Information Uncertainty and Expected Returns: Case of Korean Stock Market

Abstract:

This study examines the effect of information uncertainty on expected returns and reports empirical evidence from the Korean stock market. Traditional theory predicts that investors require a premium for uncertainty risk, implying higher expected returns. However, prior studies based on U.S. data have documented the opposite pattern: firms with greater information uncertainty tend to earn lower actual returns. Previous research on momentum also suggests that firms with high information uncertainty rely more heavily on private than public information, which raises information-acquisition costs, constrains arbitrage, and may strengthen momentum through delayed market reactions and investor overconfidence. Motivated by this literature, this study investigates whether higher information uncertainty is associated with lower average returns and whether momentum is stronger under high uncertainty for Korean listed firms from 2001 to 2020. Three proxies are used to measure information uncertainty: firm age, trading volume, and return volatility. Portfolios are formed by uncertainty level and their returns are compared. The results indicate a negative relation between information uncertainty and expected returns, whereas the momentum effect is not statistically significant. This study contributes by providing one of the first Korean empirical examinations of lower returns and momentum under information uncertainty.

Key words:-
Informationuncertainty; expected returns; momentum; investor overconfidence; arbitrage limits; Korean stock marke

Introduction:-

Information uncertainty affects how precisely investors can estimate firm value. Unlike information asymmetry, which concerns differences in the amount or quality of information held by informed and uninformed investors, information uncertainty concerns the accuracy of valuation itself. Prior studies describe it as the degree to which knowledgeable investors can estimate firm value at a reasonable cost and interpret it as value ambiguity.

In a high-uncertainty environment, estimates of firm value become less precise; in a low-uncertainty environment, valuation is relatively more reliable.

Traditional asset-pricing intuition suggests that investors should demand a premium for bearing information uncertainty, leading to higher expected returns. Yet empirical work using U.S. data reports the opposite: firms with greater information uncertainty often earn lower subsequent returns. High-uncertainty firms tend to be younger, more actively traded, and more volatile. They also exhibit slower price adjustment and lower valuation precision, which are associated with high trading volume and volatility.

Jiang et al. (2005) show that information uncertainty, proxied by firm age, volume, and volatility, is negatively related to returns and explain this pattern through investor overconfidence. Behavioral finance argues that investors can become excessively confident in private information and consequently overweight private signals while underreacting to public disclosures such as earnings announcements and news. This tendency becomes more pronounced when public information alone is insufficient to assess firm value. As a result, higher information uncertainty is positively associated with overconfidence and, on average, lower future returns.

High information uncertainty can also intensify limits to arbitrage. Because investors rely more on private than public information, the costs of acquiring and processing information rise. At the same time, heightened uncertainty increases volatility, making it more difficult for arbitrageurs to correct irrational price movements. This mechanism helps explain momentum: when public information is incorporated only gradually and investors overreact to private signals, stock prices may continue to drift upward or downward.

Based on these arguments, this study tests whether Korean data also show lower average returns under higher information uncertainty and whether momentum is stronger in such environments. The analysis first examines the industry distribution of information uncertainty. It then measures uncertainty using firm age, trading volume, and volatility, constructs portfolios by uncertainty level, and compares their returns using single sorting, double sorting, and triple sorting approaches.

The empirical results confirm that returns are lower when information uncertainty is high, consistent with prior studies. However, the momentum effect is not statistically significant. The study is meaningful in that it documents, using Korean data, a negative relation between information uncertainty and returns.

Literature Review:-

A. Information Uncertainty and Investor Overconfidence:-

Jiang et al. (2005) define information uncertainty as the degree to which knowledgeable investors can estimate firm value at reasonable cost, and interpret it as value ambiguity. Zhang (2006) similarly defines it as ambiguity about how new information affects firm value and argues that such ambiguity arises from fundamental volatility and poor information.

Both studies argue that investor overconfidence is especially pronounced among firms with high information uncertainty. Overconfident investors place excessive weight on their own beliefs and private information while underreacting to public information. They also overreact to information consistent with their prior beliefs and discount information that conflicts with them. Related Korean evidence suggests that investors are overconfident in their forecasts and slow to revise beliefs even in the presence of contradictory information.

Miller (1977) argues that young firms and firms with high trading volume or high volatility are likely to face greater information uncertainty and lower expected returns. Taken together, prior studies imply that investors may find private information relatively more persuasive than public information, which leads to inflated valuations by optimistic investors and eventually lower subsequent returns for high-uncertainty firms.

Previous empirical studies have used firm age, volume, volatility, equity duration, analyst forecast dispersion, expected growth, and the price-to-book ratio as proxies for information uncertainty. This study focuses on firm age, volume, and volatility because they are intuitive and readily measurable.

B. Information Uncertainty and Momentum:-

Momentum has been widely documented in major equity markets around the world. Prior studies attribute momentum to gradual market reactions to information, underreaction to public information, self-attribution bias, and overconfidence. Several studies also argue that psychological biases become stronger when information uncertainty is high.

Zhang (2006) argues that stronger behavioral biases in high-uncertainty firms generate more gradual incorporation of new information and therefore stronger momentum. Jiang et al. (2005), by contrast, emphasize limits to arbitrage: as uncertainty rises, information acquisition becomes more costly and volatility increases, making it harder for arbitrageurs to correct mispricing. In either case, high information uncertainty should be associated with stronger momentum.

Korean studies on investor sentiment also suggest that stock returns vary with sentiment and firm characteristics. However, the domestic momentum literature does not provide fully consistent evidence. Some studies report significant momentum profits, while others document weak or even negative momentum. This paper therefore tests the uncertainty–momentum relation directly in the Korean market.

Hypotheses and Research Design:-

A.*Hypotheses:-*

Previous research explains that there is a positive (+) relationship between information uncertainty and arbitrage costs. The higher the information uncertainty of a company, the more it relies on private signals rather than public information, which increases volatility and consequently raises arbitrage costs. This limits the ability of those who could profit from irrational stock price reactions to bring market prices back to normal, which leads to the momentum effect. Based on this, this study sets up the following hypothesis.

Hypothesis 1: The greater the degree of information uncertainty, the lower the average return.

Hypothesis 2: The greater the degree of information uncertainty, the stronger the momentum effect.

B. Research Design:-

The sample consists of firms listed on the KOSPI and KOSDAQ markets from 2001 to 2020. Financial data were obtained from DataGuide, and the sample was limited to December fiscal-year-end firms. For the momentum tests, firms with no trading within the previous month and firms with capital impairment were excluded.

Information uncertainty is measured using three variables. Firm age is defined as the time elapsed between the month in which trading began after listing and month t. Trading volume is defined as the average daily turnover over the past six months, measured as daily trading volume relative to shares outstanding. Volatility is defined as the standard deviation of daily returns over the previous 24 months.

To examine the relation between information uncertainty and returns, firms are sorted each month into groups based on the three uncertainty measures. The full sample is divided into 10 groups and 5 groups for single sorts, and additional portfolios are formed using age-volume, age-volatility, and age-volume-volatility double/triple sorts. Momentum portfolios are then constructed by combining past six-month returns with the information uncertainty measures.

Empirical Results:-

A. Descriptive Statistics and Correlations:-

Table 1 reports descriptive statistics for the three information uncertainty variables and related return measures. The average firm age is 13.7 years, mean turnover is 0.02, and mean volatility is 16.9. Table 2 presents Pearson correlations among the uncertainty measures and return variables. Age is negatively correlated with turnover, while the signs for the remaining relations are mixed. Because prior studies note that the relation between uncertainty and returns need not be monotonic, portfolio analysis is more informative than simple pairwise correlations.

Table 1. Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Minimum	Median	Maximum
Firm age (years)	489,190	13.7	11.24	0	10.93	66.45

Trading volume (%)	464,358	0.02	0.03	0.00	0.01	0.71
Volatility (std. dev.)	406,235	16.9	11.03	0	14.52	245.02
Equal-weighted average return	14,190,681	0.01	0.08	-0.96	0.00	2
Average trading volume	448,821	0.02	0.03	0.00	0.01	0.71
Average volatility	14,189,904	0.06	17.79	0	0.03	10338.20
Value-weighted average return	483,230	0.02	0.08	-0.37	0.02	0.82

Table 2. Pearson Correlations

	Age	Volume	Volatility	Avg. volume	Avg. volatility	EW return	VW return
Age	1.000						
Volume	-0.153***	1.000					
Volatility	0.006***	-0.0001	1.000				
Avg. volume	-0.129***	0.172***	0.035***	1.0000			
Avg. volatility	-0.0005*	0.0004	0.052***	0.0016***	1.000		
EW return	0.004***	-0.003***	0.0004	-0.0145***	0.029***	1.000	
VW return	0.003***	0.0312***	0.026***	0.0105***	0.002***	-0.0012***	1.000

B. Industry Analysis:-

<Figure 1> shows the industry-wise distribution of companies listed on the KOSPI and KOSDAQ from 2001 to 2020, categorized by the level of information uncertainty using the KSIC2 middle classification codes. To measure the level of uncertainty, we divided companies into three groups based on age, trading volume, and volatility. Then we counted the number of companies that belonged both to the group with the shortest company history and the group with the highest trading volume and volatility, by industry, and calculated it as a share of the total sample in each industry.

Industry-level sorting also reveals meaningful differences in information uncertainty. Industries such as agriculture, fisheries, metal mining, beverage manufacturing, tobacco manufacturing, printing and recorded media reproduction, electricity and gas supply, environmental remediation, specialized construction, restaurants and bars, broadcasting, and leasing appear relatively low in information uncertainty. By contrast, real estate, water transportation, and lodging appear relatively high in information uncertainty. Overall, the Korean industry pattern is broadly similar to that reported in prior U.S.-based research.

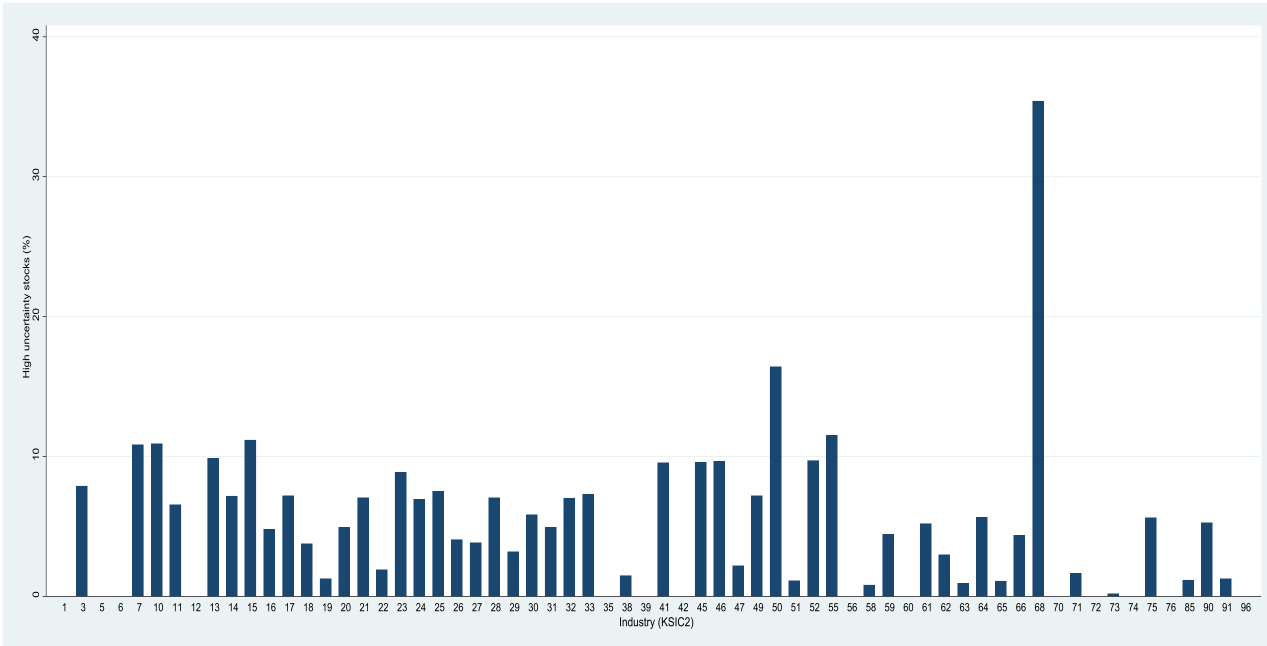

Figure 1. Distributions of Industry Wise

C. Information Uncertainty and Expected Returns:-

<Table 3-1> shows the results of forming portfolios into 10 groups based on the age of the companies and then showing the average monthly returns for each group. Group 1 represents companies with a short history, while Group 10 represents companies with a long history. The average age of Group 1, which has a short history, is 2.31, and the monthly average return is 0.0048. Group 5 has a monthly average return of 0.0055, and the oldest Group 10 has a monthly average return of 0.0131. Compared to other older groups, we can see that the return of Group 1, which has the shortest history, is lower. The t-value showing the difference in the mean of monthly average returns between Group 1 and Group 2 was –14.2. This supports the hypothesis that companies with the shortest history have lower returns.

<Table 3-2> shows the results of forming portfolios into 5 groups based on company age and showing the monthly average return for each group. As in <Table 3-1>, Group 1 represents companies with a short history, and Group 5 represents companies with a long history. The average age of Group 1 is 4.20, and the monthly average return is 0.0065, while Group 5 has an average age of 37.80 and a monthly average return of 0.0137. The t-value showing the difference in the mean of monthly average returns between Group 1 and Group 2 was –9.1. As in the results of <Table 3-1>, we can see that companies with a shorter history tend to have lower returns than companies with a longer history. In other words, whether dividing the portfolios into 5 or 10 groups, the companies with the shortest history show the lowest returns, which supports the hypothesis of this study. However, as seen in the tables, a clear, consistent trend of returns decreasing strictly with shorter company age was not observed.

Single-sort portfolio tests show that the youngest firms, the highest-turnover firms, and the most volatile firms generally earn the lowest returns. The relation is not strictly monotonic across all groups, but the highest-uncertainty portfolios consistently underperform the lower-uncertainty portfolios, supporting Hypothesis 1.

Table 3-1. Monthly Average Returns across 10 Age Portfolios

Age10	Age	Monthly average return	t-value
1	2.31	.0048	
2	6.70	.0098	-14.2
3	11.15	.0076	-7.6
4	16.24	.0104	-14.3
5	19.38	.0055	-1.5
6	22.47	.0097	-8.7
7	24.74	.0093	-7.1
8	31.32	.0089	-6.5
9	35.20	.0120	-11.2
10	40.39	.0131	-13.1
Total	13.70	.0082	

Table 3-2. Monthly Average Returns across 5 Age Portfolios

Age5	Age	Monthly average return	t-value
1	4.20	.0065	
2	13.38	.0087	-9.1
3	20.70	.0081	-4.5
4	28.01	.0095	-7.3
5	37.80	.0137	-17.1
Total	13.70	.0082	

<Table 4-1> shows portfolios divided into 10 groups based on trading volume, which is a variable of information uncertainty. Trading volume was calculated as the daily trading volume relative to the number of outstanding shares, using the average daily trading volume over the past six months. Group 1 has the highest trading volume, and Group 10 has the lowest. The average trading volume of Group 1, which has the lowest trading volume, is 0.0435, with a monthly average return of -0.4309. Group 5 had a monthly average return of 1.189, and Group 10, with the lowest trading volume, had a monthly average return of 0.9501. This shows that the group with the highest trading volume had the lowest returns. The t-value showing the difference in the average monthly returns between Group 1 and Group 2 with the highest trading volumes is -13.6. In other words, when comparing the 10 groups, the higher the trading volume, the lower the expected return, supporting the hypothesis of this study.

Table 4-1. Monthly Average Returns across 10 Volume Portfolios

Volume10	Observations	Volume	Monthly average return	t-value
1	323.96	.0435	-.4309	
2	276.97	.0276	.2170	-13.6
3	222.64	.0208	.8702	-25.9
4	172.95	.0164	1.299	-32.6

5	145.90	.0134	1.189	-29.1
6	125.73	.0104	1.197	-27.6
7	116.63	.0088	.9411	-23.1
8	105.88	.0071	.9410	-22.6
9	103.10	.0053	.9911	-22.7
10	103.03	.0035	.9501	-22.4
Total	200.72	.0204	.6435	

<Table 4-2> shows the results of forming portfolios divided into 5 groups based on trading volume using the same method as <Table 4-1>. Group 1 has the highest trading volume, and Group 5 has the lowest. The average trading volume of Group 1 with the highest trading volume is 0.0361, with a monthly average return of -0.070, and the monthly average return of Group 5 with the lowest trading volume is 0.919. This further confirms that the group with the highest trading volume had the lowest returns. The t-value showing the difference in the average monthly returns between Group 1 and Group 2 with the highest trading volumes is -34.1. That is, whether portfolios are formed by dividing into 5 or 10 groups based on trading volume, the group with the highest trading volume tends to have the lowest returns, supporting the hypothesis of this study. However, as can be seen in the table, the results do not show a simple monotonic decrease in returns as trading volume increases.

Table 4-2. Monthly Average Returns across 5 Volume Portfolios

Volume5	Observations	Volume	Monthly average return	t-value
1	591.90	.0361	-.070	
2	393.27	.0188	1.11	-34.1
3	270.54	.0120	1.17	-32.8
4	221.72	.0080	.979	-26.7
5	205.05	.0044	.919	-24.5
Total	394.67	.0204	.671	

<Table 5-1> shows portfolios divided into 10 groups based on volatility, which is the uncertainty variable of information. Volatility was calculated as the standard deviation of daily returns over the past 24 months, with Group 1 having the highest volatility and Group 10 the lowest. The average volatility of the highest-volatility Group 1 is 0.2856, with a monthly average return of -0.3722. Group 5 has a monthly average return of 1.275, and Group 10, the lowest-volatility group, has a monthly average return of 0.6766. So, it's clear that the highest-volatility group has the lowest returns. The t-value showing the difference in the average monthly returns between the highest-volatility Groups 1 and 2 is -21.3. In other words, comparing 10 groups, these results support the study's hypothesis that the groups with the highest volatility have the lowest returns.

Table 5-1. Monthly Average Returns across 10 Volatility Portfolios

Volatility10	Observations	Volatility	Monthly average return	t-value
1	302.88	.2856	-.3722	
2	246.07	.1913	.7670	-21.3
3	207.88	.1597	1.390	-31.4
4	181.28	.1385	1.430	-31.3
5	163.53	.1230	1.275	-28.5
6	148.24	.1099	.9953	-23.0

7	139.90	.0975	.8427	-20.2
8	129.41	.0858	.8194	-19.5
9	122.54	.0727	.7862	-18.7
10	150.44	.0422	.6766	-17.8
Total	195.38	.1494	.7906	

<Table 5-2> shows portfolios divided into 5 groups the same way as in Table 5-1. Group 1 has the highest volatility, and Group 5 the lowest. The average volatility of the highest-volatility Group 1 is 0.243, with a monthly average return of 0.041, while the lowest-volatility Group 5 has a monthly average return of 0.824. So again, we can see that higher volatility groups tend to have lower average returns. The t-value showing the difference in the average monthly returns between Groups 1 and 2 is -27.9. This means that whether the portfolio is split into 5 or 10 groups, the results support the hypothesis that the highest-volatility groups have the lowest returns. Just like we saw with age and trading volume earlier, we didn’t find a consistent pattern where returns go down as volatility increases.

Table 5-2. Monthly Average Returns across 5 Volatility Portfolios

Volatility5	Observations	Volatility	Monthly average return	t-value
1	538.96	.243	.041	
2	387.05	.150	1.46	-27.9
3	310.48	.117	1.10	-17.8
4	268.35	.092	.860	-11.4
5	268.92	.056	.824	-10.6
Total	383.92	.149	.891	

Tables 3, 4, and 5 show that groups with a short history and high trading volume and volatility tend to have lower average returns. In other words, we found that returns are lower in environments with higher information uncertainty compared to those with lower information uncertainty. This supports Miller's (1977) argument that as a company's age, trading volume, and volatility increase, information uncertainty rises and returns decrease. These results align with the predictions of this study and are similar to previous research showing that higher information uncertainty leads to lower returns. However, in this study, the relationship between information uncertainty and returns isn't linear, so we found that the group with the highest information uncertainty actually has the lowest returns.

<Table 6> shows the results of double sorting by a company's age and volatility, which are variables representing information uncertainty. From 2001 to 2020, at the beginning of each month, all stocks were classified based on age and volatility, and three portfolios were formed with equal weighting. A1V3 represents the group with short history and high volatility, while A3V1 represents the group with long history and low volatility. The average monthly return of the short-history, high-volatility A1V3 group was 0.603, showing that its return is lower compared to other groups. The t-value shows the difference between the average monthly return of A1V3 and each group. Therefore, it was confirmed that returns are lower when the history is short and volatility is high.

Table 6. Monthly Average Returns by Age + Volatility Portfolios

Age + Volatility	Observations	Monthly average return	t-value
A1V1	240.57	.694	-13.7
A1V2	314.46	.988	-11.33
A1V3	559.16	.603	
A2V1	129.08	.637	-13.34
A2V2	138.71	.782	-12.86
A2V3	189.41	1.49	-9.47

A3V1	83.24	1.58	-10.75
A3V2	80.72	1.26	-11.69
A3V3	75.21	1.10	-12.19
Total	313.55	.882	

<Table 7> shows the results of measuring both a company's age and turnover (age + turnover), which are variables of information uncertainty, together (double sorting). A1T3 is the group with a short history and high turnover, while A3T1 represents the group with a long history and low turnover. In A1T3, which has a short history and high turnover, the return is .258, which is lower compared to other groups. The t-value shows the difference between A1T3 and the average monthly returns of each group. Therefore, it was confirmed that companies with a short history and high turnover have lower returns.

Table 7. Monthly Average Returns by Age + Volume Portfolios

Age + Volume	Observations	Monthly average return	t-value
A1T1	162.70	.800	-30.96
A1T2	264.13	1.10	-28.37
A1T3	576.89	.146	
A2T1	106.71	.490	-32.16
A2T2	127.23	1.07	-30.44
A2T3	246.37	.973	-30.70
A3T1	87.92	1.10	-30.69
A3T2	77.82	1.41	-30.08
A3T3	73.32	.479	-32.54
Total	313.14	.675	

<Table 8> shows the results of measuring a company's age, turnover, and volatility (age + turnover + volatility) together (triple sorting), which are variables of information uncertainty. A1T3V3 is the group with a short history, high turnover, and high volatility, while A3T1V1 represents the group with a long history, low turnover, and low volatility. In A1T3V3, which has a short history, high turnover, and high volatility, the return is 0.48, the lowest compared to other groups. The t-value shows the difference between A1T3V3 and the average monthly returns of each group. Therefore, it was confirmed that returns are lower when companies have a short history and high turnover and volatility. However, as noted earlier, a monotonic increase or decrease between information uncertainty and returns could not be found.

Table 8. Monthly Average Returns by Age + Volume + Volatility Portfolios

Age + Volume + Volatility	Observations	Monthly average return	t-value
A1T1V1	88.22	.613	-28.28
A1T1V2	49.64	.922	-28.06
A1T1V3	51.58	1.42	-27.81
A1T2V1	76.78	.311	-28.80
A1T2V2	100.87	1.08	-27.53
A1T2V3	101.22	1.21	-27.55
A1T3V1	71.04	.357	-28.71
A1T3V2	158.50	1.04	-27.91
A1T3V3	395.42	.048	
A2T1V1	61.44	.422	-28.47
A2T1V2	30.19	.929	-28.07

A2T1V3	19.27	2.39	-27.70
A2T2V1	38.86	1.00	-28.05
A2T2V2	48.34	.943	-28.07
A2T2V3	39.6	1.90	-27.48
A2T3V1	36.01	.832	-28.19
A2T3V2	66.68	.953	-28.11
A2T3V3	141.80	.327	-29.59
A3T1V1	49.11	1.67	-27.29
A3T1V2	26.65	.919	-28.16
A3T1V3	16.09	.644	-28.32
A3T2V1	25.90	1.23	-27.96
A3T2V2	31.82	1.27	-27.93
A3T2V3	22.12	1.51	-27.98
A3T3V1	11.70	.133	-28.37
A3T3V2	24.26	1.38	-28.00
A3T3V3	40.61	.334	-28.76
Total	151.60	.713	

Looking at the results of <Table 6>, <Table 7>, and <Table 8>, even when using the method of measuring information uncertainty variables together (double/triple sorting), it was confirmed that returns are lower in the groups with short histories and high turnover and volatility. Therefore, these results support the hypothesis of this study that companies with higher information uncertainty have lower returns.

D. Information Uncertainty and the Momentum Effect:-

To construct momentum portfolios, past six-month returns are used to classify stocks into winners and losers. Portfolios are then formed jointly by past returns and the information uncertainty variables. The sample period applied to companies listed on the KOSPI and KOSDAQ from 2001 to 2020, but samples with no trading within a month and companies with negative equity were excluded. The sample period could have been extended, but since foreign capital began to be actively allowed in the stock market after the 1997 IMF crisis, it was judged that momentum phenomena could be significantly observed, so the sample period was limited to after 2001.

Table 9. Monthly Average Returns by Information Uncertainty and Momentum

Panel / Portfolio	V1	V2	V3	V3-V1	Avg. Obs. V1	Avg. Obs. V2	Avg. Obs. V3
Panel A. Age-based R1	1.29(2.14)	1.04(1.70)	0.96(1.50)	-0.34(-0.79)	72	128	194
Panel A. Age-based R2	1.21(2.61)	0.78(1.81)	0.72(1.65)	-0.49(-1.67)	73	134	209
Panel A. Age-based R3	1.67(3.73)	1.36(3.08)	1.41(2.62)	-0.27(-0.73)	70	134	210
Panel A. R3-R1	0.38(0.77)	0.33(0.69)	0.45(0.99)	0.07(0.15)			
Panel B. Turnover-based R1	1.01(1.97)	1.09(1.81)	0.11(0.14)	-0.90(-1.69)	109	74	92
Panel B. Turnover-	0.93(2.29)	1.62(3.01)	0.76(1.25)	-0.17(-0.39)	125	86	106

based R2							
Panel B. Turnover-based R3	1.44(3.36)	1.86(3.58)	0.51(0.79)	-0.94(-1.85)	145	83	91
Panel B. R3-R1	0.43(0.97)	0.77(1.88)	0.39(0.88)	-0.04(-0.08)			
Panel C. Volatility-based R1	1.03(2.13)	1.42(2.24)	0.45(0.64)	-0.57(-1.17)	76	69	86
Panel C. Volatility-based R2	1.03(2.53)	1.14(2.18)	1.07(1.77)	0.04(0.10)	119	73	80
Panel C. Volatility-based R3	1.61(3.90)	1.88(3.53)	0.78(1.34)	-0.83(-1.92)	124	79	78
Panel C. R3-R1	0.58(1.38)	0.47(0.97)	0.33(0.74)	-0.26(-0.52)			

<Table 9> shows the equally-weighted monthly average returns of portfolios classified based on the uncertainty of information and past returns. V3 represents portfolios with high information uncertainty (young companies, high trading volume, high volatility). On the other hand, V1 represents portfolios with low information uncertainty (older companies, low trading volume, low volatility). R1 represents loser portfolios, and R3 represents winner portfolios. The equally-weighted monthly average return shows the average monthly return for six months after forming the portfolio. The number in parentheses indicates a simple t-statistic for the monthly average return. In previous tables, the portfolios were simply created by crossing the information uncertainty variable, but in this study, since the returns of portfolios crossed with momentum were observed, it allows us to see the interaction effect between information uncertainty portfolios and momentum portfolios, which is a distinguishing feature.

In <Table 9>, we once again checked the average effect of information uncertainty (that returns decrease when information uncertainty is high). Also, for V3, which has a short history, high trading volume, and high volatility, returns were low, which aligns with the results of this study we looked at earlier.

However, unlike previous studies, <Table 9> shows that momentum effects were not significant for firms with high information uncertainty. When checking momentum patterns using the strategy of buying Winners and selling Losers (R3-R1), returns were actually higher when information uncertainty was high, but this result was not statistically significant. Even though momentum didn't appear significant, we double-checked its significance after controlling for firm age, trading volume, and volatility using a 3-factor model.

E. Three-Factor Model and Robustness Analysis:-

The study further regresses the momentum portfolio returns on a three-factor model. <Table 10> shows the relationship of alpha values analyzed based on the momentum portfolio and the 3 Factor-model.

$$r_i - r_f = a_i + b_i(r_m - r_f) + s_i SMB + h_i HML + e_i \cdots\cdots\cdots\cdots\cdots\cdots (1)$$

For the returns of the portfolios in <Table 9>, regression analysis was conducted based on <Equation 1>. Even after controlling with the 3 Factor-model, the average effect of information uncertainty could be observed in some cases (like trading volume). However, the results for R3-R1, which measure the momentum phenomenon, were 0.24, -0.001, and 0.1, indicating that the momentum effect was not statistically significant.

This suggests that both the momentum effect and the average effect lack robustness, and further analysis on the average and momentum effects for different information uncertainty variables is needed in future research.

Table 10. Information Uncertainty Variables and the Three-Factor Model

Variable	Portfolio	V1	V2	V3	V3-V1
Age	R1	0.18(0.52)	0.32(0.94)	0.24(0.70)	0.06(0.13)
Age	R2	0.28(1.40)	-0.13(-0.57)	-0.15(-0.66)	-0.43(-1.41)
Age	R3	0.42(1.88)	0.26(1.13)	0.36(1.16)	-0.06(-0.16)
Age	R3-R1	0.12(0.28)	-0.05(-0.12)	0.24(0.49)	0.11(0.24)
Turnover	R1	0.26(0.91)	0.15(0.56)	-0.81(-1.83)	-1.07(-2.23)
Turnover	R2	0.17(0.87)	0.30(1.40)	-0.51(-1.78)	-0.68(-1.76)
Turnover	R3	0.36(1.49)	0.61(2.42)	-0.81(-2.39)	-1.17(-2.78)
Turnover	R3-R1	0.1(0.22)	0.46(1.15)	-0.001(0)	-0.1(-0.19)
Volatility	R1	0.16(0.54)	0.38(1.08)	-0.65(-1.72)	-0.81(-1.78)
Volatility	R2	0.11(0.49)	-0.05(-0.21)	-0.3(-0.96)	-0.41(-0.99)
Volatility	R3	0.56(2.59)	0.42(1.49)	-0.55(-1.71)	-1.11(-2.83)
Volatility	R3-R1	0.4(0.94)	0.04(0.09)	0.1(0.22)	-0.3(-0.58)

Conclusion:-

This study examined the effect of information uncertainty on expected returns in the Korean stock market. Traditional theory predicts that investors should require a premium for information uncertainty, but prior U.S. evidence suggests the opposite. Using Korean listed firms from 2001 to 2020, this study finds that returns are lower for firms that are younger, more heavily traded, and more volatile. The result is robust across single sorts as well as double and triple sorting procedures.

By contrast, the momentum effect under high information uncertainty is not statistically significant, even after controlling for a three-factor model. The paper therefore contributes evidence that information uncertainty is negatively related to returns in Korea, but it does not provide strong support for the argument that momentum becomes stronger as information uncertainty rises.

The study is meaningful because it documents the Korean relation between information uncertainty and returns. At the same time, it has limitations. It does not fully explain the mechanism behind lower returns or the absence of significant momentum, and its uncertainty measures are limited to age, turnover, and volatility. Future research that broadens the set of proxies may yield more robust results.

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