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Continuous information and the FIP hypothesis: Empirical evidence from the Finnish stock market

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Abstract

This paper tests the FIP hypothesis in the Finnish stock market. The hypothesis predicts that there is a relationship between continuous information and momentum. The results of this paper suggest that there is a statistically significant difference between the returns of portfolios that contain continuous information and portfolios that contain discrete information. The paper shows that the returns of momentum portfolio gradually decrease when moving towards more discrete information. These findings support the FIP hypothesis, and signal that investors underreact to continuous information or have a delay in processing that.

Keywords FIP hypothesis, continuous information, information discreteness

Contents

1. Introduction

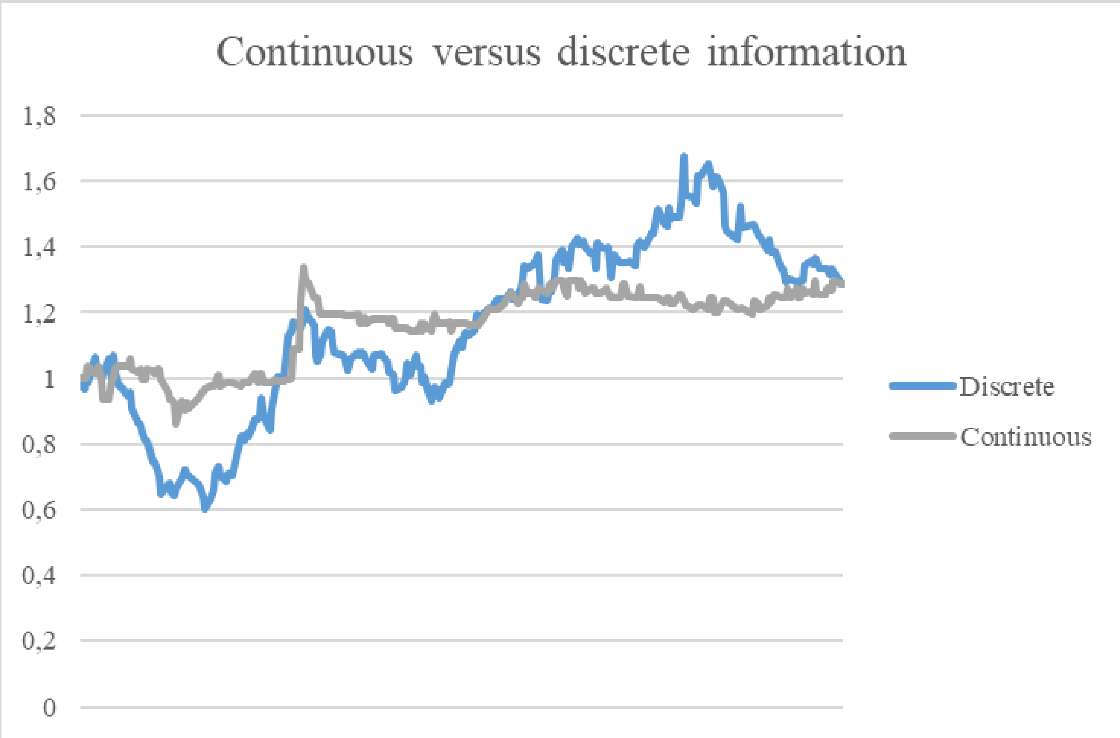
People tend to react new information differently based on the way it is received. In the study from Gino and Bazerman (2009), authors argue that large, dramatic changes induce larger amount of critical evaluation than small, gradual changes. Their study revealed that unethical behaviour had a greater acceptance when the behaviour was gradually evolving compared to dramatic shifts in behaviour.

Da, Gurun and Warachka (2014) developed the frog-in-the-pan (FIP) hypothesis that is motivated by the idea that series of gradual changes attract less investor attention than abrupt dramatic changes. Limited cognitive resources can inhibit investors ability to process all available information immediately (Da, Gurun & Warachka, 2014). This hypothesis is based on the assumption that investors are less attentive to the information arriving continuously in smaller amounts than to information that has same cumulative implications to stock price that arrives discretely in large amounts. The name frog-in-the-pan comes from the anecdote where the frog instantly jumps out of the pan if added boiling water, thus the frog shows immediate reaction to the change. When the water temperature is gradually raised, the frog shows no reaction to the changes and eventually dies. This is what the hypothesis aims to prove – investors do not have immediate reactions to the information when it is received continuously in small amounts. Instead, investors underreact to the information and thus create momentum (Da, Gurun & Warachka, 2014).

The role of limited attention in creating momentum has not been widely explored. (Da, Gurun & Warachka, 2014). Authors state that the existing literature assumes that existence of upper attention threshold limits the maximum amount of information that investors can process on all firms in short time horizon. In the study from Hirshleifer, Lim and Teoh (2009), they conclude that the large amount of information is overwhelming the investors as they found greater post-earnings announcement drift following days that consisted large number of earnings announcements. The FIP - hypothesis predicts an underreaction to information when it is received continuously in small amounts over a long time period, thus assuming the existence of a lower attention threshold. Specifically, this hypothesis predicts that investors react to continuous information with a delay (Da, Gurun & Warachka, 2014).

Figure 1 illustrates the FIP hypothesis, moreover the difference between continuous and discrete information. Figure consist of two stocks over a 250-day formation period, in which the cumulative returns are equal between the stocks.

Figure 1



In the Figure 1, the two stocks have equal cumulative returns over the time period of 250 days, but their price paths seem to be significantly different. Continuous information arrives in small amounts and it generates smoothly evolving price path, when discrete information arrives in large amounts and leads to a different, more volatile price path.

In this thesis I will partially replicate the study from Da, Gurun and Warachka (2014). I will use similar methods for testing the FIP hypothesis using different data. The main goal of my thesis is to investigate if there is similar phenomenon in Finnish stock market as there is in US stock market. Hence, the goal is to examine is there a delay in processing continuous information among investors in Finnish stock market by comparing the returns between discrete information containing portfolio and continuous information containing portfolio. As the Finnish stock market differs from the US stock market in terms of liquidity, the study will provide new perspective to the hypothesis.

To distinguish between continuous and discrete information, I will use proxy for information discreteness. Da, Gurun and Warachka (2014) created reliable measure for this separation, which is based on the return (positive or negative) and the percentage of negative and positive trading days. The proxy is denoted ID, which gives negative value if the information is continuous and positive value if the information is discrete. In Figure 1, the ID for continuous information gives the value of -0,0757 and for discrete information the value of 0,3546. However, as mentioned earlier, the Finnish stock market is somewhat illiquid, and thus the ID proxy is not the most efficient measure for information discreteness. Therefore, I will use modified proxy, denoted ID_Z, which takes zero-trading days into account. The main focus of the analysis will be on the difference between continuous and discrete information in generating momentum. The FIP hypothesis predicts that there is a conditional relationship with ID and momentum (Da, Gurun & Warachka, 2014). To test the relationship, I will investigate the influence of continuous and discrete information to the holding-period returns using double-sorted portfolios. Sorting is first done based on past returns, then on ID_Z.

I found a significant difference in momentum between the most continuous information containing portfolio, denoted Continuous, and the most discrete information containing portfolio, denoted Discrete. The differences were statistically significant with 12-month and 6-month holding periods. The alphas and t-stats both gradually decreased when portfolio was constructed with more discrete information containing stocks.

2. Literature review

Existing literature and previous studies find significant information on common phenomena that occur in the stock market. The findings often violate the capital asset pricing model (CAPM) and the efficient market hypothesis. Thus, previous literature provides support for the FIP hypothesis. In this section, I will discuss some of these phenomena that support the FIP hypothesis.

2.1. Limited investor attention

Previous studies have revealed that limited investor attention is causing underreactions to market (Hirshleifer, Lim and Teoh 2009). These studies propose that limited investor attention may provide explanation for anomalies, such as momentum (Jegadeesh & Titman 1993) and post-earnings announcement drift (Bernard & Thomas 1989). Studies from Hirshleifer and Teoh (2003) and DellaVigna and Pollet (2009) predict that investors disregard of information may lead to mispricing related to publicly available information. Hirsleifer et al. (2009) conclude that they found significantly weaker price and volume reaction and the post-announcement drift was much stronger when a greater number of earnings were announced by multiple firms. These findings support the FIP hypothesis. The hypothesis acknowledges the limited capacity of investor attention and relies on the assumption that investors underreact to the continuously arriving information. Hence, these studies provide a solid base for this hypothesis.

2.1. The Momentum Effect

The momentum effect is one of the commonly known anomalies. Basically, the momentum effect refers to a phenomenon where price movements of the stocks are predictable based on the past returns. Thus, the momentum strategy assumes that the past winners will keep winning and losers keep losing. The momentum strategy was formalized by Jegadeesh and Titman in the early 1990s, strongly motivated by Robert Levy's relative strength strategy from 1967. Robert Levy (1967) stated that the returns of buying historically strongest stocks are superior to the returns based on random selection. Thus, the idea behind Levy's strategy was very similar to momentum strategy. Jegadeesh and Titman (1993) provided statistical evidence for momentum strategy, where the idea was to buy equities with high 3-to-12-months performance and sell those with low performance and found out that this strategy provided profits of 1 percent per month for the following year. Results have been quite well accepted, but also widely debated.

Some have argued that momentum is clear evidence of market inefficiency, while others have stated that the returns are fair compensation of the risk that these strategies have (Jegadeesh & Titman, 2001). Barroso et al. (2014) state that the momentum strategy has provided investors the highest Sharpe’s ratio compared with size, value or market factors. However, momentum has also been exposed to large crashes, making it less attractive for investors who dislike negative skewness. These crashes are usually occurring during sudden upswings after a bear market (Daniel & Moskowitz, 2016). Daniel and Moskowitz also claim that the main cause for these crashes were driven by being short on the losers. Thus, authors refer to the idea that long-only momentum might be less sensitive to these crashes.

Daniel, Hirshleifer and Subrahmanyam (1998) are one of the many authors that have developed behavioural models where the momentum effect evolves as a result of delayed reaction or overreaction to information by the investors. These findings have also been discovered by Barberis, Shelifer and Vishny (1998), and Hong and Stein (1999). These previous studies are in line with the FIP hypothesis, as the investors’ underreaction is acknowledged in all of them in terms of momentum effect.

3. Data and methodology

I obtained the return data from DataStream via Thomson Reuters Eikon. Data contains both listed and delisted stocks on the time-period from January 2nd, 1998 to December 27th, 2017. The dataset includes all the equity stocks from Finnish stock market during the time period. The time period was chosen since it includes both tech-bubble and financial crisis to the review.

3.1. Proxy for information discreteness

Da, Gurun and Warachka (2014) constructed a proxy for information discreteness, denoted ID. The measure aims to separate stocks containing continuous information from the discrete information containing stocks. Thus, ID quantifies the path of the stocks price development. ID is quite similar to the return consistency measure from Grinblatt and Moskowitz (2004) in terms of construction. However, return consistency measure is a dummy variable, unlike ID, and it does not enable ranking based on its values. ID is constructed based on cumulative returns on the formation period and the signs of daily returns. Equation 1 shows the formula below.

$$\mathbf{ID} = \mathbf{sgn}(\mathbf{PRET}) * [\%\mathbf{neg} - \%\mathbf{pos}], \text{where:} \qquad (1)$$

$$\text{PRET} = \text{cumulative return on the formation period, after skipping the most recent month}$$

$$\%\text{neg} = \text{percentage of days with negative returns during the formation period}$$

$$\%\text{pos} = \text{percentage of days with positive retruns during the formation period}$$

As seen in the Equation 1, ID does not depend on the magnitude of the formation period returns. It rather uses the sign of PRET, which equals 1 when the return is positive and -1 when negative. Equation 1 implies that when stock has a positive return during the formation period and the number of days with positive return is greater than with negative returns, ID will get a negative value. Thus, the minimum value for this measure is -1, and it occurs when the PRET is positive and stock has only positive daily returns during the formation period. The closer the value of ID gets to this minimum value, the more continuous information the stock contains. Thus, negative value implies that the stock is ranked higher in terms of momentum according to the FIP hypothesis. As this proxy provided by Da, Gurun and Warachka (2014) is robust whether the PRET gets a high absolute value or is negative, it does not take zero-trading-days into account.

Fortunately, authors provide other solution for defining information discreteness by modifying Equation 1. The modified version of ID, denoted ID_Z, takes into account that the sum of the percentage of negative daily returns and positive returns does not equal 1, when there is zero-return-days included. The rate of zero return days is taken as a measure of illiquidity (Lesmond, Ogden & Trzcinka, 1999). Therefore, the new measure will observe the illiquidity issue by taking those zero-days in to equation. ID_z is constructed according to Equation 2 below.

$$\mathbf{ID_Z} = \mathbf{sgn(PRET)} * \frac{[\%\mathbf{neg} - \%\mathbf{pos}]}{[\%\mathbf{neg} + \%\mathbf{pos}]}, \tag{2}$$

which equals ID, when %zero is 0.

As seen in Equation 2, the ID_Z also ranges from -1 to 1. The values are interpreted the same as when using the ID, respectively. The fact that the Finnish stock market is somewhat illiquid makes this measure more exploitable for my analysis. Also, as shown in the Equation 2, the ID_Z equals ID whenever the percentage of zero-return-days is zero. Thus, using this measure instead of ID does not violate the FIP hypothesis, but makes it more implementable for illiquid markets.

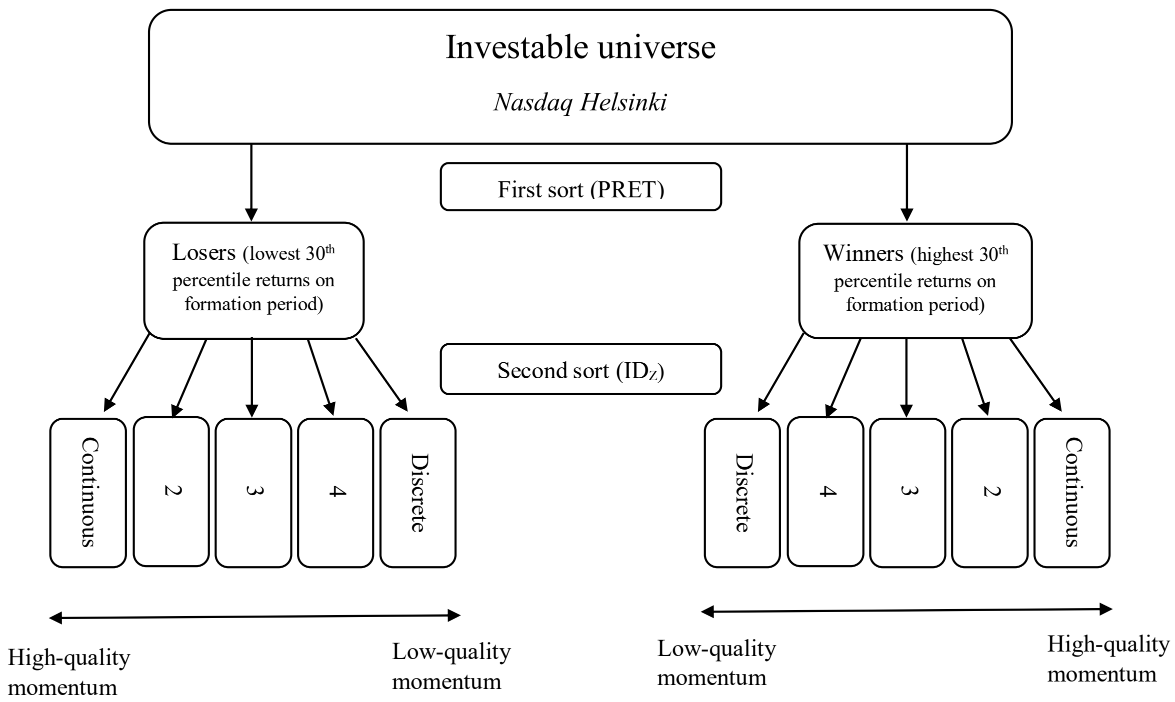
3.2. Portfolio construction

To evaluate the impact of continuous information on momentum, I will construct double-sorted portfolios. Stocks are first ranked based on the cumulative returns during the formation period. Formation period is past the 12 months, which is based on the study by Jegadeesh and Titman (1990). To avoid the short-term reversal effect, which was documented by Jegadeesh (1990) and Lehmann (1990), the most recent month before the holding period is omitted from the calculations. Short-term reversal effect refers to the situation where returns, which are realized over the recent times, such as last week or month, tend to have a negative relationship with returns over the short-future (Bali, Engle & Murray, 2016). As this phenomenon is commonly connected to liquidity (Bali, Engle & Murray, 2016), this adjustment is crucially important for my analysis on the illiquid market environment. The second sort, which distinguishes between continuous and discrete information, is done based on the discreteness proxy, denoted ID_Z.

4.2.1 Double-sort

In the first sort, which is based on cumulative returns during the formation period, denoted PRET, the highest 30th percentile and the lowest 30th percentile are calculated for each formation period. The highest are assumed to be the future winners and the lowest the future losers. Both are then subdivided based on their ID_Z in to five different quintiles. These quintiles are named Continuous, 2, 3, 4 and Discrete. The Continuous-quintile contains the lowest ID_Z measures from the first sort and the Discrete-quintile the highest. The visual illustration in the Figure 2 below reflects the portfolio construction process.

Figure 2



As seen in the Figure 2, the second sort based on ID_z subdivides the winners and the losers into quintiles, ranging from high-quality momentum to low-quality momentum. As mentioned earlier, the FIP hypothesis rises from this assumption, and states that these Continuous-quintiles will generate stronger momentum.

3.3. Risk-adjustments

I calculate the portfolio returns for each different quintile from winners to losers. I will use two different holding periods, 6-month and 12-month. The formation period for both is the same 12 months, respectively. The returns are calculated as monthly returns and annualized returns for both. Returns are computed as excess returns according to Capital Asset Pricing Model (Sharpe, 1964). The holding period returns are also risk-adjusted using the Fama-French three-factor model (1993). The model includes market, size and book-to-market factors. The formula for Fama-French three-factor model is provided below.

$$\boldsymbol{R_{it} - R_{ft} = \alpha_{it} + \beta_1\left(R_{Mt} - R_{ft}\right) + \beta_2 SMB_t + \beta_2 HML_t + \epsilon_{it}}, \text{ where}$$

R_{it} = total return of the portfolio

R_{ft} = risk free rate of return

R_{Mt} = market portfolio return

SMB_t = size premium

HML_t = value premium

α_{it} = three-factor alpha

The values for these factors were available from Kenneth French website[1]. I use the European data for my adjustments, as there were no separate values for the Finnish stock market.

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[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#International

4. Results

After computing the returns for both, 6-month and 12-month holding periods, I found significant differences between discrete and continuous quintiles. The tables below report the post-formation returns for double-sorted portfolios for both holding periods. They show the returns for winners, losers and the long-short portfolios. The CAPM-alphas and three-factor alphas are also computed, and the t-statistics are reported for the long-short (momentum) portfolios.

4.1. 12-month holding period

Panel 1

12-month holding period

Monthly returns	Average returns			CAPM		Three-Factor	
	Winner	Loser	Momentum	Alpha	t-stat	Alpha	t-stat
Continuous	0,0104	-0,0002	0,0107	0,0120	1,6531	0,0128	1,7396
2	0,0092	0,0013	0,0079	0,0088	1,4003	0,0094	1,4863
3	0,0096	0,0032	0,0064	0,0070	1,2578	0,0077	1,3615
4	0,0054	0,0079	-0,0025	-0,0021	-0,4668	-0,0018	-0,4004
Discrete	0,0052	0,0076	-0,0024	-0,0020	-0,4487	-0,0017	-0,3813
	Continuous - Discrete		0,0131	0,0140	2,1018	0,0145	2,1208

Panel 2

12-month holding period

Annualized returns	CAPM		Three-Factor	
	Alpha	t-stat	Alpha	t-stat
Continuous	0,1227	1,4328	0,1636	1,6083
2	0,0806	1,2712	0,1026	1,3039
3	0,0496	0,8908	0,0727	1,0541
4	-0,0696	-5,2281	-0,0582	-3,7263
Discrete	-0,0704	-4,4735	-0,0592	-3,1425
Continuous - Discrete	0,1931	5,9063	0,2228	4,7508

4.2. 6-month holding period

Panel 3

6-month holding period							
Monthly returns	Average returns			CAPM		Three-Factor	
	Winner	Loser	Momentum	Alpha	t-stat	Alpha	t-stat
Continuous	0,0134	-0,0030	0,0163	0,0167	2,8579	0,0167	2,7860
2	0,0089	-0,0058	0,0147	0,0144	2,4180	0,0134	2,2115
3	0,0080	-0,0042	0,0122	0,0119	2,1776	0,0107	1,9211
4	0,0048	0,0101	-0,0053	-0,0053	-5,6391	-0,0052	-5,4632
Discrete	0,0041	0,0103	-0,0061	-0,0062	-5,1140	-0,0062	-5,0182
	Continuous - Discrete		0,0225	0,0229	7,9719	0,0229	7,8042

Panel 4

6-month holding period				
Annualized returns	CAPM		Three-Factor	
	Alpha	t-stat	Alpha	t-stat
Continuous	0,2999	3,2690	0,2394	2,2126
2	0,2672	3,6147	0,1888	2,3158
3	0,2114	3,1144	0,1448	1,8574
4	-0,0706	-5,1525	-0,0655	-4,0727
Discrete	-0,0834	-4,7492	-0,0798	-3,7377
Continuous - Discrete	0,3833	8,0182	0,3192	5,9503

4.3. Evaluating the results

Panel 1 reports the monthly returns on 12-month holding period. The results show that CAPM-adjusted momentum decreases significantly from 1,20 % in the Continuous-quintile to -0,20 % in the Discrete-quintile. This difference has t-statistic of 2,1. Thus, it is statistically quite significant. After Fama-French three-factor adjustment, the difference widens. Alpha decreases from 1,28 % to -0,17 %. The t-statistic of this difference is 2,12, which is slightly greater than with CAPM-adjustments. Panel 2 reports greater significance when comparing the holding period returns. CAPM-adjusted return decreases from 12,27 % to -7,04 % when moving from Continuous-quintile to Discrete-quintile. This difference has a t-statistic of 5,91 and it is statistically highly significant. Three-factor alphas also decrease from 16,36 % to -5,92 %, and the difference has t-statistic of 4,75. It is clear that there is a difference between the returns of these portfolios, and with a high t-statistic it makes it hard to consider that this would be purely fortuitous.

Panel 3 reports the monthly returns on 6-month holding period. The findings do not change with a different holding period, rather strengthens. The CAPM-adjusted return decreases from 1,67 % in Continuous-quintile to -0,62 % in Discrete-quintile. The difference has a t-statistic of 7,97, which can be considered as a very high t-statistic. Three-factor alpha decreases from 1,67 % to -0,62 % and the difference has a t-statistic of 7,80. Panel 4 reports the annualized returns, calculated as cumulative returns over two 6-month holding periods. Hence, the differences are comparable with the 12-month holding period results. The difference between CAPM-adjusted returns has a t-statistic of 8,02 and three-factor adjusted 5,95.

As seen in the tables, the contribution on the momentum is much stronger from the past winners in both, continuous and discrete portfolios. Both, the winners and losers in the Continuous-quintile seem to follow the path with their returns, but the winners tend to dominate in terms of the magnitude of returns. In the Discrete-quintile, the losers rather tend to have reversal effect, as they have positive returns during the post-formation holding period. Thus, the losers that contain discrete information seem to follow contrarian effect rather than momentum effect. Bondt and Thaler (1985) stated that the investors tend to overreact to market events. This might explain this effect on losers, as the stocks that contain discrete information tend to have more “bumpy” price paths, caused by the large information eruptions. Investors might overreact and market corrects itself with contrarian effect. Since the losers in the Discrete-quintile tend to have positive holding period returns, it has a strong contribution to the difference on the momentum returns between Continuous-quintile and Discrete-quintile. Thus, it may explain the high t-statistics of the differences.

The results show that there is statistically significant difference between the momentum returns of the portfolios with low-ID (containing continuous information) and the portfolios with high-ID (containing discrete information). The difference is stronger with the shorter, 6-month holding period (FF t-statistic of 5,95), than with 12-month holding period (FF t-statistic of 2,12). It seems that the effect of continuous information on momentum decreases over time. However, in both, the difference is statistically significant. Both, the discrete-quintile and continuous-quintile have the same investable universe, and the only difference is the information discreteness proxy. Therefore, there is strong indicators that the difference can be explained by the difference on the information discreteness, as the FIP hypothesis states. The results strongly support the FIP hypothesis and the assumption that investors underreact to continuous information. Thus, the results imply that there are differences between returns depending on the information discreteness.

Also, the results from the Discrete-quintile signal that investors might overreact to discrete information, at least regarding the past losers. Therefore, the results do not only support the FIP hypothesis, but also the investors overreaction to the market events, when the information is considered as discrete.

The results from my analysis are in line with the previous U.S. study from Da, Gurun and Warachka (2014). Authors found a significant difference on momentum between continuous information portfolio and discrete information portfolio in the U.S. stock markets. I found similar differences in the Finnish stock market. Thus, the illiquidity of the Finnish stock market does not seem to have an impact on this phenomenon.

Even though the results show significant differences between continuous and discrete information containing portfolios, I have left out of the discussion the possibility of this continuous information based momentum strategy being anomaly. The goal of this thesis was to investigate the differences in information discreteness and their return generating abilities. The analysis does not take into account the volatilities of these portfolio returns. Thus, the returns and risk-adjusted alphas should be taken as tools for comparing, not the measure of performance.

5. Conclusions

In this thesis, I have tested the FIP hypothesis in the Finnish stock market. The hypothesis predicts that continuous information containing stocks receive less attention from the investors and it leads to greater momentum returns than with the stocks that contain discrete information. The hypothesis states that investors have a delay on processing continuous information. The previous literature supports the hypothesis as the limited investor attention is commonly known.

I have computed the formation period returns (PRET) and the information discreteness proxy (ID_Z). Based on these measures, I have constructed double-sorted portfolios, conditioning first on the formation period returns and then on information discreteness proxy. Thus, past winners and losers are divided into quintiles, based on the information discreteness. This division aims to identify high-quality momentum (low ID_Z) and low-quality momentum (high ID_Z).

I calculated the returns for both, 6-month and 12-month holding periods. Returns are computed according to CAPM and risk-adjusted with Fama-French three-factor model. Results show that the differences between the continuous information containing portfolio and the discrete information containing portfolio are statistically significant with both holding periods. The difference is greater with 6-month holding period, which implies that the impact of information discreteness on momentum decreases over time. The illiquidity of the Finnish stock market did not have an impact on the results. Thus, the findings of this study support FIP hypothesis and are in line with the previous study from Da, Gurun and Warachka (2014). There were also signs of investor overreaction to the information when the information is discrete.

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