intertemporal asset pricing theory suggests that risk-averse investors avoid cash flow risk (the "bad beta") more than discount rate risk (the "good beta"). Consequently, the price of cash flow risk is greater than the price of the "good" discount rate risk. In equilibrium, the ratio of the two prices must equal the risk aversion coefficient that makes an investor satisfied to hold the aggregate market. They subsequently show empirically that small stocks have significantly greater cash flow betas than large stocks, which can explain their higher average returns in the cross-section. The two-beta model hence implies that investors with higher tolerance for risk and a long term investment horizon will massively invest in these stocks compare to the average investor.

2.2.3.3 Liquidity

Another group of studies has tried to relate the small firm effect to liquidity risk. Amihud and Mendelson (1986) investigate whether stock returns rise with bid-ask spreads. Analyzing data between the years 1961-1980, the authors find that portfolio-risk-adjusted returns augment with the bid-ask spread, a relation that persists when firm size is incorporated as an explanatory variable in the regression equation. This result shows that liquidity effects may account for a part of the small firm effect. Likewise, Stoll and Whaley (1983) present empirical evidence that at least part of the small firm effect may be attributed to transaction costs. However, Chen and Kan (1995), who re-examine Amihud and Mendelson's results under diverse econometric approaches, discover no strong relationship between stock returns and transaction fees as measured by bid-ask spreads. The researchers question whether the cross-sectional variation in the bid-ask spread really represent a significant element of the small firm effect.

2.2.3.4 Neglected Firm Risk

Several studies suggest that additional risk related to investing in small firm stocks may exist because information on these stocks is relatively rare. Ignored firms may be riskier because (1) fewer institutions follow such companies, which increases the probability that insiders might appropriate shareholder value, and (2) there is higher uncertainty concerning firm value due to scarce information. Arbel and Strebel (1982) show that stocks of firms that are least followed by stock analysts earn a premium on a CAPM risk–adjusted basis over stocks that receive more attention.

All in all, risk-based theories for the small firm premium have generated mixed empirical results. Moreover, all of the risk-based theories are unable to describe well the time variation the small firm effect and the small firm effect's seasonality.

2.2.3.5 Behavioural Finance

In contrast to Fama and French (1993), several academics claim that the small firm effect may not be directly related to systematic risk. Rather, the small firm effect may be induced by factors external to the classic asset pricing model such as investor behaviour, institutional constraints and market frictions. Advocates of behavioural finance suggest that investors have a propensity to deviate from the assumed rational behaviour underlying the efficient market hypothesis, thereby triggering pricing anomalies.

Lemmon & Portniaguina (2006) provide evidence of a negative link between investor sentiment and the dynamic behavior of returns on small firm stocks since 1977. They argue that investors are inclined to overvalue small-cap stocks versus large-cap stocks when they are particularly bullish and undervalue them when they are bearish. Sentiment has a particularly great impact on small-cap stock valuations because small firms are usually held by individual traders who are more likely to be influenced by sentiment. However, they uncover no link between investor sentiment and small-cap returns before 1977, and provide no explanation on the decrease of the small firm effect after 1981.

2.3 Literature Review on the Cyclical Behaviour of the Small Cap Effect

As mentioned previously, the academic literature on the small firm effect has offered several reasons for the negative relationship between market capitalization and returns. One of the most cited sources of the small firm premium is that size might be related to some common risk factor that explains the negative relationship between size and stock return: firm capitalization could be a proxy for some undiversifiable source of risk and various macroeconomic variables that governs the cross-section of expected returns. In good economic environments, small firms usually grow faster than large, mature firms, but in the worst economic conditions small firms are inclined to perform poorly or even go into bankruptcy.

Periods of economic downturns typically foster investors to search for relative safety. Small firms tend to be distressed firms, even in the best of times. Over the trough of the business cycle, small-cap stocks embody the most vulnerable firms. Expecting small-cap stocks to carry the burden of a recession, investors are prone to depart from these types of stocks in search of safer investments.

In a series of seminal papers, Fama and French (1992, 1993, 1996) suggest the conjecture that the small-cap effect do not represent an anomaly, but instead reflects the greater systematic risk of small firm stocks: these firms tend to carry higher distress risk than larger firms. Because of this additional source of risk, a factor based on firm size, along with factors based on the firm's book-to-market and the market portfolio, could better describe the cross-sectional variation in stock returns. Empirically, Fama and French studies show that three determined variables, i.e., market, size, and value, perform well in describing the largest share of the cross-sectional average return of the NYSE, AMEX, and NASDAQ equity exchanges between 1963-1990. Subsequent studies investigating other equity markets and countries establish a similar conclusion. While Fama and

French (1993) mention that size and book-to-market are related to economic fundamentals or may act as proxies for firm characteristics such as profitability or relative financial distress risk, they do not develop a comprehensive theory for what the underlying systematic risk factors in their model represent.

Studying returns over the period 1976–1995, Kim and Burnie (2002) assert that differentially higher returns for small cap firms relative to large firms are observed during economic expansion phases and investigate whether that time-varying nature of the firm size effect may be attributable to the state of the business cycle per se or due to uncertainty factors including default risk, interest rate risk, and inflation risk that may be distinct from economic cycle effects for small cap vs. large cap firms. The authors find evidence that the differential returns for small firms vs. large firms are due to the business cycle, as captured by dummy variables in their regression model.

Reinganum (1982) investigates the differential return between small and large stocks between 1926 and 1989 to assess the economic cyclical dynamic and observes that the small capitalization stocks outperformed the large firm stocks, but this return behaviour was volatile and tended to reverse itself.

In a similar vein, Chan and Chen (1991) investigate the assumption that the small firm effect is influenced by the economic cycle as they observe that in periods of economic expansion small firms generate large abnormal profits; however, in periods of economic downturn no significant small firm stock returns performance is manifest. The authors assert that this assumption is based on the fact that most small firms are characterized by relatively low production efficiency, lower return on assets, high financial leverage and high sensitivity of cash flows to adverse economic developments consequently making them more vulnerable to adverse changes in business conditions and economic downturns. Using US stock returns and accounting data from 1956 to 1985, they create two size-matched return indices intended to mimic the return behaviour of small firms and find that these indices can describe the dynamic in equity returns of small and large capitalization firms. This evidence support the hypothesis that differences in relative distress risk between small and large-cap firms may account for the small firm effect.

Chan, Chen, and Hsieh (1985) report that the firm size effect vanishes when several economic factors are used, such as the change in expected inflation, unanticipated inflation, default risk premium, and a term structure variable, to alter the traditional capital asset pricing model (CAPM). Chan, Chen, and Hsieh (1985) conclude that the variations in the default risk premium are positively related to changing economic conditions.

Moscarini and Postel-Vinay (2009) assert that the small firm effect is linked to job creation: large companies lay off proportionally more employees during and following recessions, and hire proportionally more employees late in expansions, than do small firms. In their subsequent paper, Moscarini and Postel-Vinay (2010) show that this dissimilar employment pattern is able to explain in part the larger performance of U.S. small firms during periods of economic growth.

Vassalou and Xing (2004) analyze US stock return data from 1971 to 1999 and find that the small firm effect is statistically significant only for the quintile of stocks with the greatest default risk. The authors' results point to the conclusion that the size effects can be viewed as default effect and that market capitalization may reflect default-related information.

Switzer (2010) investigates the return dynamic of small-caps and large caps during periods of economic downturns and expansions and reviews the relationship between the small firm effect and the business cycle in Canada and the United States. The author finds that small-cap firms outperform large caps over the year following an economic trough but underperform in the year preceding an economic peak and also present evidence that the US small cap premium is associated with default risk.

2.4 Data Description

This paper investigates the impact of several risk factors that have been assumed to be significant exposures influencing the returns to firms (Chen, Roll, & Ross (1986), Ferson & Harvey (1991)) and that may be independent from the state of the business cycle per se in affecting the return spread between large-cap and small-cap companies. Switzer (2010) considers three such risk exposures: default risk (*Default*), term structure risk (*Term*), and inflation risk (*Inflation*). He finds that the small-cap premium is significantly influenced by the default risk in the economy, corroborating Vasilou and Xing (2004) but is unable to detect the same impact for the term structure and inflation factors.

Default risk is computed by the long term corporate to government yield spread (*Default*). A positive default risk premium is coherent with the desire of investors to hedge against unanticipated increases in the aggregate risk premium prompted by economic slowdowns (Ferson & Harvey, 1991). Fama and French (1995) suggest that the small firm premium is a proxy for a default risk factor. Beck and Demirguc-Kunt (2006) stress that small and medium size companies are more subject to default risk than large firms because of their lack of capital and liquidity. Switzer (2010) finds that the US small cap premium is significantly influenced by the default risk factor which may affect investments in R&D and innovation. And Denis & Denis (1995) present evidence that default risk is associated to macroeconomic factors and that it varies with the business cycle.

Term structure risk is also incorporated as a possible factor influencing the small cap premium. An increasing term structure signifies a higher degree of longer term assets' riskiness establishing a distinct premium for small caps firms since they are usually more exposed to leverage risk than large cap firms.

Inflation risk is also included as a factor having an impact affecting stock returns (e.g., Bekaert (2009), Boudoukh & Richardson (1993), Fama (1981)): inflation risk undermines the performance of investments and stocks that have low returns during inflationary times will hence command a risk premium. Moreover since small firms usually operate in competitive business environments, they may have less pricing power than larger companies, and hence may be more exposed to inflation uncertainty which leads to a greater inflation premium exposure relative to larger firms.

The U.S. small cap premium monthly returns is retrieved from the Ibbotson/DFA database which is available from January 1926. The US risk factors are obtained from Morningstar EnCorr. Default risk (bond default premium) is measured by the geometric difference between total returns on long-term corporate bonds and long-term government bonds. Term structure risk (bond horizon premium) is measured by the geometric difference between Government Long Bond and Treasury Bill Returns. Inflation is based on the US consumer price index. The Canadian small cap premium and the three risk factors data series are also obtained from Morningstar EnCorr database. Both the data on the U.S. and Canadian small cap premiums were retrieved from the Ibbotson Associates (IA) database whose methodology to define small stocks consists of sorting companies by market capitalization i.e. stock price multiplied by shares outstanding and then splitting the group into deciles.

Small cap stocks comprise the bottom quintile of capitalization (deciles 9-10) and the small stock premium measures the excess return of small over large stocks (first decile) over a period.

To further explore the link between the small cap premium and different risk factors in a non-linear form, a test of rejection of linearity should be carried on the dependent variable *i.e.* the small firm premium. Teräsvirta (1994)'s model will allow us to confirm or reject the non-linear dynamics of the small cap premium.

Terasvirta (1994)'s model performs a Lagrange multiplier test for linearity versus an alternative of LSTAR or ESTAR in a univariate autoregression:

$$y_t = \beta_0 + \sum_{j=1}^{p} \beta_{1j} y_{t-j} + \sum_{j=1}^{p} \beta_{2j} y_{t-j} y_{t-d} + \sum_{j=1}^{p} \beta_{3j} y_{t-j} y_{t-d}^2 + \sum_{j=1}^{p} \beta_{4j} y_{t-j} y_{t-d}^3 + e_t \qquad (2.2)$$

In this study both the lags value p and the delay parameter d equals 1[5]. The null hypothesis of linearity is therefore $\beta_2 = \beta_3 = \beta_4 = 0$. If the null hypothesis is rejected, the next step is to choose between LSTAR and ESTAR models by a sequence of nested tests:

H_{01} is a test of the first order interaction terms only: $\beta_2 = 0$

H_{02} is a test of the second order interaction terms only: $\beta_3 = 0$

H_{03} is a test of the third order interaction terms only: $\beta_4 = 0$

H_{12} is a test of the first and second order interactions terms only: $\beta_2 = \beta_3 = 0$

The decision rules of choosing between LSTAR and ESTAR models are suggested by Teräsvirta (1994): Either an LSTAR or ESTAR will cause rejection of linearity. If the null of linearity is rejected H_{12} and H_{03} become the appropriate statistic if ESTAR is the main hypothesis of interest:

[5] There exists no econometric specification that allows to precisely determine the value of the delay parameter p. Most of the literature related to non-linear STAR models uses $p = 1$.

If both H_{12} is rejected and H_{03} is accepted, this may be interpreted as a favor of the ESTAR model, as opposed to an LSTAR.

Table 2.1 exhibit the results of the Teräsvirta (1994) linearity test performed on U.S. and Canadian small cap premium and shows that the hypothesis of linearity is rejected for both countries which implies that both small cap premiums follow non-linear dynamics. Furthermore, the table indicates that hypothesis H_{12} rejection and hypothesis H_{03} acceptance do not occur simultaneously which implies that the LSTAR model is the appropriate specification for both the U.S. and Canadian small cap premiums.

Table 2.1 Teräsvirta (1994) Non-Linearity Test Results

This table shows the results of the Teräsvirta (1994)'s approach to first test for linearity of the small cap premiums in the U.S. and Canada. If the hypothesis of linearity is rejected and H_{03} is accepted while H_{12} is rejected then the specification will point toward an ESTAR instead of a LSTAR model.

	U.S. Small Cap Premium		Canadian Small Cap Premium	
	F-Value	Significance	F-Value	Significance
Linearity	5.675	0.0007	6.226	0.0004
H_{01}	14.478	0.0001	0.197	0.6571
H_{02}	2.324	0.1277	1.057	0.3042
H_{03}	0.190	0.6625	17.450	0.0000
H_{12}	1.257	0.2848	9.255	0.0001

2.5 The Regime-Switching Models

In this study, the two non-linear econometric models that are employed to investigate the relationship between the small cap premium and several macroeconomic and financial variables are the Markov regime switching framework approach of Hamilton (1989) (MSR) and the smooth-transition regression model (STAR).

More specifically the two-state Markov-chain regime-switching model and Smooth Transition Autoregressive Model (STAR) are employed to assess the marginal effects of a vector of financial and macroeconomic variables in explaining the variation in the small cap premium in the United States for the period January 1926 to December 2013 and in Canada for the period January 1970 to December 2013. The incorporation of financial and macroeconomic indicators allows estimating whether major changes in the dynamic of the small firm effect are also likely to be in response to broader changes in the macroeconomic and financial environment. Hence, the regime-switching models include a number of key macroeconomic and financial variables as controls for the underlying forces that may act as catalysts for critical variations in the small firm premium.

2.5.1 The Hamilton's (1989) Regime-Switching Model

The Hamilton (1989) Regime-Switching Model assumes that the behaviour of certain macroeconomic or financial indicators changes as a result of changes in economic activity. However, the state of economic activity, which is unobservable and which determines the process that generates the observable dependent variable is inferred through the observed behavior of this dependent variable. In the original Hamilton model (1989), it was assumed, as well as in this study, that there were two possible states of economic phases (regimes), corresponding to the condition of an economy (prosperity vs. recession).

Let y denote the macroeconomic variable for month t and for which its historical behavior can be described by the following econometric specification:

$$y_t = a_t + \sum_{k=1}^{N} b_k X_{k,t-1} + \varepsilon_t \tag{2.3}$$

where X_{t-1} is a k-vector of explanatory variables and the b_k terms are the corresponding factor loadings. The intercept term a_t follows a two-state Markov chain, taking values a_1 and a_2, with the probability π_{ij} of switching from state i to state j is given by the matrix:

$$\begin{bmatrix} \pi_{11} & \pi_{21} \\ \pi_{12} & \pi_{22} \end{bmatrix}$$

Moreover let ξ_{it} represent the probability of being in state i in month t conditional on the data and η_{jt} the densities under the two regimes which are given by:

$$\eta_{it} = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-\left(y_t - a_{jt} - \sum_{k=1}^{N} b_k X_{k,t-1}\right)^2}{2\sigma^2}\right) \tag{2.4}$$

where σ represents the volatility of the residuals ε_t which are assumed to follow an independent and identically distribution (*iid*) to allow performing standard maximum log likelihood functions.

All i and j are then sum up to compute the likelihood function f_t,

$$f_t = \sum_{i=1}^{2} \sum_{i=1}^{2} \pi_{ij} \, \xi_{i,t-1} \eta_{jt} \tag{2.5}$$

The state probabilities are then re-estimated by the recursive specification

$$\xi_{j,t} = \frac{\sum_{i=1}^{3} \pi_{ij}\xi_{i,t-1}\eta_{it}}{f_t} \tag{2.6}$$

The log likelihood function for the data can hence be estimated by summing the log likelihoods for each date by using standard maximum likelihood procedures.

2.5.2 The Smooth-Transition Regression Model

The other popular model that has been extensively used in the past two decades to modelling nonlinearities in the dynamic properties of many economic time series and for summarizing and explaining cyclical behavior of macroeconomic data and business cycle asymmetries is the Smooth Transition Autoregressive Model (STAR), which was developed by Teräsvirta (1994) and Granger and Teräsvirta (1993).

The smooth transition autoregressive (STAR) model for a univariate time series y_t, is given by:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_0 y_{t-i} + F(\xi_t, \gamma, c)\left[\beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i}\right] + \varepsilon_t \tag{2.7}$$

where $F(\xi_t, \gamma, c)$ is a transition function which controls for the switch from one regime to the other and is bounded between 0 and 1. The scale parameter $\gamma > 0$ is the slope coefficient that determines the smoothness of the transition: the higher it is the more abrupt the change from one extreme regime to the other ξ_t. The location or threshold parameter between the two regimes is represented by c and ξ_t is called the transition (threshold) variable, with $\xi_t = y_{t-d}$ (d a delay parameter).

Two popular selections for the transition function are the logistic function (LSTAR) and the exponential function (ESTAR). The LSTAR function is specified as:

$$F = [1 + \exp(-\gamma(\xi_t - c))]^{-1} \tag{2.8}$$

while the ESTAR function is specified as:

$$F = 1 - \exp(-\gamma(\xi_t - c)^2) \tag{2.9}$$

The main difference between these two STAR models relies on how they describe macroeconomic series dynamic behaviour. The LSTAR model reflects the asymmetrical adjustment process that usually characterize economic cycles: a sharper transition and sharp recovery following business cycle troughs compare to economic peaks. In contrast, the ESTAR specification suggests symmetrical adjustment dynamic.

To determine the adequate transition function to apply to the data, Terasvirta (1994) suggests a model selection procedure which is explained and applied in section 2.4.

While an exogenous variable could be employed as the transition variable, in this paper as per the majority of research studies using STAR models, the dependent variable (the macroeconomic proxies) plays this role and d equals one, meaning that the first lagged value of the macroeconomic variable investigated acts at the threshold variable.

In the Smooth Transition Autoregression (STAR) all predetermined variables are lags of the dependent variable. An extension to the STAR model is the smooth transition regression (STR) model which is an amendment to the STAR model that allows for exogenous variables $\mathrm{x}_{1\mathrm{t}}, \ldots, \mathrm{x}_{\mathrm{kt}}$ as additional regressors. In this study, the applied STR model includes other exogenous factors the *i.e.* the liquidity measures and the factors *Term*, *Cred*, *Vola*, er_m. The standard method of estimation of STR (STAR) models is nonlinear least squares (NLS), which is equivalent to the quasi-maximum likelihood approach.

Two interpretations of a STR (STAR) model are possible. First, the STR model may be thought of as a regime-switching model that allows for two regimes, associated with the extreme values of the transition function, $F(\xi_t; y, c) = 0$ and $F(\xi_t; y, c) = 1$, where the transition from one regime to the other is smooth. The regime that occurs at time t is determined by the observable variable ξ. Second, the STR model can be said to enable a continuum of states between the two extremes. The key advantage in favour of STR models is that changes in some economic and financial aggregates are influenced by changes in the behaviour of many diverse agents and it is highly improbable that all agents respond instantaneously to a given economic signal. For instance, in financial markets, with a considerable number of investors, each switching at different times (probably caused by heterogeneous objectives), a smooth transition or a continuum of states between the extremes seems more realistic.

Both the Hamilton's (1989) Markov switching regime model and the smooth transition autoregressive model assume that the series under examination are stationary. Indeed these specifications investigate time series by distinguishing non-stationary or stationarity linear systems from stationary nonlinear ones.

2.6 Empirical Results

Table 2.2 shows the descriptive statistics of the small cap premium in the U.S. and in Canada, and the three exposure risk variables (default, inflation and term).

Table 2.2 Descriptive Statistics

Descriptive statistics for the U.S. and Canada for the small cap premium, the default factor, the inflation factor, and the term risk factor. The data for the U.S. covers the period January 1926 through December 2013 while for Canada the sample spans the period January 1970 to December 2013.

U.S.

Variable	Number Obs.	Mean	Std. Dev.	Min.	Max.
Small Cap Prem.	1056	0.0027	0.046	-0.179	0.398
Default	1056	0.0004	0.013	-0.096	0.075
Inflation	1056	0.0024	0.005	-0.020	0.059
Term	1056	0.0019	0.023	-0.112	0.144

Canada

Variable	Number Obs.	Mean	Std. Dev.	Min.	Max.
Small Cap Prem.	528	0.0075	0.054	-0.278	0.251
Default	528	0.0041	0.005	-0.002	0.039
Inflation	528	0.0035	0.004	-0.010	0.026
Term	528	0.0100	0.017	-0.054	0.039

2.6.1 Empirical Results for the United States Small Cap Premium

2.6.1.1 Results for the United States Using the MSR Model

The empirical results are reported in Table 2.3. As shown, the regime-switching model identifies two distinct regimes for the small cap premium: regime 1 corresponding to a prosperity economic phase and regime 2 representing a contraction economic phase. In the first regime only one explanatory variable is statistically significant: the default rate exposure which has a value of 0.39. In the second regime all three explanatory variables are strongly significant with coefficients of 4.89, 4.50 and 9.81 for the default, inflation and term structure risk exposures respectively.

Table 2.3 U.S. Small Cap Premium – MSR Model
January 1926 – December 2013
Table 2.3 shows the parameter estimates and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model used to model the U.S. small cap premium. The regime-switching model is estimated using the monthly returns of the DFA Small Cap Premium for the period January 1926 – December 2013. The financial and macroeconomic explanatory variables are the default corporate bond, inflation and term structure described in more details in section 4. Significant coefficients of the risk factors are marked in bold.

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
Regime 1: Economic Expansion				
a_1	0.0011	0.0014	0.8160	0.4144
Default	**0.3895**	0.1114	3.4937	**0.0005**
Inflation	0.1745	0.2712	0.6435	0.5199
Term	-0.0647	0.0665	-0.9723	0.3309
Regime 2: Economic Recession				
a_2	0.0155	0.0095	1.6192	0.1054
Default	**4.8809**	0.6054	8.0619	**0.0000**
Inflation	**4.5028**	1.3996	3.2170	**0.0013**
Term	**9.8123**	0.6712	14.619	**0.0000**

2.6.1.2 Results for the United States Using the STAR Model

The empirical results for the smooth-transition regression model are reported in Table 2.4. It is interesting to observe that both the Markov switching regime model and the smooth-transition regression model provide similar results. Indeed in the first regime only one explanatory variable is statistically significant: the default rate exposure which has a value of 0.32. In the second regime all three explanatory variables are strongly significant with coefficients of 2.61, 2.32 and 1.02 for the default, inflation and term structure risk exposures respectively.

2.6.1.3 Interpretation of the Empirical Results for the United States

These results, both under the Markov regime switching and the smooth transition regression model, present evidence that default risk affects the return differential between large cap and small cap firms and that this relationship is independent from the economic activity phases: the default risk coefficients remain extremely statistically significant under both regimes. This finding corroborates Switzer's (2010) conclusion that the US small cap premium is significantly related to default risk in the economy, which may impact on investments in R&D and innovation. However, the term structure risk exposure and inflation risk exposure coefficients are positive and greatly significant under recessions (Regime 2) but not under expansion phases (Regime I) indicating that term risk and inflation risk affect differentially small cap vs. large cap firm returns under contraction economic phases.

Table 2.4 U.S. Small Cap Premium – STAR Model
January 1926 – December 2013

Table 2.4 shows the parameter estimates and their *t*-statistics from the non-linear estimation of the smooth-transition regression model to model the small cap premium. The regime-switching model is estimated using the monthly returns of the DFA Small Cap Premium for the period January 1926 – December 2013. The financial and macroeconomic explanatory variables are the default corporate bond, inflation and term structure described in more details in section 4. Significant coefficients of the risk factors are marked in bold.

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
Regime 1: Economic Expansion				
a_1	0.0020	0.0016	1.2420	0.2145
Default	**0.3181**	0.1226	2.5938	**0.0096**
Inflation	-0.0668	0.2835	-0.2356	0.8137
Term	-0.0017	0.0676	-0.0264	0.9789
Regime 2: Economic Recession				
a_2	0.0007	0.0077	0.00959	0.9235
Default	**2.6152**	0.5203	5.0260	**0.0000**
Inflation	**2.3226**	1.0078	2.3046	**0.0213**
Term	**1.0298**	0.3859	2.6677	**0.0077**

	Coefficients	*t*-Statistic
Gamma	96.707	0.005
c	0.021	0.341

Mean of Dependent of Variable	0.0026
Std Error of Dependent Variable	0.0469
Sum of Squared Residuals	2.1426
Regression *F*(3.1056)	7.8822
Significance Level of *F*	0.0000

2.6.2 Empirical Results for the Canadian Small Cap Premium

The United States is and has been for the past century the largest economy and because of its proximity with Canada has a tremendous impact and influence on the northern neighbouring country economy. For these reasons, the Canadian small cap premium will be investigated in relation to both Canadian and U.S. risk factors.

2.6.2.1 Results using Canadian Risk Factors and the MSR Model

Table 2.6 shows the empirical findings when examining the Canadian small cap premium relative to Canadian risk factors. In the first regime only one explanatory variable is statistically significant: the term spread exposure which has a coefficient of 0.0036. In the second regime two explanatory variables become statistically significant with coefficients of 13.190 and 0.0293 for inflation and term structure risk exposures respectively.

2.6.2.2 Results using Canadian Risk Factors and the STAR Model

Table 2.7 exhibits the same relationship analyzed in the previous section. In the first regime, the same risk exposure is strongly significant: the term spread exposure coefficient which has a value of 0.0065. In the second regime, only one explanatory variable is statistically significant i.e. inflation risk exposure, with a coefficient of -2.9865 for inflation.

Table 2.5 Canadian Small Cap Premium and Canadian Factors – MSR Model

Table 2.5 shows the parameter estimates and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model used to model the Canadian small cap premium. The regime-switching model is estimated using the monthly returns obtained from the Ibbotson database for the period January 1970 – December 2013. The financial and macroeconomic explanatory variables are the Canadian default corporate bond, inflation and term structure described in more details in section 4. Significant coefficients of the risk factors are marked in bold.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Regime 1: Economic Expansion				
a_1	0.0104	0.0031	3.3189	0.0009
Default	-0.0070	0.0041	-1.7067	0.0879
Inflation	-0.0009	0.0040	-0.2403	0.8100
Term	**0.0036**	0.0012	2.8032	**0.0051**
Regime 2: Economic Recession				
a_2	-0.2076	0.0319	-6.4946	0.0000
Default	0.0108	0.0203	0.5316	0.5950
Inflation	**13.190**	2.2811	5.7824	**0.0000**
Term	**0.0293**	0.0131	2.2325	**0.0256**

Table 2.6 Canadian Small Cap Premium and Canadian Factors – STAR Model

Table 2.6 shows the parameter estimates and their asymptotic t-statistics from the non-linear estimation of the smooth transition autoregressive model used to model the Canadian small cap premium. The regime-switching model is estimated using the monthly returns obtained from the Ibbotson database for the period January 1970 – December 2013. The financial and macroeconomic explanatory variables are the Canadian default corporate bond, inflation and term structure described in more details in section 4. Significant coefficients of the risk factors are marked in bold.

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
Regime 1: Economic Expansion				
a_1	-0.0083	0.0065	-1.2647	0.2065
Default	-0.0061	0.0064	-0.9595	0.3377
Inflation	2.9817	1.0086	2.9561	2.9561
Term	**0.0065**	0.0065	2.5023	**0.0126**
Regime 2: Economic Recession				
a_2	0.0212	0.0081	2.5872	0.0099
Default	-0.0096	0.0090	-1.0674	0.2862
Inflation	**-2.9865**	1.0104	-2.9557	**0.0032**
Term	-0.0030	0.0032	-0.9382	0.3485

	Coefficients	*t*-Statistic
Gamma	41.012	0.411
c	-0.0003	-0.069

Regression $F(3, 528)$	3.4767
Significance Level of F	0.00034

Table 2.7 Canadian Small Cap Premium and U.S. Factors – MSR Model

Table 2.7 shows the parameter estimates and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model used to model the Canadian small cap premium. The regime-switching model is estimated using the monthly returns obtained from the Ibbotson database for the period January 1970 – December 2013. The financial and macroeconomic explanatory variables are the U.S. default corporate bond, inflation and term structure described in more details in section 4. Significant coefficients of the risk factors are marked in bold.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Regime 1: Economic Expansion				
a_1	0.0146	0.0041	3.5790	0.0003
Default	**1.0357**	0.2160	4.7947	**0.0000**
Inflation	-0.5801	0.7534	-0.7699	0.4413
Term	0.1684	0.0873	1.9294	0.0537
Regime 2: Economic Recession				
a_2	-0.0492	0.0215	-2.2869	0.0222
Default	**1.6533**	0.5498	3.0070	**0.0026**
Inflation	4.6301	2.5783	1.7957	0.0725
Term	0.5235	0.3264	1.6038	0.1087

Table 2.8
Canadian Small Cap Premium and U.S. Factors – MSR Model

Table 2.8 shows the parameter estimates and their asymptotic t-statistics from the non-linear estimation of the regime-switching model used to model the Canadian small cap premium. The regime-switching model is estimated using the monthly returns obtained from the Ibbotson database for the period January 1970 – December 2013. The financial and macroeconomic explanatory variables are the U.S. default corporate bond, inflation and term structure described in more detail in section 4. Significant coefficients of the risk factors are marked in bold.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
		Regime 1: Economic Expansion		
a_1	-7.16e-03	5.03e-03	-1.4250	0.1547
Default	**1.9087**	0.2281	8.3684	**0.0000**
Inflation	**2.2927**	1.0138	2.2614	**0.0241**
Term	**0.2652**	0.1275	2.0797	**0.0380**
		Regime 2: Economic Recession		
a_2	0.0200	6.42e-03	3.1043	0.0020
Default	**1.0975**	0.3327	3.2988	**0.0010**
Inflation	**-3.2988**	1.2786	2.4038	**0.0165**
Term	-0.0619	0.1681	-0.3682	0.7128
	Coefficients		*t*-Statistic	
Gamma	145.484		0.2975	
c	-5.7040		-0.1503	
Regression $F(3, 528)$			21.521	
Significance Level of F			0.0000	

Table 2.9 U.S. Small Cap Premium – MSR Model

January 1970 – December 2013

Table 2.9 shows the parameter estimates and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model used to model the U.S. small cap premium. The regime-switching model is estimated using the monthly returns of the DFA Small Cap Premium for the period **January 1970 – December 2013**. The financial and macroeconomic explanatory variables are the default corporate bond, inflation and term structure described in more details in section 4. Significant coefficients of the risk factors are marked in bold.

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
Regime 1: Economic Expansion				
a_1	0.006	0.004	1.261	0.207
Default	**0.321**	0.1102	**2.914**	**0.006**
Inflation	0.364	0.714	0.509	0.610
Term	-0.009	0.052	-0.178	0.858
Regime 2: Economic Recession				
a_2	0.003	0.002	1.163	0.244
Default	**2.123**	0.537	**3.947**	**0.003**
Inflation	**-1.423**	0.531	**-2.679**	**0.007**
Term	**-0.167**	0.062	**-2.659**	**0.007**

Table 2.10 U.S. Small Cap Premium – STAR Model

January 1970 – December 2013

Table 2.10 shows the parameter estimates and their *t*-statistics from the non-linear estimation of the smooth-transition regression model to model the small cap premium. The regime-switching model is estimated using the monthly returns of the DFA Small Cap Premium for the period January 1970 – December 2013. The financial and macroeconomic explanatory variables are the default corporate bond, inflation and term structure described in more details in section 4. Significant coefficients of the risk factors are marked in bold.

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
Regime 1: Economic Expansion				
a_1	-0.004	0.004	-1.019	0.308
Default	**0.574**	0.205	**2.786**	**0.005**
Inflation	0.210	0.919	0.228	0.819
Term	0.083	0.106	0.786	0.431
Regime 2: Economic Recession				
a2	0.011	0.005	2.139	0.032
Default	**0.8640**	0.375	**2.282**	**0.022**
Inflation	-0.432	1.088	-0.397	0.691
Term	-0.239	0.133	-1.786	0.074

	Coefficients	*t*-Statistic
Gamma	188.18	0.049
c	0.011	0.685

2.6.2.3 Results using U.S. Risk Factors and the MSR Model

Table 2.7 exhibits the results when examining the Canadian small cap premium relative to U.S. risk factors. In both regimes a sole explanatory variable is statistically significant: the default spread exposure which has a coefficient of 1.0357 in regime 1 and 1.6533 in regime 2.

2.6.2.4 Results using U.S. Risk Factors and the STAR Model

Table 2.8 which looks at the relationship between the Canadian small firm premium and U.S. risk factors using the smooth transition autoregressive model, shows that in the first regime, all three risk exposure coefficients are distinguishable from zero with values of 1.9087, 2.2927 and 0.2652 for the default, inflation and term factors respectively. In the second regime, two explanatory variables are strongly significant i.e. default risk factor with a coefficient of 1.0975 and the inflation risk exposure, with a coefficient of -3.2988.

2.6.2.5 Interpretation of the Empirical Results for Canada

Under both the Markov regime switching and the smooth transition regression model, it is interesting to note that the Canadian default spread factor plays no role on the dynamics of the Canadian small cap premium over the period analyzed. In contrast, the U.S. default risk exposure appears to influence tremendously the return differential between large cap and small cap firms and that this effect is not related to the economic activity phases: the U.S. default risk coefficients are strongly significant under both regimes. A possible explanation for this outcome would be that Canadian small firms export mainly to U.S. companies and hence when the level of bankruptcy increases in those latter firms, Canadian small companies suffer from this lesser degree of activity.

The Canadian inflation and term spread factors seem have effects on the country small cap premium that dependend on the economic activity phase and on the econometric model employed; on the other hand, the U.S. inflation and term spread risk exposures appear to be independent from the Canadian small cap premium when using the Markov switching regime model. When applying the logistic smooth transition autoregressive model, inflation in the United States seems to affect the return differential between large cap and small cap firms: higher prices in the U.S. economy may affect the aggregate exports of Canadian small firms.

Tables 2.9 and 2.10 exhibit results regarding the U.S. small cap premium for a shorter sample time period *i.e.* January 1970 to December 2013 in order to make a comparative analysis with the Canada for a similar time span. The findings show that the U.S. default risk premium continues to affect strongly the U.S. small cap premium for this more recent time period. However it can be noticed that the U.S. inflation and term structure risk factors are also greatly related to the U.S. small cap effect only during economic contraction conditions when the Markov switching-regime is performed on the data. However the STAR model show that this connection is absent under both regimes. These last findings mirror the ones obtained for the Canadian small cap premium for which the U.S. default premium strongly has a tremendous effect and for which the impact of the inflation and term structure risks is unclear: the coefficients on these variables are only significant during weak economic environments (recessions) and solely under the Markov switching-regime model.

2.6.3 Goodness of Fit of the STAR and Markov Switching-Regime Models

Several diagnostic tests are conducted in this section to assess the best models between the STAR and Markov switching-regime models. Table 2.11 shows that the Markov switching-regime model is more suitable than the STAR model since the former specification shows smaller values for the the Mean-Square Error (MSE) and Root-Mean-Square Error (RMSE) measures. Finally the QQ Plots of the standardized error terms depicted in Figures 2.1 to 2.3 for the U.S. small cap premium, and the Canadian small cap premium in relation to the Canadian and U.S. factors corroborate the evidence that the Markov switching-regime performs superiorly than the STAR model.

Table 2.11 Mean-Square Error and Root-Mean-Square Error of the STAR and Markov Switching- Regime Models

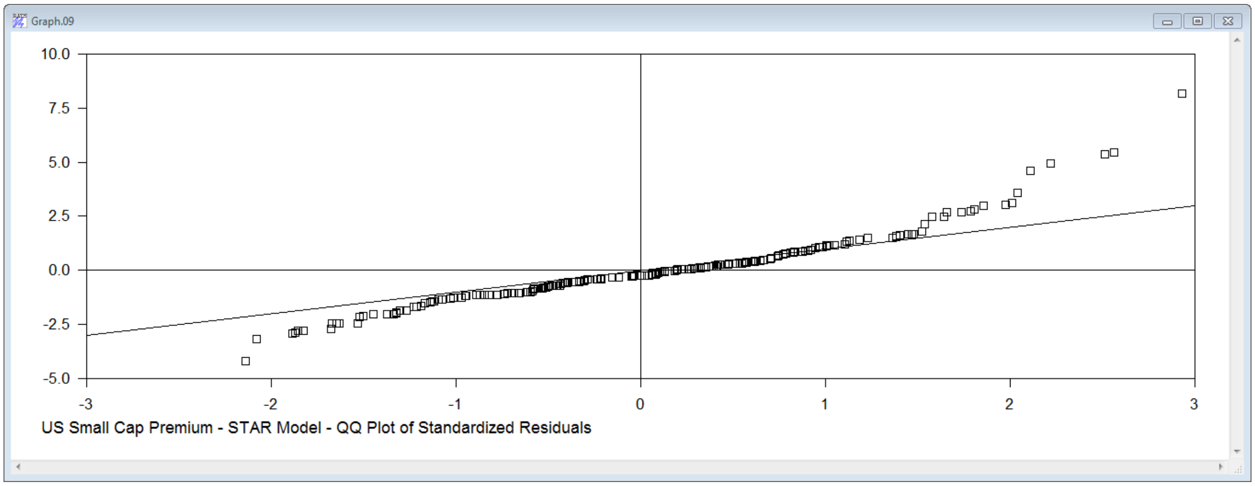
STAR Model

	US SCP	CDN SCP - CDN Factors	CDN SCP - US Factors
MSE	0.0021	0.0028	0.0026
RMSE	0.0463	0.0528	0.0509

Markov Switching-Regime Model

	US SCP	CDN SCP - CDN Factors	CDN SCP - US Factors
MSE	0.0019	0.0027	0.0023
RMSE	0.0435	0.0526	0.0479

Figure 2.1 Comparison of QQ Plots from the STAR and Markov Switching-Regime Models – US Small Cap Premium



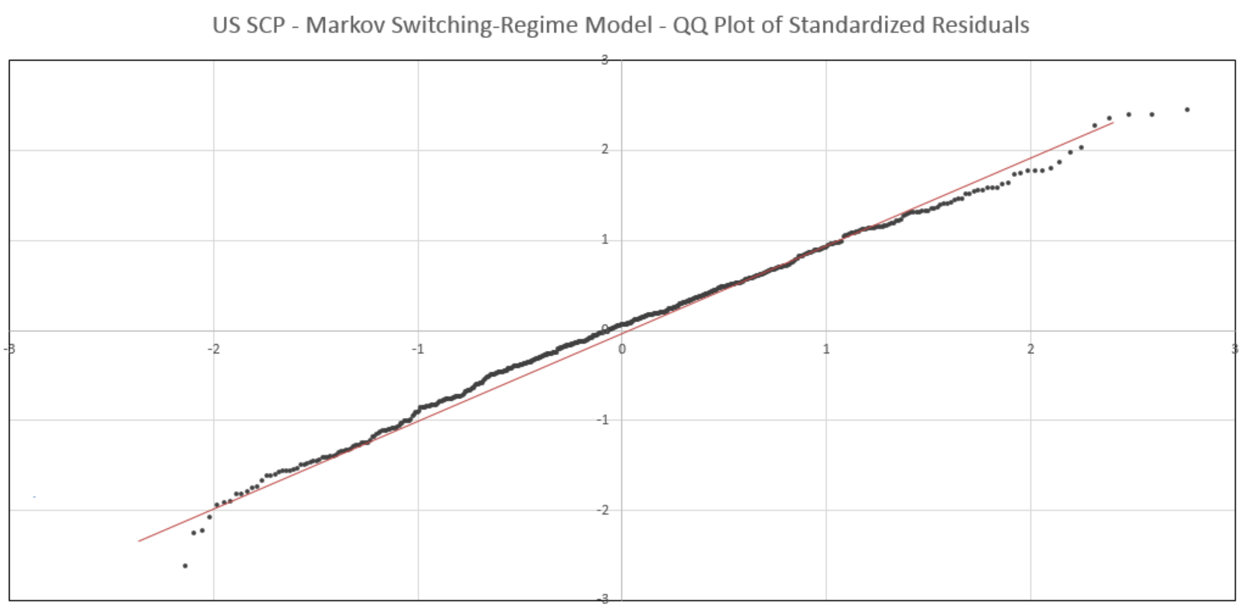
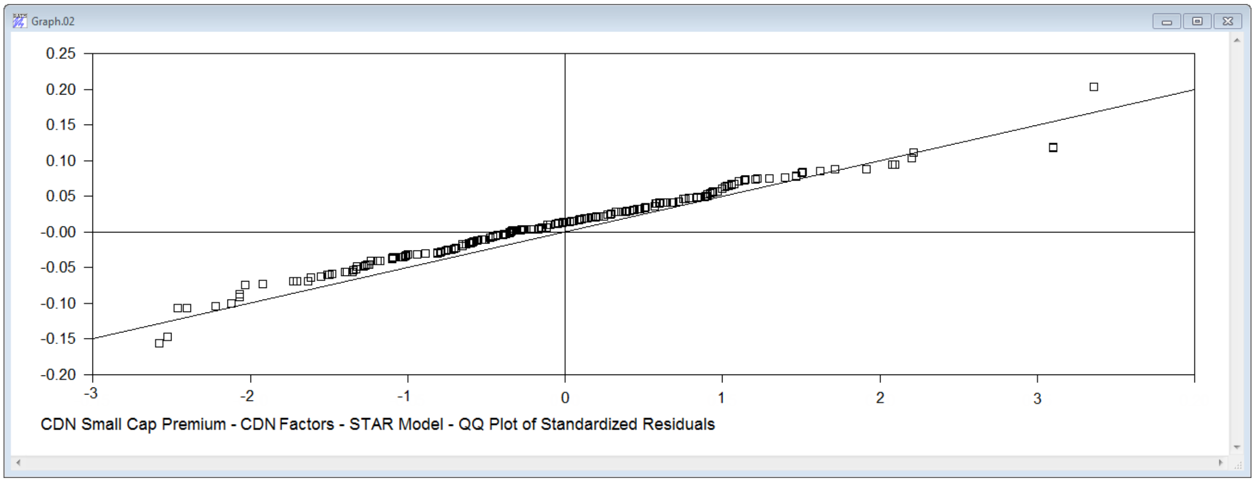


Figure 2.2 Comparison of QQ Plots from the STAR and Markov Switching-Regime Models – Canadian Small Cap Premium & Canadian Factors



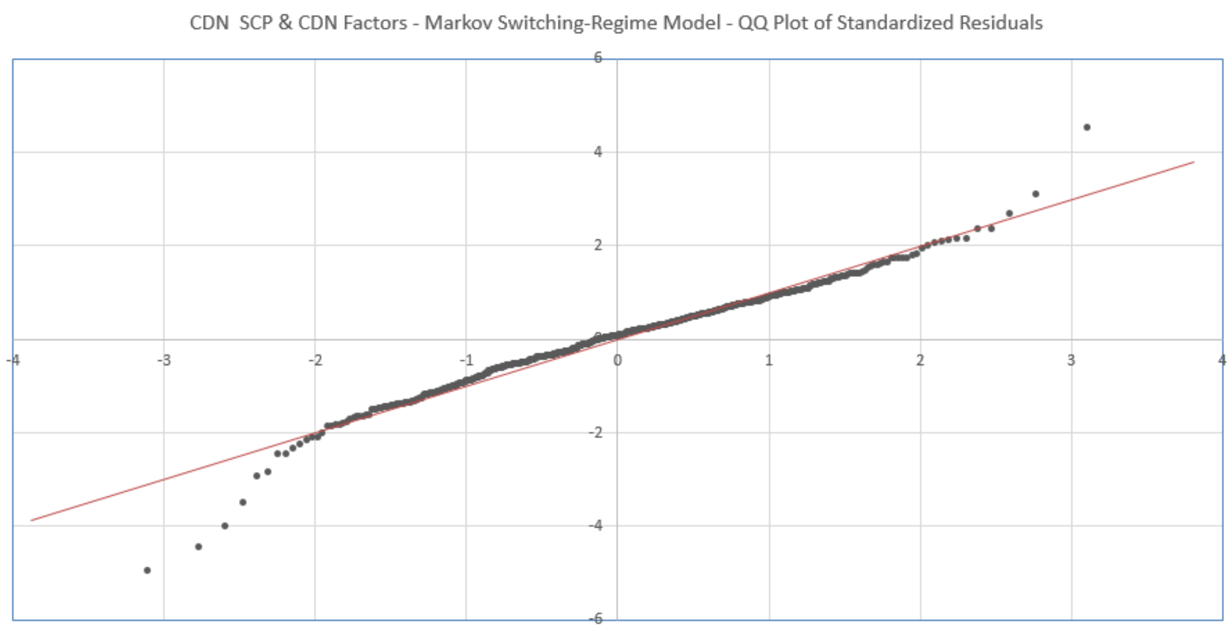
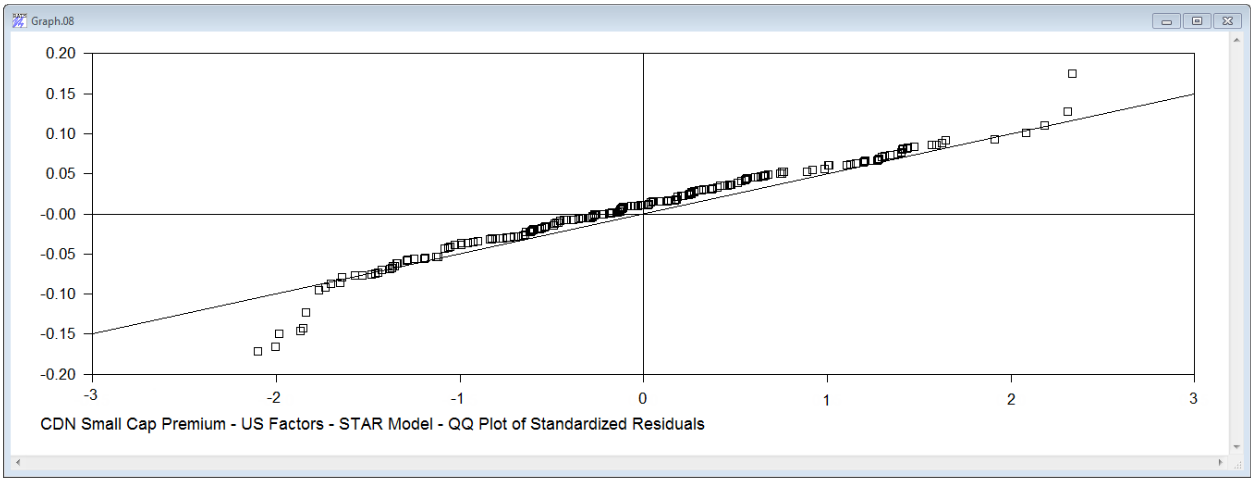
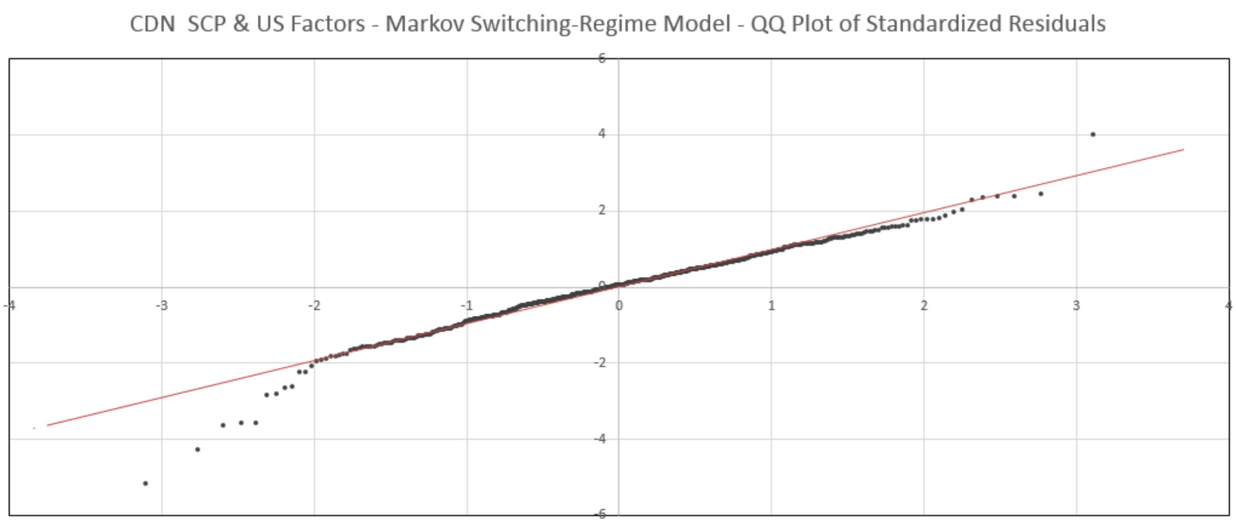


Figure 2.3 Comparison of QQ Plots from the STAR and Markov Switching-Regime Models – Canadian Small Cap Premium & U.S. Factors





2.7 Conclusion

Since at least 1981 when Banz (1981) presented empirical evidence that small-cap stocks generated higher average returns than larger firms, a plethora of studies has emerged on the small firm effect to investigate the validity and persistence of the small-cap premium and to offer explanations for the empirical outperformance of small-cap stocks over the long term. While the small firm premium in the United States has been determinant on average over the long term, it unveils strong time-varying properties with long periods of underperformance over time.

This observation led to the suggestion that the small firm constitutes a systematic risk premium and that excess returns on small-cap stocks represent a compensation for risk. Academics do not suggest that firm size per se is the source of the risk driving the dynamic of expected returns, but that size is a proxy for one or more underlying risk factors associated to smaller firms. Links have been uncovered between the small firm effect and default, distress risk and bankruptcy, as well as between the small firm effect and several macroeconomic variables.

This paper contributes to the extensive literature that has investigated the links between the small firm premium and various financial and macroeconomic variables. Indeed, this study employs recent advances in nonlinear time series models, and more specifically the Hamilton's (1989) Markov switching regime and the smooth-transition regression models, to explore the relationship between the small firm premium and financial and macroeconomic variables in the Canadian and U.S. economies. The findings under both models present evidence that the U.S. default risk affects the return differential between large cap and small cap firms both in the U.S. and Canadian economies and that these relationships are independent from the economic activity phases.

These results are important for portfolio management decisions; introducing regimes and financial and macroeconomic risk exposures into the dynamic/active asset allocation problematic has the potential to cause great alteration in portfolio allocations and investment opportunity sets across regimes. Indeed, if it is well established that the U.S. and Canadian small cap premiums are associated to the risk inherent in the business cycle and particularly to the U.S. default risk, indications about the probabilities of future recessions and economic expansions are particularly valuable not just for academics, but for policymakers and portfolio managers as well.

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CHAPTER 3

Stock Market Liquidity and Economic Cycles

3.1 Introduction

In financial markets, liquidity is defined as the degree to which a security or an asset can be purchased or sold without affecting significantly its price. Because liquidity is a central aspect of stock markets, empirical research finance has devoted important attention of its role in asset pricing, behavioural finance and market efficiency. One recent strand of this research, focuses on the predictive power of liquidity on stock market returns and future economic growth. The underlying motivation of this work relies on a central premise of finance theory: that financial markets are "forward looking." Indeed since news and information about future states of the economy are continuously processed by market participants, their views and expectations about upcoming economic conditions as well as their risk preferences and tolerances are also continually affected. Investors hence reallocate their stock portfolios in response to new information to reflect changes in their beliefs which in turn induce them to trade, which causes relative stock prices and stock market indices to fluctuate. Since trading levels are directly related to liquidity, one might expect that aggregate liquidity should also convey information about future macroeconomic conditions. For instance, the "flight to quality" phenomenon, which reflects the "forward looking" nature of equity markets, usually occurs prior to difficult economic times when investors shift their equity allocation to completely move away from the stock market or invest into safer securities to construct portfolios that are more defensive and more focused on wealth preservation. During a "flight to quality" episode, an unusual amount of asset trading occurs in a short period of time which leads to important price changes, greater stock volatilities and causes aggregate liquidity to worsen (illiquidity increases). Hence, stemming from these observations, recent empirical literature asserts that lower levels of market-wide liquidity could act as a leading indicator of depressing future economic conditions.

In a recent study that examines the relationship between economic growth and financial market illiquidity, Næs et al. (2011) use various measures of stock market liquidity and macroeconomic variables, to proxy for future states of the real economy, to investigate the possible leading indicator property of financial market aggregate liquidity on macroeconomic fundamentals. The authors conclude that economic cycles can be predicted by the levels of aggregate illiquidity *i.e.* financial markets liquidity are good leading indicators of economic cycles. Analyzing data for the United States during the period 1947 to 2008, they provide evidence, even after controlling for many factors associated with financial markets, that market-wide liquidity contains leading information about the future state of the real economy. Næs et al. (2011) claim that the predictive power of aggregate stock market liquidity on subsequent economic conditions might indicate that "liquidity measures provide information about the real economy that is not fully captured by stock returns." The authors support the conclusion that "liquidity seems to be a better predictor than stock price changes" by referencing Harvey (1988) who argues that stock prices comprise a more complex mix of information that distort the signals from stock returns.

However, Næs et al. (2011)'s results are estimated on a problematic framework: the predictability of aggregate liquidity on future outcomes of the real economy is based on a linear regression framework, this despite increasing evidence that macroeconomic variables (such as the ones employed in Næs et al. (2011)'s study *i.e.* real GDP, real Investment, real Consumption) follow nonlinear behaviours. Hence their findings may not be robust to a more appropriate model that links aggregate illiquidity and economic cycles.

This paper looks to re-examine Næs et al. (2011), by using a non-linear approach for analyzing the connection between market-wide liquidity and business cycles, and providing new evidence on whether liquidity, contains critical information about future economic growth and consequently acts as a leading indicator of subsequent economic conditions.

This paper uses two important econometric nonlinear models: the Markov switching regimes and smooth transition autoregressive models which are discussed in greater detail in the following sections.

3.2 Literature Review

The literature that has analyzed the link between stock market aggregate liquidity and economic fundamentals is relatively scant. Levine and Zervos (1998) find that stock market liquidity -- as measured both by the ratios of the value of stock trading to the size of the stock market and to the size of the economy -- is positively and significantly correlated, after controlling for economic and political factors, with present and subsequent rates of economic growth, capital accumulation, and productivity growth. Gibson and Mougeot (2004) show that over the 1973 to 1997 period, the U.S. stock market liquidity risk premium is linearly associated to an “Experimental Recession Index”. Eisfeldt (2004) presents a model in which liquidity fluctuates with real fundamentals such as economic productivity and investment.

One strand of work that is related to this study has analyzed whether aggregate order flow in financial markets contain valuable information about future macroeconomic conditions.

Beber et al. (2011) for instance investigate, over the period 1993 to 2005, the predictive power of financial markets orderflow movements across equity sectors on economic cycles. The authors point out two observations: 1) empirical literature shows that asset prices and returns are good predictors of business cycles and 2) order flow is the process by which stock prices vary. Synthesizing these two observations, Beber et al. (2011) thus question how order flow itself is associated with contemporaneous and subsequent economic conditions. Their findings show that an order flow portfolio constructed on cross-sector movements is able to forecast next quarter economic conditions.

Evans and Lyons (2008) present evidence that foreign exchange order flows predict future macroeconomic factors such as money growth, inflation and output growth; and future exchange rates. Finally, Kaul and Kayacetin (2009) provide evidence that market wide order flow on the New York Stock Exchange and order flow differentials (the difference in the order flow between large cap and small cap firms) can forecast variations in industrial production and U.S. real GDP.

3.3 Liquidity Measures, Macroeconomic and Financial Variables

3.3.1 Liquidity Measures

In order to construct quarterly aggregate liquidity measures, data on all ordinary common shares traded on the New York Stock Exchange (NYSE) during the period January 1947 through December 2012 is retrieved from the Center for Research in Security Prices (CRSP). The data consists of stock prices, returns, and trading volume for each common share and covers more than 65 years and 10 recessions.

Liquidity is an unobservable factor and has several aspects that cannot be assessed in a single measure; to address these issues numerous studies have developed diverse liquidity proxies. This study focuses on the market wide liquidity proxies, described below, that are analyzed in Næs et al. (2011) *i.e.* the Roll (1984) implicit spread estimator, the Amihud (2002) illiquidity ratio, and Lesmond, Ogden, and Trczinka (1999) measure (LOT). The relative spread (RS) measure is dropped from the analysis since the high frequency microstructure data that are needed to measure effective and quoted spreads are not always obtainable for the sample period prescribed for the analysis.

The three liquidity measures are computed on a quarterly basis for each common share. Aggregate liquidity proxies are obtained by taking the equally weighted average of the liquidity measures of the individual securities each quarter.

3.3.1.1 Roll Liquidity Measure (1984)

The Roll (1984) measure uses a model to estimate the effective spread based on the time series properties of observed market prices *i.e.* the serial covariance of the change in price.

Let V_t denote the unobservable equilibrium value of the stock which evolves as follows on day t:

$$V_t = V_{t-1} + \varepsilon_t \tag{3.1}$$

where ε_t is the unobservable innovation in the true value of the asset between transaction $t-1$ and t. ε_t is serially uncorrelated with a mean-zero and constant variance σ_ε^2.

Let P_t denote the last observed transaction price of the same given asset on day t, oscillating between bid and ask quotes that depend on the side originating the trade. The observed price can be described as follows:

$$P_t = V_t + \frac{1}{2} S Q_t, \tag{3.2}$$

where S denote the effective spread, and Q_t is an indicator for the last trade that equals, with equal probabilities, +1 for a transaction initiated by a buyer and −1 for a transaction initiated by a seller. Q_t is serially uncorrelated, and is independent of ε_t.

Taking the first difference of Equation (3.2) and incorporating it in Equation (3.1) yields

$$\Delta P_t = \frac{1}{2} S \, \Delta Qt + e_t \tag{3.3}$$

where Δ is the change operator.

Using this specification, Roll (1984) demonstrates that the serial covariance is

$$\operatorname{cov}(\Delta P_t, \ \Delta P_{t-1}) = \frac{1}{4} S^2 \tag{3.4}$$

from which we obtain:

$$S = 2\sqrt{-\text{cov}(\Delta P_t, \Delta P_{t-1})} \tag{3.5}$$

The formula above is only defined when Cov < 0. When the sample serial covariance is positive (cov > 0), a default numerical value of zero is substitute into the specification. Equation (3.5) specifies the measure of spread proposed by Roll (1984). Roll's estimator is hence calculated by estimating the autocovariance and solving for *S*. The reasoning behind Equation (3.5) is that the more negative the return autocorrelation is, the lower the liquidity of a given stock will be.

3.3.1.2 Lesmond, Ogden, and Trzcinka (1999) Liquidity Measure

Using only the time series of daily security returns, Lesmond, Ogden, and Trzcinka (1999) develop a proxy for liquidity (*LOT*). The measure is the proportion of days with zero returns:

$$LOT = (\text{\# of days with zero returns})/\text{T}, \tag{3.6}$$

where "T" is the number trading days in a month.

The intuition behind the *LOT* measure is that if the value of the public and private information is lower than to the costs of trading on a particular day, fewer trades (or no trades) will occur, and hence prices will no change from the previous day (zero return). The authors argue that the frequency of zero returns is directly related to both the quoted bid-ask spread and Roll's measure of the effective spread.

3.3.1.3 Amihud (2002) Liquidity Measure

Amihud (2002) who developed a price impact measure of liquidity based on the daily price response associated with one dollar of trading volume. The measure is computed as the daily ratio of absolute stock return to dollar volume:

$$Illiq_i = \frac{|r_i|}{DVOL_i} \tag{3.7}$$

where r_i is a daily stock return of stock i, and $DVOL_i$ is daily dollar volume.

Amihud (2002) asserts that there are finer and better measures of illiquidity, such as the bid-ask spread (quoted or effective) or transaction-by-transaction market impact, but these measures necessitate a great deal of microstructure data that are not obtainable in many stock markets and even if available, the data do not cover long lasting periods of time. Hence, Amihud (2002) stresses that this measure allows constructing long time series of illiquidity that are needed to test the effects over time of illiquidity on ex ante and contemporaneous stock excess return.

Figure 3.1 depicts the relationship between the time series of the three liquidity measures and recession periods (grey bars) according to the National Bureau of Economic Research (NBER). The figure suggests that market wide liquidity deteriorates (liquidity measures increases) ahead of several recessions.

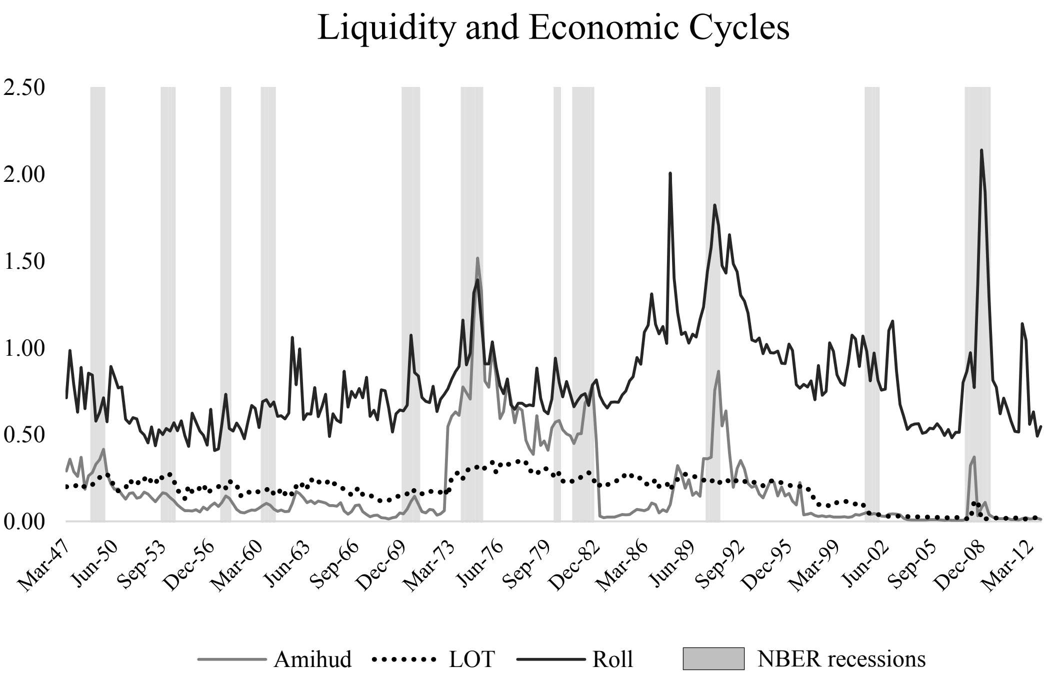

Figure 3.1 Liquidity and Economic Cycles. The figure depicts time series of the Amihud (2002), LOT (1999() and Roll (1984) illiquidity measures for the United States during the period 1947 to 2012. NBER recession periods are represented by the grey shaded areas. Higher values of the liquidity measures indicates lower levels of aggregate liquidity.

3.3.2 Macroeconomic and Financial Variables

The following standard set of macroeconomic variables commonly used in the empirical finance and economic research is employed to proxy for the US economic condition during the period January 1947 through December 2012: real GDP (*RGDP*), unemployment rate (*UE*), real consumption (*RCONS*), and real investment by the private sector (*GPDI*).

Several financial variables that have proven in the literature to be leading indicators of the trend of the state of the economic are also incorporated in the analysis as control variables: The market premium (er_m) which is computed as the return on the value-weighted S&P500 market index in excess of the three-month Treasury bill rate and market volatility (*Vola*) which is computed as the quarterly standard deviation of daily returns in the sample. The Credit spread (*Cred*) factor, calculated as the spread between Moody's Baa credit index[6] and the rate on a 30-year U.S. government bond and the term spread variable (*Term*), which corresponds to the spread between the yield on a 10-year Treasury bond and the yield on the three-month Treasury bill are also included in the analysis.

Results in Tables 3.1 to 3.3 show that applying the linear regression approach of Næs et al. (2011) on an extended sample period ending December 2012 (comparetively to December 2008 for Næs et al. (2011)) indicate that the evidence of the liquidity measures acting as strong leading indicators to economic cycles may be sensitive to the sample period selection and that a non-linear specification might be more appropriate and suitable in investigating the link between liquidity measures and macroeconomic variables.

[6] The Moody's long-term corporate bond yield index comprises seasoned corporate bonds with maturities close to 30 years.

Table 3.1
Amihud Liquidity Measure Predictive Power on Macroeconomic Proxies using a Linear Regression Model

The table shows the results from predictive regressions following Næs et al. (2011) approach in which next-quarters growth in different macro variables are regressed on three proxies for market illiquidity for the period 1947-2012. Market illiquidity (*LIQ*) in this table is proxied by the Amihud Illiquidity ratio (*Amihud*) which is log differenced to preserve stationarity. The macroeconomic variables are real GDP growth (*dGDPR*), growth in the unemployment rate (*dUE*), real consumption growth (*dCONSR*) or growth in private investments (*dINV*). One lag of the dependent variable (y_t) and *Term* , *dCred*, *Vola* and *erm* as control variables.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
			Amihud Liquidity Measure				
dGDPR	0.508	**-0.429**	0.335				
	(7.16)	**(-3.02)**	(6.26)				
dCONSR	0.658	-0.236	0.206				
	(10.21)	(-1.83)	(3.99)				
dGPDI	-0.071	**-2.939**	1.24				
	(-0.19)	**(-3.94)**	(4.18)				
dUNRATE	3.829	1.450	-4.378				
	(7.21)	(1.36)	(-10.30)				
dGDPR	0.568	**-0.324**	0.325	0.052	-0.016		
	(7.86)	**(-2.28)**	(5.69)	(3.72)	(-1.16)		
dCONSR	0.661	-0.202	0.220	0.042	0.030		
	(10.18)	(-1.58)	(4.27)	(3.33)	(2.34)		
dGPDI	0.228	**-2.495**	1.051	0.148	-0.174		
	(0.59)	**(-3.31)**	(3.46)	(1.98)	(-2.28)		
dUNRATE	3.556	1.009	-4.223	-0.186	0.117		
	(6.46)	(0.93)	(-9.68)	(-1.74)	(1.07)		
dGDPR	1.106	**-0.312**	0.290	0.052	-0.047	-0.025	-0.173
	(4.79)	**(-2.21)**	(4.94)	(3.72)	(-1.53)	(-1.28)	(-2.29)
dCONSR	1.075	-0.190	0.187	0.041	0.006	-0.020	-0.159
	(5.62)	(-1.49)	(3.54)	(3.31)	(-0.23)	(-1.14)	(-2.34)
dGPDI	1.969	**-2.460**	0.912	0.148	-0.322	-0.120	-0.676
	(1.74)	**(-3.26)**	(2.91)	(1.98)	(-1.95)	(-1.13)	(-1.68)
dUNRATE	1.721	1.020	-4.071	-0.191	0.394	0.215	0.726
	(1.05)	(0.94)	(-9.03)	(-1.78)	(1.67)	(1.41)	(1.25)

Table 3.2

Lesmond, Ogden, and Trczinka (1999) Liquidity Measure Predictive Power on Macroeconomic Proxies using a Linear Regression Model

The table shows the results from predictive regressions following Næs et al. (2011) approach in which next-quarters growth in different macro variables are regressed on three proxies for market illiquidity for the period 1947-2012. Market illiquidity (*LIQ*) in this table is proxied by the Lesmond, Ogden, and Trczinka Illiquidity ratio (*LOT*) which is log differenced to preserve stationarity. The macroeconomic variables are real GDP growth (*dGDPR*), growth in the unemployment rate (*dUE*), real consumption growth (*dCONSR*) or growth in private investments (*dINV*). One lag of the dependent variable (y_t) and *Term* , *dCred*, *Vola* and *erm* as control variables.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
			LOT Liquidity Measure				
dGDPR	0.499	-0.441	0.369				
	(6.94)	(-1.05)	(6.41)				
dCONSR	0.652	-0.494	0.212				
	(10.10)	(-1.31)	(4.10)				
dGPDI	-0.131	-2.749	1.342				
	(-0.34)	(-1.23)	(4.39)				
dUNRATE	3.860	1.080	-4.427				
	(7.24)	(0.34)	(-10.41)				
dGDPR	0.575	-0.677	0.323	0.059	-0.025		
	(7.95)	(-1.64)	(5.60)	(4.28)	(-1.72)		
dCONSR	0.666	-0.479	0.218	0.047	0.024		
	(10.23)	(-1.29)	(4.20)	(3.73)	(1.91)		
dGPDI	0.279	-4.206	1.045	0.203	-0.203		
	(0.72)	(-1.90)	(3.38)	(2.71)	(-2.98)		
dUNRATE	3.535	2.137	-4.215	-0.210	0.143		
	(6.42)	(0.68)	(-9.63)	(-1.98)	(1.30)		
dGDPR	1.105	-0.755	0.280	0.058	-0.039	-0.014	-0.202
	(5.17)	(-1.79)	(4.72)	(4.21)	(-1.27)	(-0.71)	(-2.66)
dCONSR	1.135	-0.549	0.180	0.045	0.011	-0.012	-0.179
	(5.90)	(-1.45)	(3.37)	(3.67)	(0.42)	(-0.70)	(-2.61)
dGPDI	2.579	**-4.616**	0.860	0.196	-0.275	-0.047	-0.876
	(2.24)	**(-2.03)**	(2.69)	(2.62)	(-1.64)	(-0.43)	(-2.13)
dUNRATE	1.475	1.872	-4.051	-0.211	0.375	0.185	0.807
	(0.90)	(0.58)	(-8.91)	(-1.99)	(1.57)	(1.19)	(1.38)

Table 3.3
Roll Liquidity Measure Predictive Power on Macroeconomic Proxies using a Linear Regression Model

The table shows the results from predictive regressions following Næs et al. (2011) approach in which next-quarters growth in different macro variables are regressed on three proxies for market illiquidity for the period 1947-2012. Market illiquidity (*LIQ*) in this table is proxied by the Roll Illiquidity ratio (*Roll*) which is not log differenced. The macroeconomic variables are real GDP growth (*dGDPR*), growth in the unemployment rate (*dUE*), real consumption growth (*dCONSR*) or growth in private investments (*dINV*). One lag of the dependent variable (y_t) and *Term* , *dCred*, *Vola* and er_m as control variables.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
			Roll Liquidity Measure				
dGDPR	0.497	**-0.715**	0.374				
	(6.97)	**(-2.42)**	(6.58)				
dCONSR	0.652	-0.287	0.216				
	(10.08)	(-1.07)	(4.18)				
dGPDI	0.140	**-3.552**	1.373				
	(-0.37)	**(-2.26)**	(1.37)				
dUNRATE	-0.264	-2.962	1.412				
	(-0.71)	(-1.92)	(4.77)				
dGDPR	0.561	-0.419	0.339	0.053	-0.016		
	(7.70)	(-1.39)	(5.87)	(3.73)	(-1.13)		
dCONSR	0.658	-0.218	0.228	0.043	0.013		
	(10.04	(-0.80)	(4.39)	(3.37)	(2.27)		
dGPDI	0.203	-2.097	1.136	0.168	-0.185		
	(0.52)	(-1.29)	(3.66)	(2.19)	(-2.35)		
dUNRATE	0.080	-1.499	1.178	0.173	-0.183		
	(0.21)	(-0.94)	(3.90)	(2.32)	(-2.39)		
dGDPR	0.992	-0.423	0.304	0.053	-0.053	-0.030	-0.167
	(4.56)	(-1.33)	(5.10)	(3.75)	(-1.70)	(-1.45)	(-2.17)
dCONSR	1.069	-0.194	0.194	0.043	0.003	-0.022	-0.158
	(5.46)	(-0.68)	(3.63)	(3.37)	(0.13)	(-1.18)	(-2.29)
dGPDI	1.949	-2.167	0.996	0.168	-0.353	-0.135	-0.682
	(1.66)	(-1.26)	(3.09)	(2.19)	(-2.07)	(-1.20)	(-1.64)
dUNRATE	1.684	-1.599	1.050	0.173	-0.345	-0.130	-0.627
	(1.47)	(-0.95)	(3.34)	(2.32)	(-2.09)	(-1.19)	(-1.55)

3.4 The Regime-Switching Models

There is growing evidence that many financial and economic indicators tend to behave differently during high and low economic cycles and that, consequently, the empirical models of these economic time series are characterized by parameter variability. This has generated considerable interest in time-varying parameter models. For instance, GDP growth rates typically stay around a higher level and are more persistent during expansions, but they fluctuate at a relatively lower level and less persistent during contractions. For financial series, bear markets are usually more volatile than bull markets which implies that prices go down faster than they go up. This means that we can expect the variance of bear markets to be higher than the bull markets. For such series data, it would not be realistic to assume a single, linear model to model these distinct dynamics.

Roughly speaking, two main classes of statistical models have been proposed which reinforce the notion of existence of different regimes. The first popular time-varying parameter model is the Markov regime switching framework approach of Hamilton (1989) to modeling macroeconomic and financial data. It has been employed to study the dynamic of GNP growth rates (Hamilton (1989)), real interest rates (Garcia and Perron (1996)), stock returns (Hamilton and Susmel (1994)) and corporate bond default risk (Giesecke et al. (2011)). The second model is the smooth-transition regression model which has been employed to analyze non-linearities in UK consumption and industrial production (Öcal and Osborn (2000)), non-linear relationships between US GNP growth and leading indicators (Granger and Teräsvirta (1993)) and between stock returns and business cycle variables (McMillan (2001)).

3.4.1 The Hamilton's (1989) Regime-Switching Model

The Hamilton (1989) Regime-Switching Model assumes that the behaviour of certain macroeconomic or financial indicators changes as a result of changes in economic activity. However, the state of economic activity, which is unobservable and which determines the process that generates the observable dependent variable (in this study the macroeconomic variables), is inferred through the observed behavior of the dependent variable. In the original Hamilton model (1989), it was assumed, as well as in this study, that there were two possible states of economic phases (regimes), corresponding to the condition of an economy (prosperity vs. recession).

In this study, the two-state Markov-chain regime-switching model is employed to evaluate the effects of different liquidity measures in explaining the growth dynamic in several macroeconomic variables for the United States for the period January 1947 to December 2012.

Let y denote the macroeconomic variable for quarter t and for which its historical behavior can be described by the following econometric specification:

$$y_t = a_t + \sum_{k=1}^{N} b_k X_{k,t-1} + \varepsilon_t \tag{3.8}$$

where X_{t-1} is a k-vector of explanatory variables and the b_k terms are the corresponding factor loadings. The intercept term a_t follows a two-state Markov chain, taking values a_1 and a_2, with the probability π_{ij} of switching from state i to state j is given by the matrix:

$$\begin{bmatrix} \pi_{11} & \pi_{21} \\ \pi_{12} & \pi_{22} \end{bmatrix}$$

Moreover let ξ_{it} represent the probability of being in state i in quarter t conditional on the data and η_{jt} the densities under the two regimes which are given by:

$$\eta_{jt} = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-\left(y_t - a_{jt} - \sum_{k=1}^{N} b_k \; X_{k,t-1}\right)^2}{2\sigma^2}\right) \tag{3.9}$$

where σ represents the volatility of the residuals ε_t which are assumed to follow an independent and identically distribution (*iid*) to allow performing standard maximum log likelihood functions. All *i* and *j* are then sum up to compute the likelihood function f_t,

$$f_t = \sum_{i=1}^{2} \sum_{i=1}^{2} \pi_{ij} \; \xi_{i,t-1} \eta_{it} \tag{3.10}$$

The state probabilities are then re-estimated by the recursive specification

$$\xi_{j,t} = \frac{\sum_{i=1}^{3} \pi_{ij} \xi_{i,t-1} \eta_{it}}{f_t} \tag{3.11}$$

The log likelihood function for the data can hence be estimated by summing the log likelihoods for each date by using standard maximum likelihood procedures.

3.4.2 The Smooth-Transition Regression Model

The other popular model that has been extensively used in the past two decades to modelling nonlinearities in the dynamic properties of many economic time series and for summarizing and explaining cyclical behavior of macroeconomic data and business cycle asymmetries is the Smooth Transition Autoregressive Model (STAR), which was developed by Teräsvirta (1994) and Granger and Teräsvirta (1993).

The smooth transition autoregressive (STAR) model for a univariate time series y_t, is given by:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_0 y_{t-i} + F(\xi_t, \gamma, c)\left[\beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i}\right] + \varepsilon_t \qquad (3.12)$$

where $F(\xi_t, \gamma, c)$ is a transition function which controls for the switch from one regime to the other and is bounded between 0 and 1. The scale parameter $\gamma > 0$ is the slope coefficient that determines the smoothness of the transition: the higher it is the more abrupt the change from one extreme regime to the other ξ_t. The location or threshold parameter between the two regimes is represented by c and ξ_t is called the transition (threshold) variable, with $\xi_t = y_{t-d}$ (d a delay parameter).

Two popular selections for the transition function are the logistic function (LSTAR) and the exponential function (ESTAR). The LSTAR function is specified as:

$$F = \left[1 + \exp(-\gamma(\xi_t - c))\right]^{-1} \qquad (3.13)$$

while the ESTAR function is specified as:

$$F = 1 - \exp(-\gamma(\xi_t - c)^2) \qquad (3.14)$$

The main difference between these two STAR models relies on how they describe macroeconomic series dynamic behaviour. The LSTAR model reflects the asymmetrical adjustment process that usually characterize economic cycles: a sharper transition and sharp recovery following business cycle troughs compare to economic peaks. In contrast, the ESTAR specification suggests symmetrical adjustment dynamic.

To determine the adequate transition function to apply to the data, Terasvirta (1994) suggests a model selection procedure which is explained and applied in the section 3.5 (Empirical Results).

While an exogenous variable could be employed as the transition variable, in this paper as per the majority of research studies using STAR models, the dependent variable (the macroeconomic proxies) plays this role and d equals one, meaning that the first lagged value of the macroeconomic variable investigated acts at the threshold variable.

In the Smooth Transition Autoregression (STAR) all predetermined variables are lags of the dependent variable. An extension to the STAR model is the smooth transition regression (STR) model which is an amendment to the STAR model that allows for exogenous variables $\mathrm{x}_{1\mathrm{t}},\ldots,\mathrm{x}_{\mathrm{kt}}$ as additional regressors. In this study, the applied STR model includes other exogenous factors the *i.e.* the liquidity measures and the factors *Term*, *Cred*, *Vola*, er_m. The standard method of estimation of STR (STAR) models is nonlinear least squares (NLS), which is equivalent to the quasi-maximum likelihood approach.

Two interpretations of a STR (STAR) model are possible. First, the STR model may be thought of as a regime-switching model that allows for two regimes, associated with the extreme values of the transition function, $\mathrm{F}(\xi_t; y, \mathrm{c}) = 0$ and $\mathrm{F}(\xi_t; y, \mathrm{c}) = 1$, where the transition from one regime to the other is smooth. The regime that occurs at time t is determined by the observable variable ξ. Second, the STR model can be said to enable a continuum of states between the two extremes. The key advantage in favour of STR models is that changes in some economic and financial aggregates are influenced by changes in the behaviour of many diverse agents and it is highly improbable that all agents respond instantaneously to a given economic signal. For instance, in financial markets, with a considerable number of investors, each switching at different times (probably caused by heterogeneous objectives), a smooth transition or a continuum of states between the extremes seems more realistic.

Both the Hamilton's (1989) Markov switching regime model and the smooth transition autoregressive model assume that the series under examination are stationary. Indeed these specifications investigate time series by distinguishing non-stationary or stationarity linear systems from stationary nonlinear ones.

Note that while the empirical literature shows that all studies related to economic regimes employ the first difference of the variables under consideration to make them stationary, some studies investigate, in addition, the levels of macroeconomic time series for robustness purposes. Implementing this approach in my essay, the results present question the conclusion that stock market liquidity may act as a leading indicator to economic cycles.

3.5 Empirical Results

In order to investigate the link between stock market liquidity and business cycles in a non-linear specification, the dependent variables, *i.e.* the macroeconomic proxies *dRGDP*, *dCONS*, *dGPDI* and *dUE*, need to be tested to verify whether linearity should be rejected or not. Terasvirta (1994)'s model allows to perform this test by doing a Lagrange multiplier test for linearity versus an alternative of LSTAR or ESTAR in a univariate autoregression:

$$y_t = \beta_0 + \sum_{j=1}^{p} \beta_{1j} y_{t-j} + \sum_{j=1}^{p} \beta_{2j} y_{t-j} y_{t-d} + \sum_{j=1}^{p} \beta_{3j} y_{t-j} y_{t-d}^2 + \sum_{j=1}^{p} \beta_{4j} y_{t-j} y_{t-d}^3 + e_t \qquad (3.15)$$

As mentioned previously, in this study both the lags value p and the delay parameter d equals 1[7]. The null hypothesis of linearity is therefore $\beta_2 = \beta_3 = \beta_4 = 0$. If the null hypothesis is rejected, the next step is to choose between LSTAR and ESTAR models by a sequence of nested tests:

H_{01} is a test of the first order interaction terms only: $\beta_2 = 0$

H_{02} is a test of the second order interaction terms only: $\beta_3 = 0$

H_{03} is a test of the third order interaction terms only: $\beta_4 = 0$

H_{12} is a test of the first and second order interactions terms only: $\beta_2 = \beta_3 = 0$

The decision rules of choosing between LSTAR and ESTAR models are suggested by Teräsvirta (1994): Either an LSTAR or ESTAR will cause rejection of linearity. If the null of linearity is rejected H_{12} and H_{03} become the appropriate statistic if ESTAR is the main hypothesis of interest:

[7] There exists no econometric specification that allows to precisely determine the value of the delay parameter p. Most of the literature related to non-linear STAR models uses $p = 1$.

If both H_{12} is rejected and H_{03} is accepted, this may be interpreted as a favor of the ESTAR model, as opposed to an LSTAR.

Table 3.4 presents the results of the Teräsvirta (1994) linearity test performed on the macroeconomic proxies of interest which show that the specification rejects the hypothesis of linearity for three variables: *dRGDP*, *dGPDI* and *dCONSR*. However, the hypothesis of linearity cannot be rejected for the unemployment rate (*dUE*) proxy triggering the exclusion of this variable from the analysis. These findings are important since they provide evidence that Næs et al. (2011), by using a linear framework, improperly analyzed the link between stock market liquidity and the variables *dRGDP*, *dGPDI* and *dCONSR* since these macroeconomic proxies behave according to non-linear behaviours. Moreover, hypothesis H_{12} is rejected and hypothesis H_{03} is not rejected simultaneously only for the variable *dGPDI* which implies that the LSTAR model is the appropriate specification for the variables *dRGDP* and *dCONSR* and that the ESTAR model will be applied to investigate the variable *dGPDI.*

Table 3.4 Tests of Linearity and LSTAR vs ESTAR Models

This table shows the results of the Teräsvirta (1994)'s approach to first test for linearity of the dependent variable. If the hypothesis of linearity is rejected and H_{03} is accepted while H_{12} is rejected then the specification will point toward an ESTAR instead of a LSTAR model.

	dRGDP		*dUE*		*dGPDI*		*dCONSR*	
	F-Value	Significance	F-Value	Significance	F-Value	Significance	F-Value	Significance
Linearity	6.733	0.0002	0.073	0.9742	2.607	0.0522	18.258	0.0000
H_{01}	8.236	0.0045	0.005	0.9418	3.746	0.0540	16.619	0.0001
H_{02}	7.944	0.0052	0.159	0.3897	4.051	0.0452	17.966	0.0000
H_{03}	3.625	0.0580	0.056	0.8128	0.011	0.9162	16.808	0.0001
H_{12}	8.202	0.0004	0.107	0.8978	3.921	0.0210	17.955	0.0000

Table 3.5 provides descriptive statistics for the liquidity measures of interest as well as for the macroeconomic variables. Panel A shows that the mean of the liquidity measures *Amihud*, *LOT* and *Roll* investigated in this study are over the period 1947 through 2012 are 1.040, 0.188 and 0.768 respectively. Sub-period averages reveal that all three liquidity measures were the lowest for the last time span of the period covered *i.e.* 2000 to 2012. This implies that stocks are more liquid in the most recent era.

Correlations between the liquidity measures (Panel B) present evidence of a strong positive correlation between *Amihud* and *LOT* (0.63). The *Roll* liquidity is more highly correlated with the *Amihud* liquidity proxy (0.30) than with the *LOT* measure (0.10).

Panel C and D of Table 3.5 presents the corresponding statistics for the macroeconomic proxies. The sub-period 2000-2012 has generated the lowest economic growth according to all three economic variables. This relative underperformance of the U.S. economy during that time period comparatively to previous ones may be explained by the severe economic recession that has hit the nation in 2008 and 2009 and which was not followed by a usually observed sharp economic recovery.

Finally, Panel D shows that the three macroeconomic proxies during the period analyzed are highly and positively correlated since 70% of U.S. GDP is due to consumer spending[8] and that private fixed investment represents 15% of the U.S. economy.[9]

[8] http://research.stlouisfed.org/fred2/graph/?g=hh3

[9] http://data.worldbank.org/indicator/NE.GDI.FTOT.ZS

Table 3.5 Descriptive Statistics

Panels A and B exhibit descriptive statistics for the U.S. liquidity measures for the period 1947 through 2012. The liquidity measures analyzed are the Lesmond, Ogden, and Trzcinka (1999) (*LOT)*, the Amihud (2002) *(Amihud)* and the Roll (1984) implicit spread estimator (*Roll*). Panel A present the mean and median of the liquidity measures, and average liquidity measures for different subperiods. Panel B shows correlation coefficients between the liquidity measures. Panels C and D show equivalent statistics for U.S. macroeconomic proxies *i.e.* real GDP growth (*dRGDP*), growth in private investment (*dGPDI*), and real consumption growth (*dCONSR*).

Panel A: Descriptive Statistics, Liquidity Measures

	Mean	Median	Means, Subperiods					
			1947–59	1960–69	1970–79	1980–89	1990–99	2000–12
Amihud	1.040	0.919	1.465	0.762	1.246	1.397	1.132	0.252
LOT	0.188	0.200	0.209	0.176	0.263	0.239	0.192	0.030
Roll	0.768	0.733	0.592	0.378	0.822	0.929	1.081	0.792

Panel B: Correlation Coefficients, Liquidity Measures

	LOT	*Amihud*
Amihud	0.63	
Roll	0.10	0.30

Panel C: Descriptive Statistics, Macroeconomic Variables

	Mean	Median	Means, Subperiods					
			1947–59	1960–69	1970–79	1980–89	1990–99	2000–12
dRGDP	0.811	0.777	0.939	1.025	0.861	0.789	0.811	0.444
dGPDI	0.842	1.009	0.880	1.073	0.834	0.851	0.886	0.533
dCONSR	0.895	0.832	0.865	0.973	1.206	0.721	1.471	0.147

Panel D: Correlation Coefficients, Macroeconomic Variables

	dCONSR	*dRGDP*
dRGDP	0.59	
dGPDI	0.24	0.79

The main results of this study are presented in Tables 3.3 through 3.8 for the Markov switching-regime model and Tables 3.9 through 3.14 for the STAR frameworks. The models applied allow to determine whether change in growth in the macro proxy y_{t+1} (*dRGDP*, *dCONSR* and *dGPDI*) over quarter t + 1. LIQ_t is the liquidity measure (*Amihud*, *Roll* and *LOT*) and the variables *Term*, *Cred*, *Vola*, er_m, and the lag of the dependent variable y_t represent the control variables included in the models. Three different specifications are investigated. In the first, y_t is regressed on its lag and the liquidity measure; in the second, y_t is regressed on the previous two explanatory variables and the variables *Term* and *Cred*; in the third, the variables *Vola* and er_m are added to the previous four.

The findings, using the Markov switching-regime model, for the relationship between the dependent variable and the Amihud (2002) liquidity measure as well as the other explanatory variables under the economic expansion regime and the economic contraction regime are presented in Tables 3.6 and 3.7 respectively. Results show that the coefficients for the Amihud (2002) measure are not significant for all three macroeconomic variables when the economy is going toward an expansion phase (Table 3.6). When the economy is moving to a recession the coefficient of the Amihud (2002) measure becomes significant and negative for the variables *rGDP* and *rCONSR* when the dependent variable is regressed on this liquidity measure and the lag of the explained variable: this means that when aggregate liquidity worsens (liquidity measures increase) growth in the macroeconomic proxies decline which explain the negative coefficients. However, these coefficients remain robust to the inclusion of the bond variables *Term* and *Cred* but not to the adding of the equity variables *Vola* and er_m (3rd specification).

The corresponding results for the Amihud (2002) liquidity measure using the LSTAR model (Tables 3.12 and 3.13) indicate that this measure has even less predictive power for the subsequent quarter of the state of the economy. Indeed, the coefficients are again all not significant for the growth phase of the economy but the findings related to the economic contraction phase show that only the specification using the liquidity measure and the lag of the dependent variable provides a significant coefficient that however doesn't stay robust to the addition of other explanatory variables.

Using the Markov switching-regime, the Roll (1984) liquidity measure also has no forecasting power for the subsequent quarter when the state of the economy is heading toward a recession (Table 3.9): the coefficients of this liquidity measure are all insignificant at the 5% level except for *dRGDP* in the third specification. In the expansion phase of the business cycle (Table 3.8), the *Roll* variable presents a more forecasting prowess as the coefficients on this liquidity measure become significant for all three macroeconomic proxies under the first and second specifications. However, using all control variables (third specification) only the coefficient for *dGDPR* remains distinguishable from zero.

Applying the LSTAR model (Tables 3.14 and 3.15), findings show that *Roll* possesses a strong ability to predict future growth of the *dGPDI* variable as represented by the significant coefficients of this liquidity measure for all three specifications and for both the expansion and contraction regimes. Coefficients are also different from zero under the recession phase (Table 3.15) for *dRGDP* and *dCONSR* in the second regime but both these significances disappear when including the control variables related to the stock market *i.e. Vola* and er_m.

Finally, when the Markov switching-regime is applied to investigate the relationship between the *LOT* measure and upcoming economic conditions, only one coefficient of this liquidity measure is significant for forecasting an expansion phase (Table 3.10) *viz*. when *dGPDI* is the forecasted variable under the second specification. However, this coefficient turns out insignificant when adding the explanatory variables *Vola* and er_m. For predicting the recession phase (Table 3.11), *LOT* liquidity measure is able to forecast the future growth of the *dCONSR* variable under the third specification.

Using the STAR models (Tables 3.16 and 3.17), similar results are observed for both regimes: *LOT* liquidity measure has the ability to predict the growth of *dGDPR* even when including some or all control variables (second and third specification).

All in all, while some coefficients of the three liquidity measures are significant in the prediction of the future growth of macroeconomic proxies, only few remain distinguishable from zero after including the control variables. This critical fact implies that the findings are not strong and reliable enough to affirm with confidence that aggregate liquidity is a strong leading indicator and contains significant additional information about future economic growth as claimed by Næs et al. (2011). It is also important to mention that the analysis in this study was also performed using the levels of the macroeconomic variables as well as the liquidity measures instead of their log differences. This alternative approach permitted analysis of three other relationships: levels of the macroeconomic proxies versus levels and versus log differences of the liquidity measures as well as the log differences of the economic variables versus levels of liquidity measures. The results obtained are even less significant and robust to the ones presented previously.

Table 3.6
Amihud (2002) Liquidity Measure Predictive Power on Macroeconomic Proxies using the Markov-Switching Model

The table shows the parameter estimates under the economic expansion regime and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Amihud (2002) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
	Amihud Liquidity Measure – Economic Expansion Regime						
dGDPR	0.718	-0.131	0.207				
	(7.43)	(-0.86)	(2.73)				
dCONSR	0.782	-1.671	-0.412				
	(1.47)	(-0.68)	(-1.57)				
dGPDI	0.977	-0.420	0.161				
	(3.71)	(-0.57)	(1.85)				
dGDPR	2.809	2.151	-0.486	0.045	0.232		
	(4.72)	(0.80)	(-1.17)	(0.08)	(0.37)		
dCONSR	1.085	-2.101	-0.506	0.484	0.177		
	(1.81)	(-0.81)	(-1.75)	(0.90)	(0.61)		
dGPDI	0.988	-0.482	0.200	0.480	0.284		
	(3.86)	(-0.71)	(2.32)	(3.42)	(3.33)		
dGDPR	3.804	1.668	-0.847	-0.322	0.108	-0.485	0.207
	(2.61)	(0.68)	(-1.96)	(-0.806	(0.34)	(-0.78)	(1.75)
dCONSR	4.245	-1.208	-0.581	0.462	0.174	-1.453	-0.034
	(1.18)	(-0.45)	(-1.92)	(0.66)	(0.55)	(-0.83)	(-0.18)
dGPDI	2.295	-1.993	0.122	0.274	-0.024	-0.659	0.494
	(0.94)	(-1.00)	(0.992)	(1.11)	(-0.21)	(-0.70)	(2.49)

Table 3.7
Amihud (2002) Liquidity Measure Predictive Power on Macroeconomic Proxies using the Markov-Switching Model

The table shows the parameter estimates under the economic contraction regime and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Amihud (2002) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
	Amihud Liquidity Measure – Economic Contraction Regime						
dGDPR	-0.431	**-1.079**	0.999				
	(-1.63)	**(-2.03)**	(4.76)				
dCONSR	0.583	**-0.222**	0.307				
	(7.76)	**(-2.13)**	(4.49)				
dGPDI	0.044	-3.093	0.147				
	(0.143)	(-1.35)	(1.17)				
dGDPR	0.388	**-0.312**	0.427	0.075	0.025		
	(5.44)	**(-2.31)**	(7.66)	(2.48)	(1.35)		
dCONSR	0.585	**-0.224**	0.306	0.006	0.004		
	(7.83)	**(-2.11)**	(4.48)	(0.25)	(0.26)		
dGPDI	0.151	-2.615	0.226	0.441	0.022		
	(0.32)	(-1.23)	(7.66)	(1.95)	(0.29)		
dGDPR	0.556	-0.258	3.78	0.064	0.199	-0.043	0.038
	(2.63)	(-1.91)	(6.36)	(2.17)	(1.04)	(-0.585)	(2.75)
dCONSR	0.796	-0.198	0.261	0.004	0.000	-0.065	0.017
	(4.39)	(-1.81)	(3.49)	(0.24)	(0.05)	(-1.11)	(1.33)
dGPDI	1.726	-0.099	0.188	0.474	0.275	-0.264	0.191
	(1.89)	(-0.21)	(2.13)	(3.28)	(2.99)	(-0.79)	(3.08)

Table 3.8
Roll (1984) Liquidity Measure Predictive Power on Macroeconomic Proxies using the Markov-Switching Model

The table shows the parameter estimates under the first regime and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Roll (1984) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
Roll Liquidity Measure – Economic Expansion Regime							
dGDPR	0.552	0.126	0.265				
	(5.82)	(0.44)	(2.39)				
dCONSR	0.844	2.859	-0.398				
	(1.42)	(0.85)	(-1.48)				
dGPDI	0.280	-1.627	0.982				
	(0.75)	(-1.23)	(2.85)				
dGDPR	0.699	0.478	0.145	-0.020	0.001		
	(6.43)	(1.53)	(1.23)	(-0.86)	(0.10)		
dCONSR	1.885	1.013	-0.943	1.224	0.138		
	(2.83)	(0.452)	(-3.98)	(1.84)	(0.43)		
dGPDI	0.266	-0.961	1.086	0.469	0.272		
	(0.70)	(-0.68)	(3.17)	(3.22)	(2.85)		
dGDPR	0.836	**-0.993**	0.315	0.070	0.009	-0.096	0.064
	(2.36)	**(-2.11)**	(3.93)	(1.43)	(0.24)	(-0.68)	(2.62)
dCONSR	0.950	-0.201	0.250	-.002	-0.003	-0.108	0.026
	(4.88)	(-0.76)	(3.27)	(-0.12)	(0-0.21)	(-1.70)	(2.07)
dGPDI	0.850	0.299	0.959	0.483	0.283	-0.158	0.183
	(0.80)	(-0.21)	(2.76)	(3.10)	(2.65)	(-.044)	(2.93)

Table 3.9
Roll (1984) Liquidity Measure Predictive Power on Macroeconomic Proxies using the Markov-Switching Model

The table shows the parameter estimates under the second regime and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Roll (1984) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
			Roll Liquidity Measure – Economic Contraction Regime				
dGDPR	0.533	**-1.305**	0.355				
	(4.82)	**(-2.72)**	(4.63)				
dCONSR	0.568	**-0.541**	0.321				
	(8.08)	**(-2.45)**	(4.99)				
dGPDI	-0.533	**-8.567**	1.277				
	(-0.61)	**(-2.04)**	(2.12)				
dGDPR	0.500	**-1.284**	0.404	0.091	0.016		
	(4.67)	**(-2.77)**	(5.39)	(1.93)	(0.48)		
dCONSR	0.599	**-0.588**	0.282	-0.001	-0.004		
	(8.20)	**(-2.39)**	(4.19)	(-0.06)	(-0.20)		
dGPDI	-0.696	**-8.405**	1.556	0.361	-0.015		
	(-0.78)	**(-1.95)**	(2.52)	(1.57)	(-0.16)		
dGDPR	0.822	**-0.651**	0.072	-0.28	-0.009	-0.248	0.015
	(4.04)	**(-2.31)**	(0.674)	(-0.91)	(-0.56)	(-2.13)	(1.17)
dCONSR	-0.859	-2.631	-0.719	0.534	0.197	0.288	-0.066
	(-0.80)	(-1.66)	(-6.52)	(2.93)	(1.97)	(0.77)	(-1.42)
dGPDI	0.816	-6.490	1.019	0.229	-0.052	-0.332	0.376
	(0.31)	(-1.49)	(1.51)	(0.65)	(-0.23)	(-0.35)	(1.79)

Table 3.10
Lesmond, Ogden, and Trczinka (1999) Liquidity Measure Predictive Power on Macroeconomic Proxies using the Markov-Switching Model

The table shows the parameter estimates under the first regime and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Lesmond et al. (1999) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
		LOT Liquidity Measure - Economic Expansion Regime					
dGDPR	0.540	0.287	0.289				
	(5.45)	(0.62)	(2.30)				
dCONSR	0.816	0.890	-0.369				
	(1.43)	(0.21)	(-1.44)				
dGPDI	0.969	2.504	0.172				
	(3.69)	(1.26)	(1.91)				
dGDPR	3.008	-0.683	-1.202	0.044	-0.065		
	(0.69)	(-0.04)	(-2.88)	(0.04)	(-0.07)		
dCONSR	-0.196	-4.526	-0.829	0.083	-0.343		
	(-0.39)	(-1.44)	(-6.64)	(0.22)	(-1.24)		
dGPDI	2.407	**-4.345**	-0.640	0.595	0.319		
	(1.51)	**(-2.34)**	(-2.37)	(1.06)	(0.83)		
dGDPR	1.038	-0.982	0.294	0.080	0.017	-0.172	0.076
	(2.65)	(-1.33)	(3.40)	(1.57)	(0.45)	(-1.07)	(2.96)
dCONSR	1.079	-0.251	0.182	0.012	0.008	-0.129	0.021
	(5.64)	(-0.71)	(2.45)	(0.44)	(0.48)	(-2.07)	(1.66)
dGPDI	1.729	-0.156	0.198	0.475	0.278	-0.272	0.190
	(1.95)	(-0.12)	(2.24)	(3.29)	(3.09)	(-0.84)	(3.02)

Table 3.11
Lesmond, Ogden, and Trczinka (1999) Liquidity Measure Predictive Power on Macroeconomic Proxies using the Markov-Switching Model

This table shows the parameter estimates under the second regime and their asymptotic t-statistics from the maximum likelihood estimation of the Markov regime-switching model for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Lesmond et al. (1999) liquidity measure (*LIQ*), the lag of the dependent variable (*yt*), *Term*, *dCred*, *Vola*, and e*rm*. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$
LOT Liquidity Measure - Economic Contraction Regime							
dGDPR	0.506	-0.769	0.374				
	(4.37)	(-1.02)	(4.64)				
dCONSR	0.560	0.116	0.335				
	(7.65)	(0.35)	(5.06)				
dGPDI	0.210	-6.093	0.198				
	(0.29)	(-1.01)	(1.72)				
dGDPR	0.820	-0.605	0.359	0.065	0.030		
	(3.89)	(-1.51)	(5.92)	(2.11)	(1.50)		
dCONSR	0.617	-0.110	0.310	0.014	0.013		
	(8.53)	(-0.33)	(4.76)	(0.57)	(0.82)		
dGPDI	0.309	-1.682	0.476	0.604	0.284		
	(0.839)	(-0.53)	(4.96)	(2.94)	(2.28)		
dGDPR	0.667	0.242	0.247	-0.022	-0.009	-0.032	0.013
	(2.92)	(0.44)	(1.99)	(-0.63)	(-0.45)	(-0.49)	(0.99)
dCONSR	1.230	**-7.753**	-0.733	-0.470	-0.608	-0.901	0.122
	(0.75)	**(-2.80)**	(-5.24)	(-2.04)	(-3.11)	(-1.33)	(-1.72)
dGPDI	2.624	-4.981	0.129	0.250	-0.026	-0.754	0.536
	(0.94)	(-0.79)	(-1.04)	(-0.60)	(-0.08)	(-0.68)	(2.65)

Table 3.12

Amihud (2002) Liquidity Measure Predictive Power on Macroeconomic Proxies using the LSTAR and ESTAR Models

The table shows the parameter estimates under the first regime and their asymptotic t-statistics from the nonlinear least squares estimation of the LSTAR and ESTAR models for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Amihud (2002) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. The last three columns show the *F* value of the model and its p-value, and the parameters *Gamma* and *c* and their *t*-statistics. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	***F***	***Gamma***	***c***
				Amihud Liquidity Measure – Economic Expansion Regime						
dGDPR	0.354	0.944	-0.444					8.388	191.47	-0.562
	(1.45)	(1.74)	(-2.18)					(0.00)	(0.11)	(-11.4)
dCONSR	1.050	-0.080	-0.514					6.381	32.609	1.414
	(0.21)	(-0.01)	(0.10)					(0.03)	(0.63)	(23.1)
dGPDI	3.519	0.572	-0.387					4.143	0.688	4.762
	(1.87)	(0.14)	(-1.85)					(0.02)	(0.91)	(2.04)
dGDPR	0.003	0.732	-0.075	-0.133	-0.021			5.91	4.197	0.382
	(0.01)	(-1.35)	(-0.46)	(-1.63)	(-0.42)			(0.00)	(0.18)	(1.19)
dCONSR	0.720	-0.093	-0.801	-0.174	-0.139			4.227	54.935	1.542
	(3.14)	(-0.29)	(-5.14)	(-1.96)	(-2.03)			(0.00)	(0.25)	(23.5)
dGPDI	4.291	2.132	-0.492	-0.614	0.076			4.508	0.585	5.268
	(1.94)	(0.45)	(-2.03)	(-0.96)	(0.15)			(0.00)	(1.24)	(2.43)
dGDPR	-0.379	0.439	0.244	-0.049	-0.006	0.007	-0.153	6.264	32.722	-0.416
	(-0.84)	(1.39)	(1.67)	(-0.76)	(-0.15)	(0.05)	(-3.86)	(0.00)	(0.60)	(-7.22)
dCONSR	-76.46	3.570	-21.74	-12.36	-7.028	48.680	2.397	3.683	1.259	5.547
	(-0.08)	(0.06)	(-0.08)	(-0.08)	(-0.08)	(0.08)	(0.07)	(0.00)	(1.37)	(0.49)
dGPDI	10.00	-4.273	-0.443	-0.879	-0.135	-3.155	0.514	5.097	308.90	7.394
	(1.37)	(-0.67)	(-2.47)	(-1.46)	(-0.25)	(-0.94)	(-1.60)	(0.00)	(0.00)	(0.00)

Table 3.13
Amihud (2002) Liquidity Measure Predictive Power on Macroeconomic Proxies using the LSTAR and ESTAR Models

The table shows the parameter estimates under the second regime and their asymptotic t-statistics from the nonlinear least squares estimation of the LSTAR and ESTAR models for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Amihud (2002) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. The last three columns show the *F* value of the model and its p-value, and the parameters *Gamma* and *c* and their *t*-statistics. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	*F*	*Gamma*	*c*
				Amihud Liquidity Measure – Economic Recession Regime						
dGDPR	0.217	**-1.106**	0.737					8.388	191.47	-0.562
	(0.93)	**(-2.12)**	(3.80)					(0.00)	(0.11)	(-11.4)
dCONSR	0.530	-0.181	0.230					6.381	32.609	1.414
	(6.51)	(-1.21)	(3.01)					(0.03)	(0.63)	(23.1)
dGPDI	0.063	-1.569	0.235					4.143	0.688	4.762
	(0.12)	(-1.59)	(3.05)					(0.02)	(0.91)	(2.04)
dGDPR	0.523	-0.679	0.402	0.148	0.036			5.91	4.197	0.382
	(3.87)	(-1.77)	(3.32)	(2.75)	(1.10)			(0.00)	(0.18)	(1.19)
dCONSR	0.603	-0.233	0.309	0.031	0.017			4.227	54.935	1.542
	(7.80)	(-1.41)	(4.08)	(1.01)	(0.91)			(0.00)	(0.25)	(23.5)
dGPDI	-0.094	-1.877	0.293	0.667	0.228			4.508	0.585	5.268
	(-0.18)	(-1.87)	(3.72)	(3.33)	(1.91)			(0.00)	(1.24)	(2.43)
dGDPR	1.330	-0.491	0.089	0.073	0.010	-0.184	0.174	6.264	32.722	-0.416
	(3.83)	(-1.88)	(0.69)	(1.40)	(0.31)	(-1.72)	(4.78)	(0.00)	(0.60)	(-7.22)
dCONSR	1.272	-0.212	0.111	0.048	0.021	-0.225	0.028	3.683	1.259	5.547
	(4.86)	(-0.99)	(1.04)	(1.10)	(0.80)	(-2.04)	(1.39)	(0.00)	(1.37)	(0.49)
dGPDI	1.200	-0.966	0.216	0.530	0.204	-0.229	0.329	5.097	308.90	7.394
	(1.19)	(-1.29)	(3.28)	(3.18)	(1.94)	(-0.60)	(4.41)	(0.00)	(0.00)	(0.00)

Table 3.14
Roll (1984) Liquidity Measure Predictive Power on Macroeconomic Proxies using the LSTAR and ESTAR Models

The table shows the parameter estimates under the first regime and their asymptotic t-statistics from the nonlinear least squares estimation of the LSTAR and ESTAR models for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Roll (1984) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. The last three columns show the *F* value of the model and its p-value, and the parameters *Gamma* and *c* and their *t*-statistics. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	F	*Gamma*	c
				Roll Liquidity Measure – Economic Expansion Regime						
dGDPR	0.330	0.878	0.833					8.893	227.41	-0.446
	(1.71)	(0.96)	(5.31)					(0.00)	(0.00)	(0.00)
dCONSR	17.812	2.656	-1.092					8.304	0.676	1.220
	(0.621)	(1.06)	-0.77)					(0.00)	(1.26)	(1.25)
dGPDI	-7.490	**13.435**	-0.501					5.054	0.936	-4.187
	(-2.36)	**(2.81)**	(-1.62)					(0.02)	(0.93)	(-4.17)
dGDPR	0.622	1.590	0.658	0.061	0.129			6.501	1518	-.0286
	(3.96)	(1.58)	(4.54)	(1.65)	(2.31)			(0.00)	(0.30)	(0.00)
dCONSR	1.074	**1.844**	-0.523	0.004	0.019			4.662	183.10	1.407
	(0.17)	**(2.46)**	(-4.22)	(0.05)	(0.31)			(0.00)	(0.08)	(0.00)
dGPDI	-7.063	**14.268**	-0.567	-0.072	0.235			4.950	2.646	-3.438
	(-2.93)	**(3.28)**	(-2.08)	(-0.13)	(0.96)			(0.00)	(0.85)	(-5.88)
dGDPR	1.503	1.300	0.939	-0.143	-0.176	-0.541	-0.189	6.511	40.891	-0.417
	(1.97)	(0.99)	(2.19)	(-2.16)	(-1.71)	(-2.28)	(-3.20)	(0.00)	(0.50)	(-8.29)
dCONSR	8.281	3.028	-1.216	-0.348	-0.134	-0.319	-0.070	4.695	1.158	1.461
	(1.61)	(1.58)	(-1.79)	(-1.60)	(-1.01)	(-0.74)	(-0.79)	(0.00)	(2.19)	(2.77)
dGPDI	-8.493	**10.429**	-0.499	-0.138	0.193	0.648	-0.155	5.00	2.840	-3.181
	(-2.73)	**(2.15)**	(-1.91)	(-0.34)	(0.82)	(-0.75)	(-0.77)	(0.00)	(0.89)	(-6.72)

Table 3.15
Roll (1984) Liquidity Measure Predictive Power on Macroeconomic Proxies using the LSTAR and ESTAR Models

The table shows the parameter estimates under the second regime and their asymptotic t-statistics from the nonlinear least squares estimation of the LSTAR and ESTAR models for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Roll (1984) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. The last three columns show the *F* value of the model and its p-value, and the parameters *Gamma* and *c* and their *t*-statistics. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	F	$Gamma$	c
				Roll Liquidity Measure - Economic Contraction Regime						
dGDPR	0.254	-1.803	-0.558					8.893	227.41	-0.446
	(1.71)	(-1.87)	(-3.31)					(0.00)	(0.00)	(0.00)
dCONSR	-4.943	-1.498	-1.854					8.304	0.676	1.220
	(-0.43)	(-1.43)	(-0.74)					(0.00)	(1.26)	(1.25)
dGPDI	7.796	**-16.204**	0.780					5.054	0.936	-4.187
	(2.52)	**(-3.71)**	(2.59)					(0.02)	(0.93)	(-4.17)
dGDPR	-0.167	**-.2653**	-0.328	-0.063	-0.100			6.501	151.8	-.0286
	(-0.90)	**(-2.50)**	(-2.07)	(-1.39)	(-1.46)			(0.00)	(0.30)	(0.00)
dCONSR	0.534	**-0.627**	0.215	0.012	-0.001			4.662	183.10	1.407
	(6.65)	**(-1.97)**	(2.82)	(0.38)	(-0.09)			(0.00)	(0.08)	(0.00)
dGPDI	7.350	**-16.510**	0.890	0.545	0.004			4.950	2.646	-3.438
	(3.13)	**(-4.24)**	(3.43)	(1.49)	(0.02)			(0.00)	(0.85)	(-5.88)
dGDPR	-0.673	-1.816	-0.580	0.154	0.217	0.412	0.221	6.511	40.891	-0.417
	(-0.94)	(-1.44)	(-1.36)	(2.50)	(2.25)	(1.88)	(3.93)	(0.00)	(0.50)	(-8.29)
dCONSR	-0.540	-1.222	-0.771	0.120	0.041	-0.025	0.036	4.695	1.158	1.461
	(-0.32)	(-1.64)	(-1.46)	(1.43)	(0.90)	(-0.16)	(1.30)	(0.00)	(2.19)	(2.77)
dGPDI	9.037	**-11.536**	0.797	0.545	0.024	-0.695	0.432	5.00	2.840	-3.181
	(3.29)	**(-2.60)**	(3.22)	(1.59)	(0.13)	(-1.03)	(2.40)	(0.00)	(0.89)	(-6.72)

Table 3.16

Lesmond, Ogden, and Trczinka (1999) Liquidity Measure Predictive Power on Macroeconomic Proxies using the LSTAR and ESTAR Models

The table shows the parameter estimates under the first regime and their asymptotic t-statistics from the nonlinear least squares estimation of the LSTAR and ESTAR models for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Lesmond et al. (1999) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. The last three columns show the *F* value of the model and its p-value, and the parameters *Gamma* and *c* and their *t*-statistics. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	***F***	***Gamma***	***c***
				LOT Liquidity Measure – Economic Expansion Regime						
dGDPR	0.147	1.384	-0.477					0.054	215.7	-0.394
	(0.70)	(1.13)	(-2.76)					(0.98)	(0.00)	(0.00)
dCONSR	-39.812	1.476	-7.609					0.962	0.373	-0.222
	(-0.16)	(0.30)	(-0.24)					(0.38)	(0.52)	(-0.04)
dGPDI	0.022	1.861	0.276					4.020	0.722	4.104
	(0.04)	(0.63)	(3.57)					(0.00)	(0.99)	(2.30)
dGDPR	-0.084	**3.556**	-0.052	-0.197	-0.112			4.662	510.64	0.123
	(-0.505)	**(3.02)**	(-0.39)	(-2.94)	(-2.48)			(0.00)	(0.14)	(5.18)
dCONSR	3.955	5.496	-3.974	-1.151	-0.986			3.266	1.038	3.702
	(0.92)	(0.51)	(-1.10)	(-0.83)	(-0.91)			(0.00)	(1.29)	(1.62)
dGPDI	-0.084	2.142	0.342	0.675	0.233			4.483	0.609	4.813
	(-0.172)	(0.71)	(4.21)	(3.35)	(1.88)			(0.00)	(1.28)	(2.35)
dGDPR	-0.564	**3.657**	0.195	-1.08	-0.076	0.073	-0.156	6.920	14.09	0.109
	(-1.19)	**(3.11)**	(1.33)	(-1.61)	(-1.71)	(0.47)	(-3.64)	(0.00)	(0.176)	(5.39)
dCONSR	16.526	-1.439	-2.089	-0.502	-0.242	-0.260	-0.148	4.501	0.771	1.868
	(0.75)	(-0.99)	(-1.27)	(-1.04)	(-0.42)	(-1.04)	(1.42)	(0.00)	(1.42)	(1.65)
dGPDI	1.408	-1.184	0.230	0.541	0.222	-0.299	0.353	5.079	19.306	6.309
	(1.36)	(-0.53)	(3.51)	(3.20)	(2.06)	(-0.76)	(4.69)	(0.00)	(0.09)	(29.94)

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Table 3.17
Lesmond, Ogden, and Trczinka (1999) Liquidity Measure Predictive Power on Macroeconomic Proxies using the LSTAR and ESTAR Models

The table shows the parameter estimates under the second regime and their asymptotic t-statistics from the nonlinear least squares estimation of the LSTAR and ESTAR models for the period 1947 through 2012. The dependent variables are the three macroeconomic proxies *dGDPR*, *dCONSR* and *dGPDI* and the explanatory variables are the Lesmond et al. (1999) liquidity measure (*LIQ*), the lag of the dependent variable (y_t), *Term*, *dCred*, *Vola*, and er_m. The last three columns show the *F* value of the model and its p-value, and the parameters *Gamma* and *c* and their *t*-statistics. Significant coefficients for the liquidity measure are in bold font.

Dependent Variable y_{t+1}	$\hat{\alpha}$	$\hat{\beta}^{LIQ}$	$\hat{\gamma}^{y}$	$\hat{\gamma}^{TERM}$	$\hat{\gamma}^{CRED}$	$\hat{\gamma}^{Vola}$	$\hat{\gamma}^{er_m}$	F	*Gamma*	c
				LOT Liquidity Measure – Economic Contraction Regime						
dGDPR	0.409	-1.474	0.779					0.054	215.7	-0.394
	(2.12)	(-1.30)	(4.84)					(0.98)	(0.00)	(0.00)
dCONSR	77.370	-2.521	1.645					0.962	0.373	-0.222
	(0.19)	(-0.34)	(0.10)					(0.38)	(0.52)	(-0.04)
dGPDI	3.196	-10.783	-0.423					4.020	0.722	4.104
	(2.30)	(-1.45)	(-2.08)					(0.00)	(0.99)	(2.30)
dGDPR	0.591	**-3.346**	0.408	0.223	0.119			4.662	510.64	0.123
	(4.08)	**(-3.10)**	(3.54)	(4.15)	(3.21)			(0.00)	(0.14)	(5.18)
dCONSR	0.542	-0.348	0.352	0.069	0.052			3.266	1.038	3.702
	(3.08)	(-0.50)	(2.20)	(1.11)	(1.22)			(0.00)	(1.29)	(1.62)
dGPDI	3.846	-14.862	-0.593	-0.473	0.244			4.483	0.609	4.813
	(2.13)	(-1.60)	(-2.31)	(-0.79)	(0.52)			(0.00)	(1.28)	(2.35)
dGDPR	1.493	**-3.642**	0.114	0.133	0.08	-0.022	0.181	6.920	14.096	0.109
	(3.96)	**(-3.36)**	(0.88)	(2.43)	(2.20)	(-2.04)	(4.54)	(0.00)	(0.176)	(5.39)
dCONSR	-2.339	0.163	-1.273	0.167	0.078	-0.046	0.064	4.501	0.771	1.868
	(-0.38)	(0.14)	(0.86)	(1.19)	(1.02)	(-0.24)	(1.83)	(0.00)	(1.42)	(1.65)
dGPDI	2.212	-10.483	0.558	-0.533	0.249	0.219	-0.592	5.079	19.306	6.309
	(0.59)	(-1.31)	(-3.28)	(-1.04)	(0.58)	(0.14)	(-2.21)	(0.00)	(0.09)	(29.94)

3.6 Robustness Tests: Cointegration Analysis

Cointegration analysis has been widely used over the past three decades since its introduction by Engle and Granger (1987). Basically the approach tests for a long run equilibrium relationship between two or more non-stationary random time series based on the existence (or non-existence) of a linear combination of such variables that divulges the property of stationarity. Equivalently if two or more data time series are individually integrated (*i.e.* presence of unit roots) and if there exists a linear combination of them which displays a lesser order of integration, then the time series are said to be cointegrated. For instance, an equity market index and its corresponding futures contract price may follow individual random walks while an equilibrium relationship exists between the two variables because a linear combination of the two time series presents a lesser order of integration, especially if it is I(0), and which would imply that the two time series are cointegrated.

This study employs two popular methods for testing whether the time series of macroeconomic proxies and liquidity measures are cointegrated: The Johansen (1988) (including a recursive Cointegration test) and Gregory and Hansen (1996) cointegration tests.

However before tests of cointegration can be performed on the data series it is critical to test for the presence of unit roots (or the property of non-stationarity) and in the affirmative whether they are integrated of the same order. By applying the Augmented Dickey-Fuller unit root test it is found that all macrovariables and liquidity measures previously investigated in this study present the characteristic of nonstationarity except the *Roll* liquidity measure which is consequently removed from the following cointegration analysis. Moreover the variables presenting evidence of units roots (*i.e. RGDP*, *GPDI*, *RPCE*, *Amihud*, *LOT*) are all integrated of order 1 meaning that if they are differenced once the series become stationary and which also implies that they can be jointly tested for cointegration with the two previously mentioned models.

In practice, cointegration is often used and is more generally applicable for two series, but it can be used to analyse additional relationships: Multicointegration or multivariate cointegration tests, which are also performed in this essay, extend the cointegration methodology beyond two variables.

3.6.1 Johansen's (1988) Cointegration Test

The Johansen's methodology (1988) takes its starting point in the vector autoregression (VAR) of order p given by:

$$z_t = c + A_1 z_{t-1} + \ldots + A_p z_{t-p} + \mu_t \tag{3.16}$$

where z_t is a n×1 vector of variables that are integrated of order one — commonly denoted $I(1)$ — and μ_t is a zero mean white noise vector process. This VAR can be re-written as:

$$\Delta z_t = c + \Pi\, z_{t-1} + \sum_{i=1}^{p-1} \Gamma_i\, \Delta_i + \mu_t \tag{3.17}$$

where $\Pi = \sum_{i=1}^{p} \mathrm{A}_i - I$ and $\Gamma_i = -\sum_{j=i+1}^{p} \mathrm{A}_j$. If the coefficient matrix has reduced rank $r < n$, then there exist $n \times r$ matrices α and β each with rank r such that = $\alpha\beta'$ and $\beta' z_t$ is stationary. r is the number of cointegration relationships, the elements of α are known as the adjustment parameters in the vector error correction model and each column of β is a cointegrating vector. It can be shown that for a given r, the maximu likelihood estimator of β defines the combination of z_{t-1} that yields the r largest canonical correlations of z_t with z_{t-1} after correcting for lagged differences and deterministic variables when present. Johansen proposed two different likelihood ratio tests of the significance of these canonical correlations and thereby the reduced rank of the matrix, that is the trace (λ_{trace}) and maximum eigenvalue (λ_{max}) test,which are computed by using the following formulas:

$$\lambda_{trace} = -T\sum_{j=r+1}^{k}\ln(1-\hat{\lambda}_j) \tag{3.18}$$

$$\lambda_{max} = -T\ln(1-\hat{\lambda}_{r+1}) \tag{3.19}$$

where T is the sample size, $\hat{\lambda}_j$ and $\hat{\lambda}_{r+1}$ are the estimated values of the characteristic roots obtained from the matrix. The trace test tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of n cointegrating vectors, while the maximum eigenvalue tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of r+1 cointegrating vectors.

To reflect the potential time-varying co-movement, the recursive cointegration methodology is also employed in the section. This dynamic approach examines whether a group of variables becomes progressively cointegrated by visually evaluating the cointegration over time.

In the recursive analyse Johansen's (1988) trace statistic is estimated over the initial observations which are kept fixed and then recursively recomputed as additional observations are added to the base sample. This approach allows to plot and graphically evaluate the trace statistics.

If a cointegration property between the variables is significantly present, it should be revealed by an increasing number of cointegrating vectors emerging over time as the data generating process is being gradually governed by the same shocks with a permanent effect.

3.6.2 Gregory & Hansen's (1996) Cointegration Test

Gregory and Hansen (1996) propose a test that allows for a possible structural break in the cointegration relationship. More specifically the Gregory and Hansen (1996) methodology tests the null hypothesis that the series are not cointegrated against the alternative hypothesis of cointegration with a single structural break at a single unknown time during the sample period. The timing of the structural change is estimated endogeneously rather than arbitrarily selected or assumed on the basis of market history.

According to Gregory and Hansen (1996) cointegration with the existence of a structural change can be thought of a relationship occuring over some prolonged period of time and then shifting to a new long-run equilibrium relationship.

Structural changes can manifest themselves through changes in the long-term relationship either in the form of a change in the intercept, or a change in the cointegrating vector. Gregory and Hansen (1996) propose three alternative models that accommodate variation in parameters of the cointegration vector.

The first one is the so-called level shift model (or C model) that allows for the change only in the intercept.

$$y_t = \mu_1 + \mu_2\, \varphi_{t\tau} + \alpha' x_t + e_t \quad t = 1,\ldots,n. \tag{3.20}$$

The second model accommodates a trend in the data, while also restricting the changes to shifts in the level (C/T model).

$$y_{1t} = \mu_1 + \mu_2\, \varphi_{t\tau} + \beta_t + \alpha' x_t + e_t \quad t = 1,\ldots,n. \tag{3.21}$$

The last model allows for changes both in the intercept and in the slope of the cointegration vector (C/S model).

$$y_{1t} = \mu_1 + \mu_2\, \varphi_{t\tau} + \alpha'_1\, x_t + \alpha'_2\, x_t\, \varphi_{t\tau} + e_t \quad t = 1,...,n. \tag{3.22}$$

where: y_1 is the dependent variable, x is the independent variable, t is time subscript, e is the error term τ is the break date.

The dummy variable φ_t which captures the structural change is defined as follows:

$$\varphi_{t\tau} = \begin{cases} 0, & t \leq [n\tau] \\ 1, & t > [n\tau] \end{cases} \tag{3.23}$$

where $\tau \in(0,1)$ is a relative timing of the change point. Equations (3.20)–(3.22) are estimated sequentially with the break point changing over the interval $\tau \in(0,1)$. The nonstationarity of the obtained residuals, expected under the null hypothesis, is verified by the ADF test.

3.6.3 Results of Johansen (1988), Gregory and Hansen (1996) and the Recursive Analysis Cointegration Tests

The findings of the Johansen's (1988) cointegration under a bivariate setting are presented in Panel A of Table 3.18 and provide no evidence that a long-run relationship exists between the macroeconomic variables and the liquidity proxies.

The results of the Gregory and Hansen (1996)'s bivariate cointegration test over the extended period analyzed show that one equilibrium relationship is present between the *Real Investment in the Private Sector* (*GPDI*) variable and the *Amihud* liquidity measure under the C/S model. Moreover this model indicates that a structural break occured in the first quarter of the year 1990 which corresponds to the period preceding by 2 quarters the July 1990-March 1991 recession in the United States.

Models C/T and C/S also reveal some co-movements between the *LOT* and *GPDI* variables with a structural break taking place on the fourth quarter of 1996, a time period that corresponds to no major economic event in the United States.

Table 3.19 exhibits the findings of the Johansen's (1988) cointegration under a multivariate setting and present some evidence of cointegration between the variables *RGDP - Amihud & LOT* and *RPCE - Amihud & LOT* since at least one cointegration equation exists for each of these two sets of variables.

The Gregory and Hansen's (1996) multivariate test results (Table 3.20) show that the null hypothesis of no cointegration is not rejected under all model specifications (C, C/T, and C/S) considered except for the set of variables *GPDI - Amihud & LOT* (Model C/S) with a structural break once more occuring in the first quarter of the year 1990.

Finally, Figures 3.2 to 3.4 depict the results from the recursive cointegration analysis. For ease of interpretation the test statistics in these figures have been scaled by their critical values such that the number of lines above 1.0 indicates the number of cointegrating relationships. These graphs indicate one cointegrating vector between the macroeconomic variable *RGDP* and the *Amihud* and *Roll* liquidity measures. Note that during the period analyzed no other cointegrating vector is appearing at any point in time. The same conclusion is also observed between the macroeconomic proxy *RPCE* and both liquidity measures.

The dynamic Trace Test Statistic involving the relationship between the macroeconomic variable *GPDI* and the *Amihud* and *Roll* liquidity measures only rise above one for some time intervals and not in the entirity of the sample period indicating a quasi-non-existent cointegration association between these three variables.

These visual findings corroborate the static Johansen's (1988) multivariate cointegration test results (Table XVII) for all three relationships.

All in all, while some evidence of cointegration may exist between some of the macroeconomic fundamentals and some liquidity measures under the Johansen (1988), the Gregory and Hansen (1996) and the recursive cointegration tests, these findings are not overall convincing since the majority of the results do not allow to assert with certitude that liquidity measures are cointegrated with economic cycles.

Table 3.18 Johansen (1988) and Gregory & Hansen (1996) Cointegration Tests (Bivariate Setting)

Panel A: Johansen's (1988) Cointegration Test (Bivariate Setting)

	RGDP	*GPDI*	*RPCE*
Amihud	12.22	8.32	14.23
LOT	10.48	7.30	10.51

The null is that the hypothesized number of cointegration equations between the variables amounts to none. The test statistics are based on the Trace approach. Results obtained with the Eigenvalue methodology are equivalent. 5% Critical Value: 15.494.

Panel B: Gregory & Hansen (1996) Cointegration Test (Bivariate Setting)

Variables	Test Statistic	Date of Structural Shift
Model C (5% Critical Value: -4.61)		
Amihud - RGDP	-4.34	1971:02
Amihud - GPDI	-4.24	1971:03
Amihud - RPCE	-4.44	1971:02
LOT- RGDP	-3.23	1973:03
LOT - GPDI	-3.65	1973:03
LOT - RPCE	-3.32	1971:04
Model C/T (5% Critical Value: -4.99)		
Amihud - RGDP	-3.44	1963:04
Amihud - GPDI	-4.65	1966:02
Amihud - RPCE	-3.24	1966:03
LOT- RGDP	-3.80	1963:04
LOT - GPDI	**-5.09***	1996:04
LOT - RPCE	-3.18	1966:01
Model C/S (5% Critical Value: -5.50)		
Amihud - RGDP	-3.74	2003:01
Amihud - GPDI	**-6.42***	1990:01
Amihud - RPCE	-3.26	1990:01
LOT- RGDP	-4.90	2000:02
LOT - GPDI	**-5.98***	1996:04
LOT - RPCE	-3.27	1993:03

The null hypothesis states that there is no cointegration between the two variables. Critical values are obtained from Gregory and Hansen (1996). The model specifications are denoted by C—level shift, C/T—level shift with a trend, C/S—regime shift (see Section 6.2).

Table 3.19 Johansen's (1988) Cointegration Test (Multivariate Setting)

Panel A — Variables: *RGDP - Amihud & LOT*

Hypothesized Number of Cointegration Equations	Trace Statistic	5% Critical Value	Significance at 5% Level
None	**44.84**	42.91	*Yes*
At most 1	16.63	25.87	*No*
At most 2	6.358	12.51	*No*

Panel B — Variables: *GPDI - Amihud & LOT*

Hypothesized Number of Cointegration Equations	Trace Statistic	5% Critical Value	Significance at 5% Level
None	37.49	42.91	*No*
At most 1	14.02	25.87	*No*
At most 2	4.52	12.51	*No*

Panel C — Variables: *RPCE - Amihud & LOT*

Hypothesized Number of Cointegration Equations	Trace Statistic	5% Critical Value	Significance at 5% Level
None	**43.46**	42.91	*Yes*
At most 1	18.39	25.87	*No*
At most 2	5.60	12.51	*No*

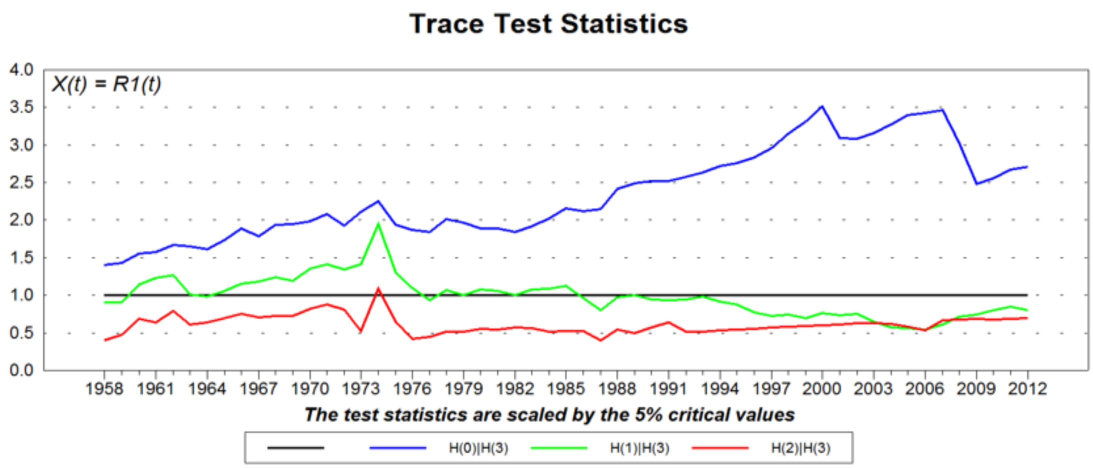
The null is that the hypothesized number of cointegration equations between the variables amounts to none. The test statistics are based on the Trace approach. Results obtained with the Eigenvalue methodology are quivalent. 5% Critical Value: 15.494.

Table 3.20 Gregory & Hansen (1996) Cointegration Test (Multivariate Setting)

Variables	Test Statistic	Date of Structural Shift
Model C - (5% Critical Value: -4.92)		
RGDP - Amihud & LOT	-3.81	1971:02
GPDI - Amihud & LOT	-4.01	1971:04
RPCE - Amihud & LOT	-3.90	1971:02
Model C/T - (5% Critical Value: -5.29)		
RGDP - Amihud & LOT	-3.70	1963:03
GPDI - Amihud & LOT	-4.94	1998:02
RPCE - Amihud & LOT	-3.06	1966:03
Model C/S - (5% Critical Value: -5.96)		
RGDP - Amihud & LOT	-3.99	1993:01
GPDI - Amihud & LOT	**-6.41***	1990:01
RPCE - Amihud & LOT	-3.58	1993:01

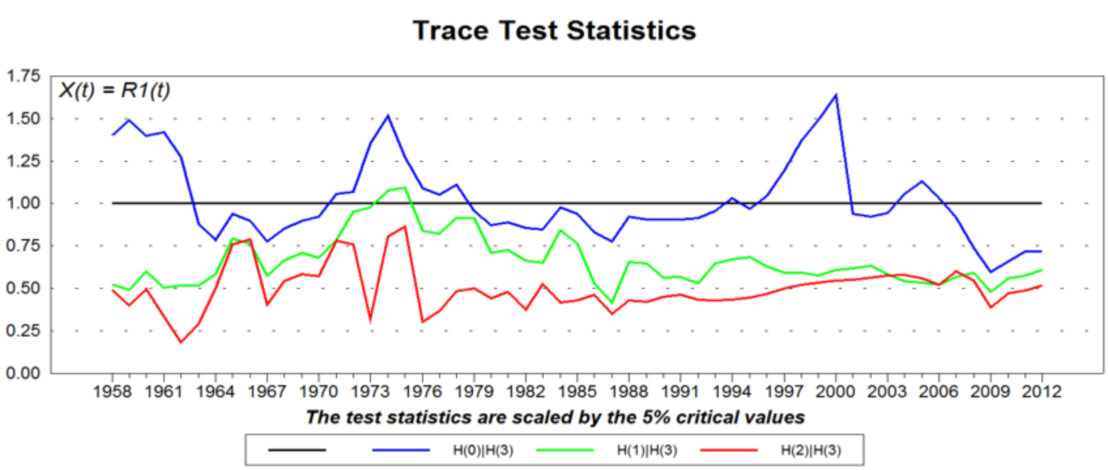
The null hypothesis states that there is no cointegration between the variables. Critical values are obtained from Gregory and Hansen (1996). The model specifications are denoted by C—level shift, C/T—level shift with a trend, C/S—regime shift (see Section 6.2).

Figure 3.2 – Recursive Cointegration Analysis - Variables: *RGDP ROLL AMIHUD*



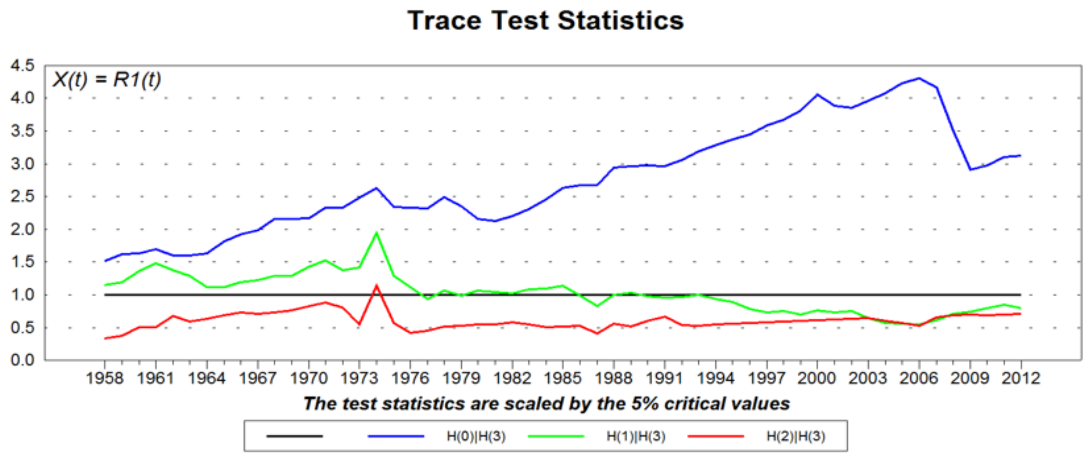
The test statistics in this figure has been scaled by their critical values such that the number of lines above 1.0 indicates the number of cointegrating relationships.

Figure 3.3 – Recursive Cointegration Analysis - Variables: *GPDI ROLL AMIHUD*



The test statistics in this figure has been scaled by their critical values such that the number of lines above 1.0 indicates the number of cointegrating relationships.

Figure 3.4 – Recursive Cointegration Analysis - Variables: *RPCE ROLL AMIHUD*



The test statistics in this figure has been scaled by their critical values such that the number of lines above 1.0 indicates the number of cointegrating relationships.

3.7 Conclusion

In an provocative recent paper, Næs et al. (2011) suggest that stock market aggregate liquidity is a leading indicator of subsequent economic cycles. Using several macroeconomic variables to proxy for the state of the economy, they show that different liquidity measures possess a predictive power of the future state of the real economy even after controlling for the present economic conditions and several bond and stock market factors. This forecasting power leads the authors of the paper to assert that "stock market liquidity contains useful information for estimating the future state of the economy" since equity market investors rebalance their portfolio into more secure securities before economic downturns causing greater variations in aggregate liquidity. While this idea is intuitively appealing, the analysis suffers from an important shortcoming since this predictability ability is established upon a linear functional form even though the empirical research has documented over the years that macroeconomic series follow non-linear behaviour.

This paper hence re-examines the relationship between business cycles and market wide liquidity upon a non-linear approach in order to reflect the non-linear dynamics of macroeconomic series. Applying two popular econometric frameworks i.e. the Markov switching-regime and the STAR models, the findings present weak evidence that liquidity fundamentals act as leading indicators of future economic conditions. Indeed, the significance of the liquidity measure coefficients are not sufficiently constant and steady under both regimes and both econometric approaches and are not robust to the inclusion of other explanatory financial variables. Hence, the claim that stock market aggregate liquidity could be exploited to predict the future state of the economy may be premature at best.

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