QRAFT

New Model of AI Driven Asset Management
Higher Alpha with Lower Cost through AI Technologies

QRAFT Market Anomaly Series

R&D Capital To Asset

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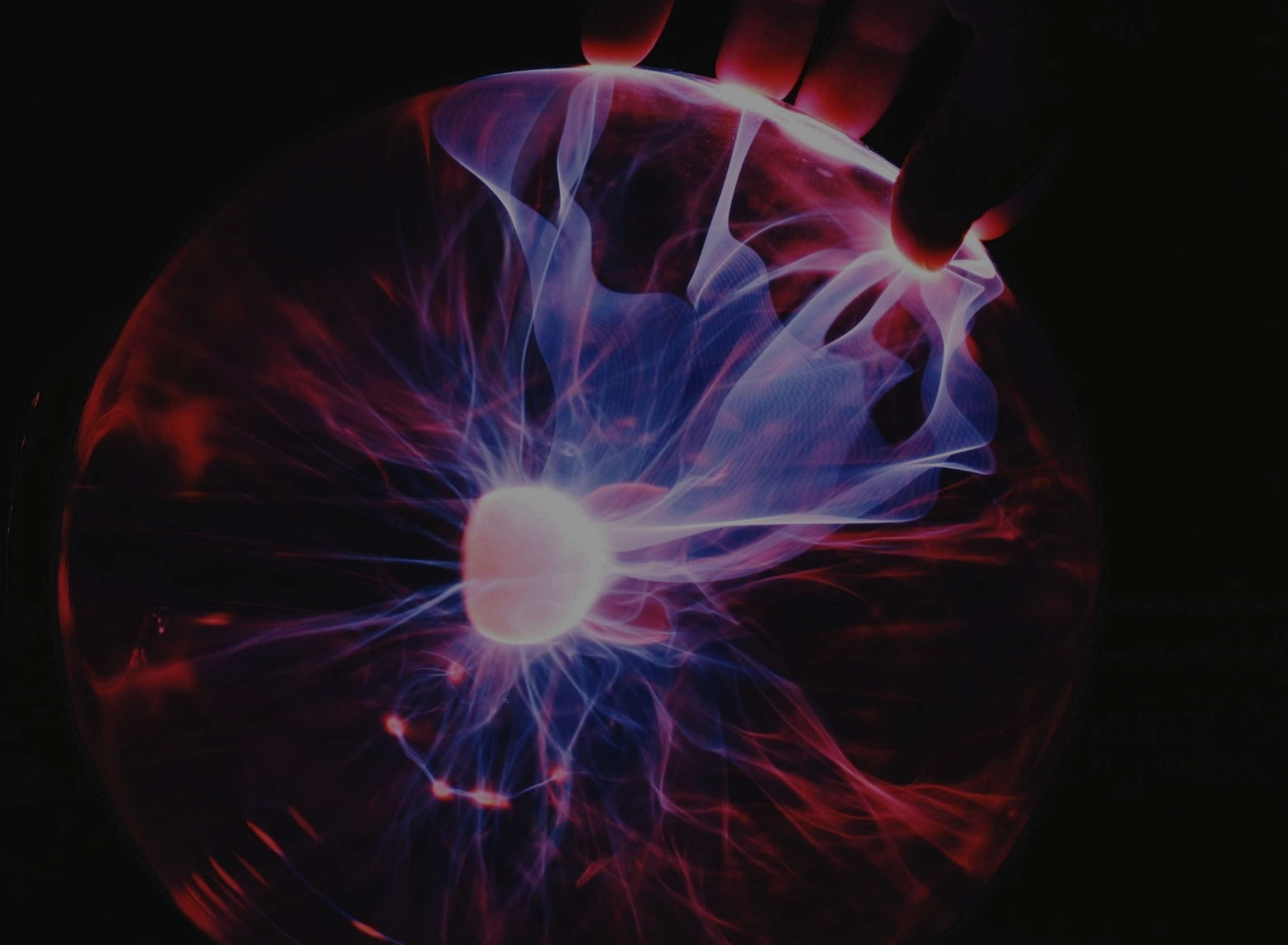

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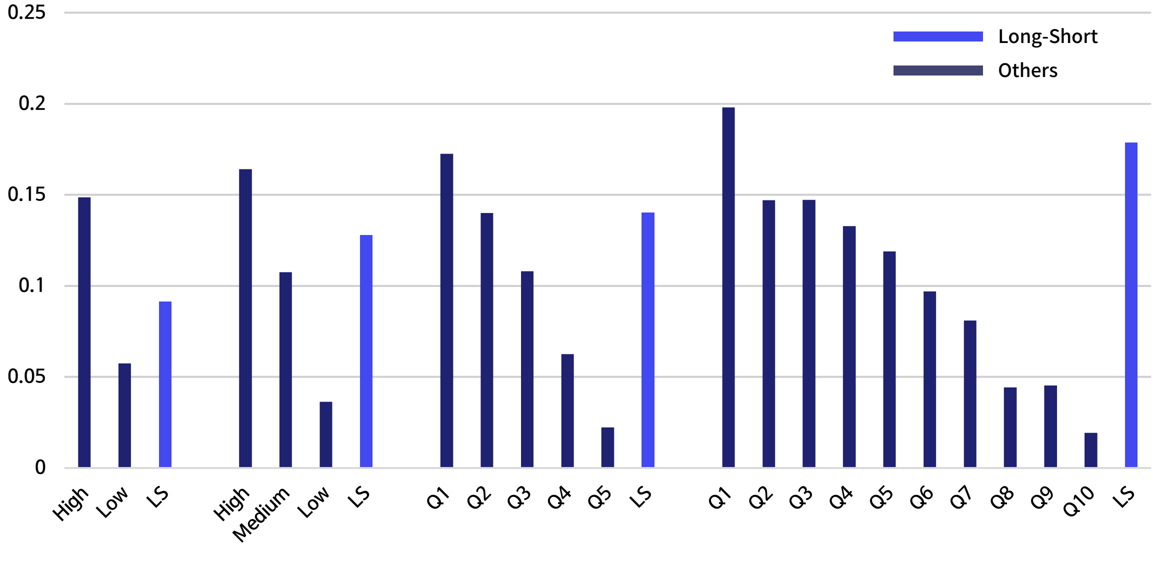
Summary

The COVID-19 pandemic has shaken the global economy and changed the landscape of the market in many aspects. It is worthwhile to pay attention to changes in the proportion of assets of global companies. The proportion of intangible assets has been on the rise since 1950. Industrial property rights, R&D costs and patents can often be classified as intangibles. This report has validated whether, of these intangible assets, R&D costs could lead to actual returns.

The R&D capital to Asset(Rca) covered in this report is calculated by applying linear depreciation rate of 20% on annual R&D costs over the past five years, and dividing them into total assets. Having analyzed the Rca factor, the effect of the factor is clear, and the effect has been growing in recent years. This suggests that the long-only play, which buys stocks with high Rca factor values, and the long-short strategy, which combines selling stocks with low factor values, can be very effective.

Rca Anomaly Quartile Portfolio

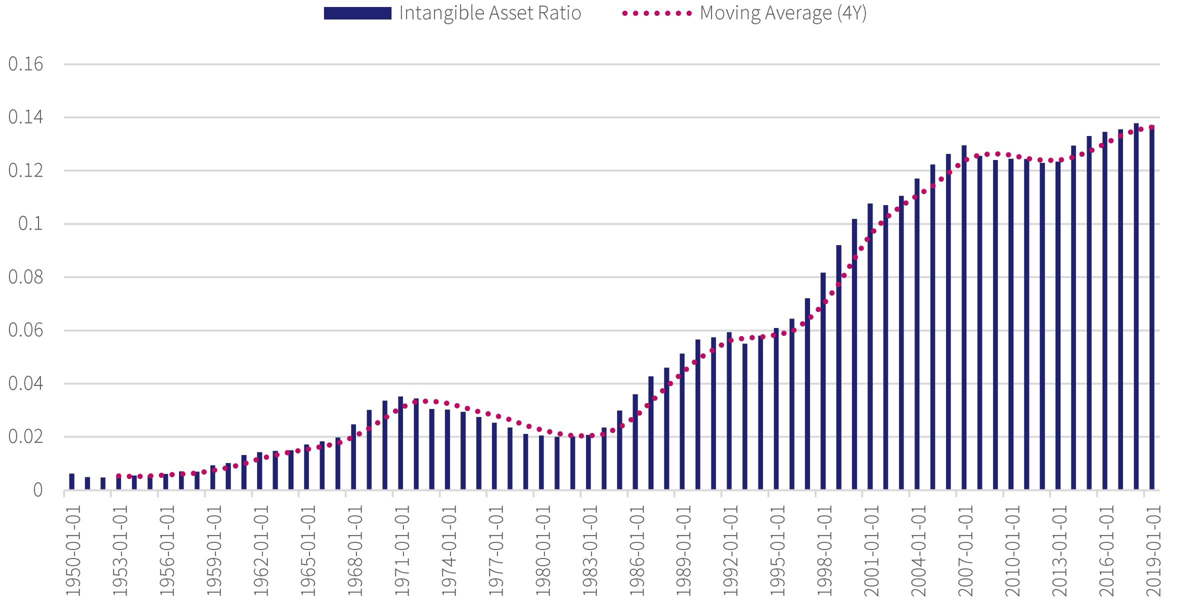


Source : Qraft Technologies, Compustat

R&D Capital To Asset Introduction

The COVID-19 pandemic has shaken the global economy and changed the landscape of the market in many aspects. It is worthwhile to pay attention to changes in the proportion of assets of global companies. The proportion of intangible assets has been on the rise since 1950([Figure 1]). Industrial property rights, R&D costs and patents can often be classified as intangibles.

Figure 1. Proportion of Intangible Assets[1]



Source : Qraft Technologies, Compustat

In the past, intangible assets accounted for very little of total assets, because many entities were running their business which were based on manufacturing, primarily focused on secondary industries, and the proportion of tangible assets, which were used to produce goods or services, was relatively high. However, unlike in the past, current economic structure has evolved in many ways through “digital transformation” from the structure of the era of secondary industries. In addition, the increasing proportion of intangible assets of companies, combined with IT, has an aspect that contributes to economic growth and productivity growth (Bank of Korea 2020[2]).

R&D expenses should be looked into along with the intangible assets. R&D, or research and development, include activities for developing new products or new technologies, and with a few exceptions[3] in both IFRS and US GAAP accounting standards , most of the R&D expenses are classified as costs. Therefore, it is necessary to have a look at R&D cost accounts to analyze an enterprise's R&D trend.

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[1] Data of companies listed in NYSE, NASDAQ, and AMEX

[2] Bank of Korea, 2020, The Rise of Intangible Economy, BOK Issue Note

[3] For example, development cost can only be capitalized when the development takes shape and meets certain standards under the IFRS, and a software company can only assetize R&D costs when the related technology becomes feasible and meets certain conditions under the US GAAP

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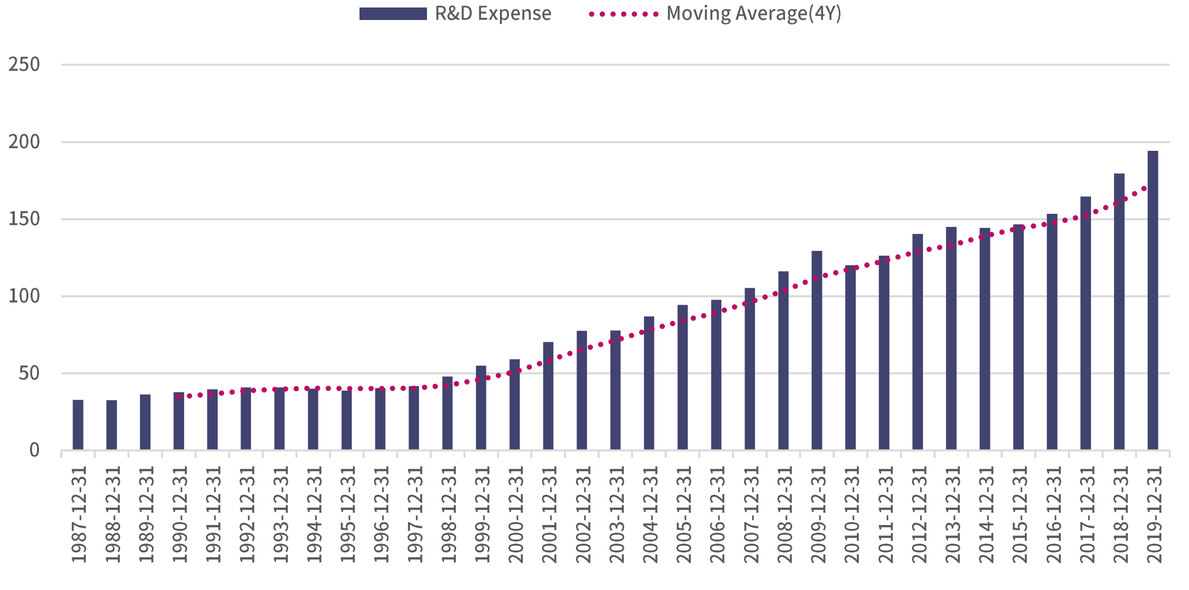
$$RORC(Return\ on\ Reserach\ Capital) = \frac{Gross\ \ Profit_t}{R\&D\ \ Expense_{t-1}}$$

[Figure 2] shows the trend of R&D costs, exemplifying a steady rise, and RORC is also at a higher level than in the past as shown in [Figure 3]. As such, companies have historically generated a large amount of gross revenue through high R&D costs.

What do companies' R&D costs mean, and how can they lead to actual returns in the financial market? There are budget constraints for companies and because of that, the budget cannot be spent on R&D alone. The allocation of R&D costs is decided by considering financial budget constraints and maximizing the company's value under the constraints (Li, 2011[4]) . That is, these R&D costs are determined by the entity's enterprise-wide judgment to be sufficient to lead to an economic moat of the company, even considering the budget constraints.

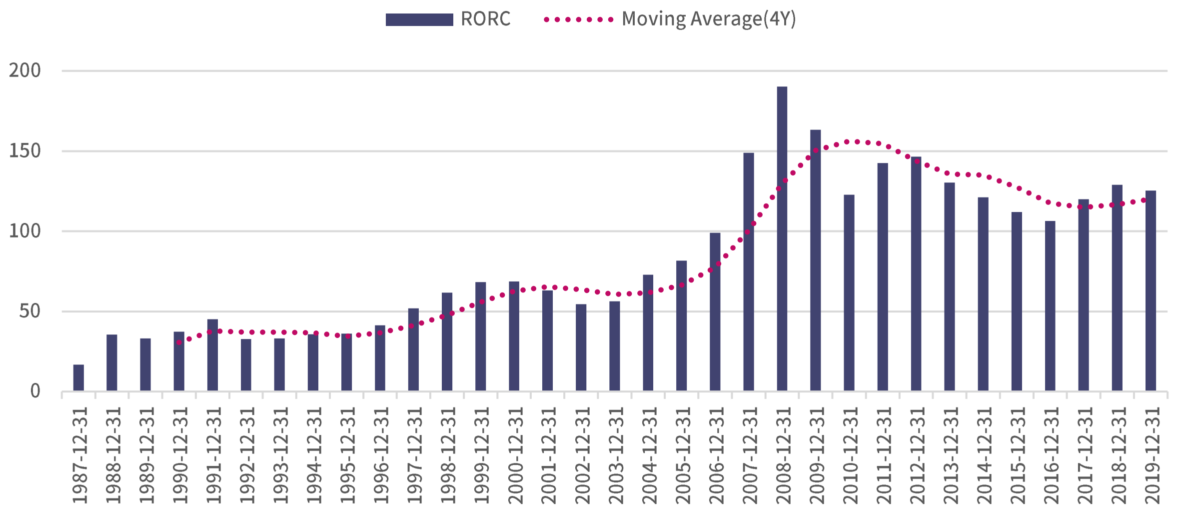
Figure 2. Average R&D Cost Trend



Souce :Qraft Technologies, Compustat

4 Li, Dongmei, 2011, Financial constraints, R&D investment and stock returns, Review of Financial Studies 24, 2974–3007.

Figure 3. Average RORC Trend



Source: Qraft Technologies, Compustat

It is necessary to look at how companies that spend high R&D costs derive high expected returns from the perspective of risk premium. As mentioned earlier, budget constraints are the biggest challenge that all companies face in R&D spending, and these budget constraints vary from company to company. Companies with relatively large sizes, or large total assets in this case, will have relatively less of these budget constraints and take less risks even if they spend the same amount of R&D expenses. In other words, a relatively small company would have to overcome a higher cash flow threshold to continue and maintain the project that is currently initiated by R&D spending, and the company is likely to be in danger. The factor that was analyzed in this report is Rca, which is R&D capital to the total assets of the entity. This means that companies with small total assets and large R&D capital take higher risks and have higher expected returns.

Methodology

- ✓ Investment Universe: NYSE + NASDAQ Market Cap Top 20% stocks
- ✓ Stock Weighting: equal-weighted & market cap-weighted
- ✓ Benchmark: S&P500
- ✓ Rebalancing: stocks selected in June every year and held for one year (yearly rebalancing)

According to research carried out by Li (2011), R&D capital is calculated by applying linear depreciation rate of 20% on annual R&D costs (Compustat: XRD) over the past five years.

$$\boldsymbol{Rc_{i,t}} = \boldsymbol{XRD_{i,t}} + 0.8\boldsymbol{XRD_{i,t-1}} + 0.6\boldsymbol{XRD_{i,t-2}} + 0.4\boldsymbol{XRD_{i,t-3}} + 0.2\boldsymbol{XRD_{i,t-4}}$$

Rc is then divided by total assets (Compustat: AT). The calculated factor is Rca and portfolio is made up by sorting stocks based on year t-1 Rca and holding stocks from July of year t to June of year t+1. Rebalancing is done in June every year, and holding period is one year after the rebalancing. The codes using Qraft's proprietary Kirin API for factor calculation and rebalancing is as follows ([Figure 4]).

Figure 4. QRAFT Kirin API Code

```
elif factor_name == 'Rca':
1)    XRD = api.high_level.equity.us.get_fundamental_data("XRD",   backtest_mode=False)
2)    AT = api.high_level.equity.us.get_fundamental_data("AT",   backtest_mode=False)
3)    Rc= XRD + 0.8*XRD.shift(12) + 0.6*XRD.shift(24) + 0.4*XRD.shift(36)+ 0.2*XRD.shift(48)
4)    Rca = Rc[Rc > 0]/ AT
5)    Rca = Rca.shift(12)
6)    rebalancing = [6]
      return Rca, rebalancing
```

Line 1 and 2 are functions to retrieve financial data using Qraft's proprietary Kirin API. XRD and AT are the required data to calculate Rca and they are retrieved by line 1 and 2. In addition, backtest_mode is designated as false, which is a feature that makes it automatically lag according to the point of data disclosure. In this analysis, the function is set to off in order to make it explicit the collective 1-year lagging. Line 3 is the calculation of Rc, and Line 4 is the process of selecting stocks with positive Rc values and adjusting them to AT. Line 5 means that Rca explicitly lags the calculated dates for one year to build a portfolio in year t based on year t-1 data. Rebalancing in line 6 means that portfolio rebalancing is carried out on an annual basis in June.

Historical Performance Check on Rca Anomaly

Based on the Rca factor, the results of the quintile portfolio from January 1992 to May 2020 are as follows:

Figure 5. EW portfolio

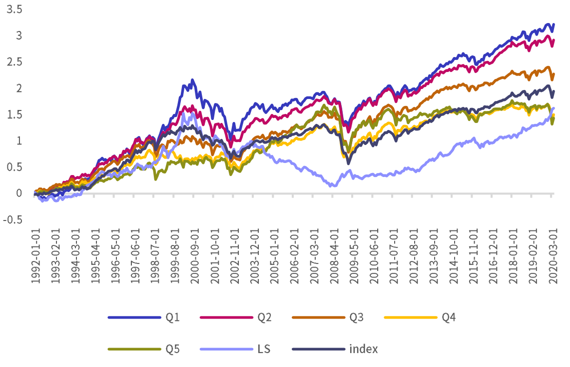
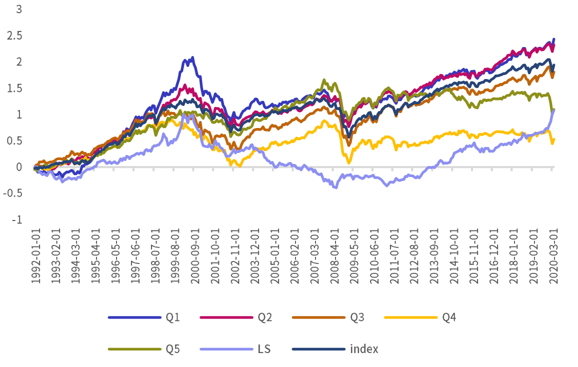


FIgure 6. VW portfolio



Source: Qraft Technologies, Compustat

[Figure 5] and [Figure 6] show the results of equal-weighted portfolios and market cap-weighted portfolios, respectively. In the cases of EW portfolios, the return of the first quintile portfolio is the most dominant, and the return becomes lower as the quintile gets lower to fifth quintile. Market cap-weighted portfolios show similar results to the EW portfolios, showing that the returns of the first and second quintile portfolios are higher, and that the returns in the fourth and fifth quintile portfolios are noticeably lower. This exemplifies that when a portfolio is made up with high Rca factor stocks, the return could be improved. Specific results can be seen in [Table 1].

Table 1. Portfolio performance

Panel A: EW portfolio

	Ann CAGR	Ann Std	Ann Sharp	Mdd	Win Ratio
Q1(High)	0.1236	0.2188	0.6447	-0.6813	0.5894
Q2	0.111	0.1827	0.6709	-0.5456	0.6217
Q3	0.0853	0.1713	0.5663	-0.5415	0.6188
Q4	0.0566	0.1572	0.4311	-0.5186	0.5953
Q5(Low)	0.053	0.1773	0.3825	-0.5821	0.566
Long-Short	0.0612	0.1666	0.4395	-0.7504	0.5455

Panel B: VW portfolio

	Ann CAGR	Ann Std	Ann Sharp	Mdd	Win Ratio
Q1(High)	0.0915	0.1788	0.5811	-0.7103	0.6012
Q2	0.0872	0.1654	0.5903	-0.5725	0.5982
Q3	0.0675	0.163	0.4843	-0.5197	0.61
Q4	0.0204	0.151	0.2107	-0.5832	0.566
Q5(Low)	0.0407	0.1646	0.3258	-0.5375	0.5543
Long-Short	0.0393	0.1537	0.327	-0.7535	0.5455

Source: Qraft Technologies, Compustat

There are several ways to examine the robustness of a factor in a factor investment, and in this case, the significance relations between the IC values and alphas, or excess returns, will be looked into. The IC value is calculated by the Pearson's correlation between the factor value at t-1 and the rate of return at t(Grinold. 1989). [5]

$$IC_t = Correlation(Return_t, Factor\ Value_{t-1})$$

The higher this value, the greater the rate of return-predictive effect of the factor. In the case of rank IC, on the other hand, Spearman's correlation is used because only the ranking is taken into consideration, and the factor value and rate of return are neglected.

Table 2. IC Table

	Coefficient	Std. Error	t-value
IC	0.0235**	0.012	1.945
Rank IC	0.0237**	0.012	2.026

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10
Source: Qraft Technologies, Compustat

[Table 2] shows that the IC and rank IC are measured at 0.0235 and 0.0237, respectively, and these numbers are positively correlated and statistically significant. Therefore, the Rca factor can be concluded to be price-predictive.

In order to validate effectiveness of excess returns, three alphas are calculated to examine statistical significance. The excess return vs. risk free rate, the alpha of CAPM(1964) [6], and the alpha of FF3F(1993) [7] need to be calculated, and these alphas are verified by the Newey-West's T-test(1987) [8] using a lag of 12.

Table 3. Alpha result

The table shows alphas of quintile portfolios constructed by Rca figures: the average monthly return that exceeds risk-free rate of each quintile portfolio, the alphas calculated by using Sharpe's CAPM (1964), the alphas of Fama and French 3-Factor model (1993). The values in parentheses are Newey-West's t-statistics using lag of 12 (1987).

	Excess Return Mean	CAPM Alpha	Fama 3 factor Alpha
Q1(High)	0.0098(2.8428)**	0.0041(1.6936)	0.0046(2.8107)**
Q2	0.0079(2.773)**	0.0026(1.8382)	0.0027(2.5828)**
Q3	0.0059(2.185)*	0.0009(0.7294)	0.0005(0.4788)
Q4	0.0036(1.4738)	-0.0009(-0.5488)	-0.0014(-1.1091)
Q5(Low)	0.0035(1.2634)	-0.0013(-0.6232)	-0.0019(-1.0804)
Long Short	0.0043(1.6393)	0.0034(0.9915)	0.0045(1.9189)

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10
Source: Qraft Technologies, Compustat

The results of the EW portfolios in [Table 3] show that the excess returns of the top first and second quintile portfolios are positively correlated and statistically significant. The alpha of CAPM may not be statistically significant, but the alpha proves to be statistically significant even when it is measured under the situation where the factors of FF3F are controlled.

[5] Grinold, Richard C., 1989, The Fundamental Law of Active Management, Journal of Portfolio Management 15-3, 30-37
[6] William F. Sharpe. ,1964, Capital Asset Prices : A Theory of Market Equilibrium under Conditions of Risk, The Journal of FINANCE 6-3, 425-442
[7] Fama, E. F., French, K. R. , 1993, Common risk factors in the returns on stocks and bonds, Journal of Financial Economics 33, 3-56
[8] hitney K. Newey and Kenneth D. West., 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, Econometrica 55-3, 703-708

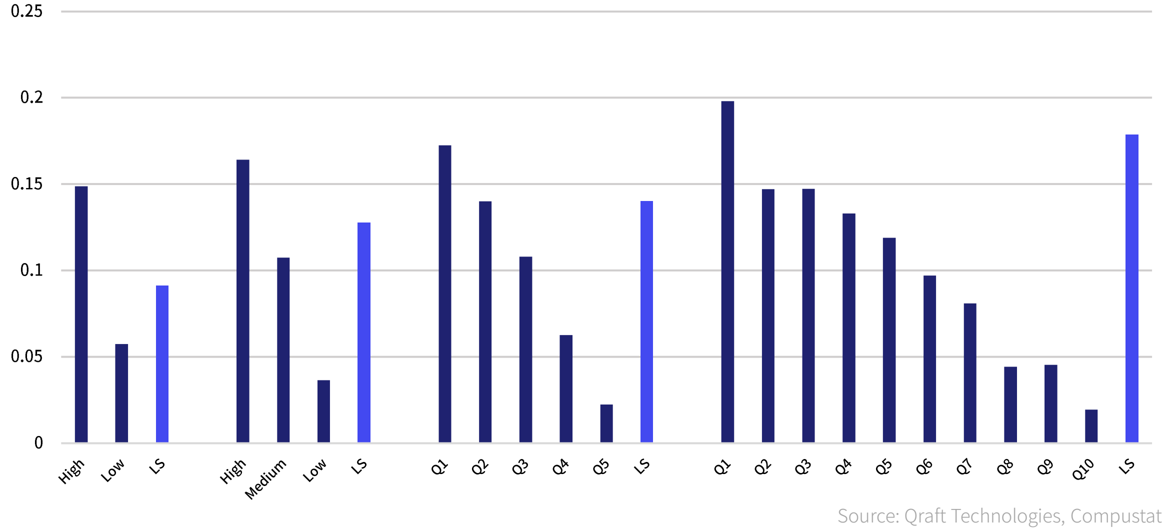
Rca Anomaly Proven to be Effective in factor Robustness Over the last 10 Years

Next, we analyze long-only portfolio returns and long-short portfolio returns of various quantiles over the last ten years from June 2010 to May 2020. Portfolios of various quantiles are constructed based on the Rca factor, and annualized returns of each portfolio are as follows:

- ✓ Half (least concentrated) = 9.25%
- ✓ Tercile (1/3s) = 12.47%
- ✓ Quintile (1/5s) = 13.75%
- ✓ Decile (most concentrated) = 16.93%

In the case of long-short returns, the half portfolio divides stocks into top and bottom 50% on a factor basis, so the concentration level of the factor effect is the lowest, and the concentration level of the factor effect becomes greater as the quantile nears to decile. For this reason, if a factor works well, the performance can be expected to improve as the concentration level gets higher.

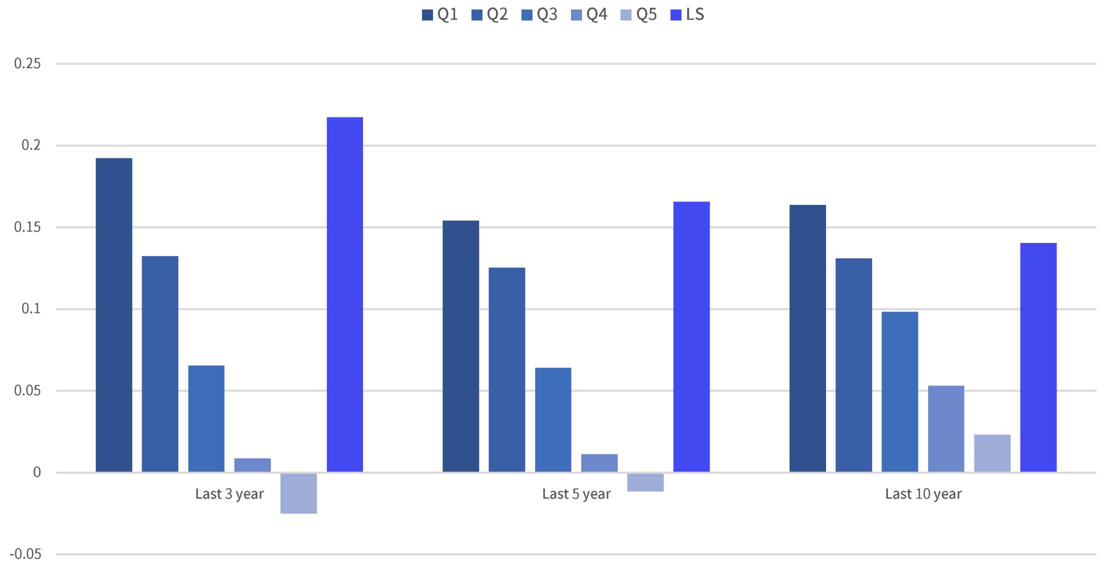
Figure7. Portfolio performance



Source: Qraft Technologies, Compustat

As shown in [Figure 7], the higher the Rca factor, the higher the return in general, and the return of the most strictly selected top 10% group is higher than the simply-constructed, top 50% group. At the same time, in the case of groups of lower factor values, the rate of return is decreasing as the quantile nears to decile from half. This means that the higher the value of the factor, the higher the rate of return, and vice versa. Therefore, this figure supports the robustness the factor.

Figure 8. Recent period Portfolio Average Return



Source: Qraft Technologies, Compustat

The effect of the factor is greatly influenced by the nature of the factor and the overall market situation. Therefore, even if a factor worked well in the past, it is crucial to check that it is still working. Therefore, we examine the returns of the quintile portfolios by the time periods of the last 10 years, 5 years and 3 years. [Figure 8] shows that the more recent it is, the clearer the differentiation of the rate of return by the quantile. This elaborates that the effect of the Rca factor is getting stronger in recent years.

Table 4. Recent Period IC Table

		Coefficient	Std. Error	t-value
Last 3 years	IC	0.0544***	0.022	2.591
	Rank IC	0.0818***	0.021	3.925
Last 5 years	IC	0.0520***	0.016	3.243
	Rank IC	0.0707***	0.017	4.170
Last 10 years	IC	0.0491***	0.012	4.041
	Rank IC	0.0565***	0.012	4.715

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10
Source: Qraft Technologies, Compustat

The trend of increasing IC values recently is shown in [Table 4]. Analyzing the above table, we can conclude there has been a strong positive correlation of factor effects in the last ten years. It is also noteworthy that the predictive effects of the factor become more effective in recent years.

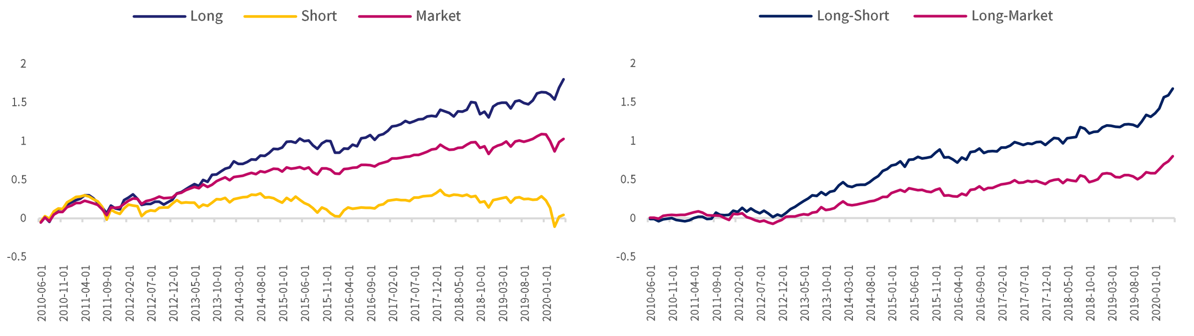
In sum, stocks with higher factor values tend to be more profitable, while stocks with lower factor values tend to be the opposite. In addition, the effects of Rca factors have been increasing significantly in recent years. This shows that a long-only play, which buys stocks with high factor values, is valid, and that a long-short strategy, which shorts stocks with low factor values, can also be effective.

Strategies with Rca Anomaly

As the robustness of the Rca factor has been maintained strongly recently, long-only strategies and long-short strategies using these effects can be carried out. For the long-only strategy, the group in the top 10% of the Rca factor can be equal-weighted or market cap-weighted to construct a portfolio.

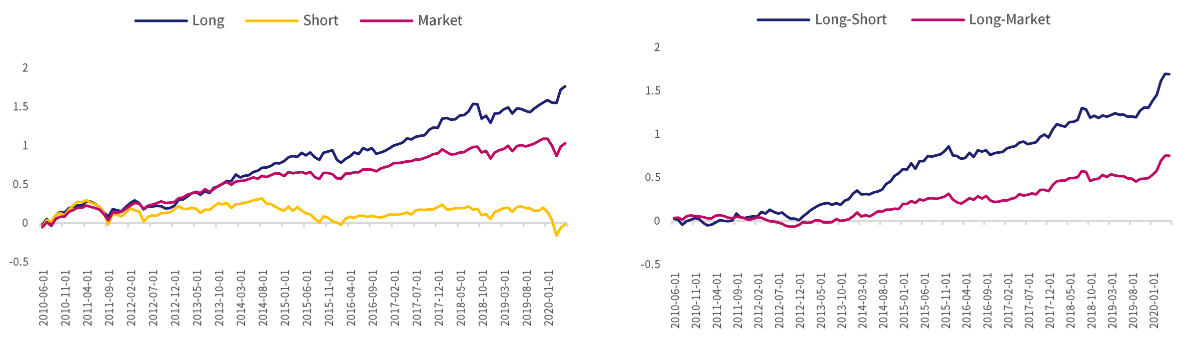
In the case of a long-short strategy, a portfolio can be constructed to buy (long) stocks in the top 10% of the factor and to sell (short) stocks in the bottom 10% of the factor. In addition, by buying stocks belonging to the upper group of factor criteria and shorting the benchmark index, a strategy that pursues pure alpha, which is the excess return compared to the market, can be implemented. The following [Figure 9] and [Figure 10] show the performances of each strategy in the last ten years.

[Figure 9 : EW Long-Short Strategy Performance based on the Factor]



Source: Qraft Technologies, Compustat

[Figure 10 : MV Long-Short Strategy Performance based on the Factor]



Source: Qraft Technologies, Compustat

Appendix

Long/Short List

Source: Qraft Technologies, Compustat

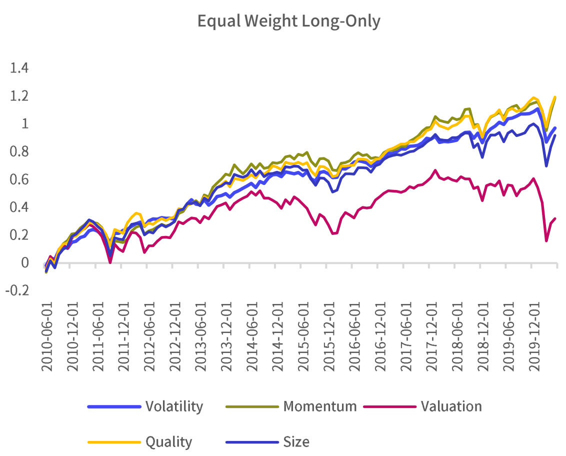
Long Stock			
Ticker	Name	Sector	Market Cap($: MM)
KLAC	KLA CORP	Information Technology	27,282
LOGI	LOGITECH INTERNATIONAL SA	Information Technology	9,920
LRCX	LAM RESEARCH CORP	Information Technology	39,725
LLY	LILLY (ELI) & CO	Health Care	138,640
BRKR	BRUKER CORP	Health Care	6,675
GSK	GLAXOSMITHKLINE PLC	Health Care	104,297
PTC	PTC INC	Information Technology	8,837
STM	STMICROELECTRONICS NV	Information Technology	22,098
AZPN	ASPEN TECHNOLOGY INC	Information Technology	7,141
DXCM	DEXCOM INC	Health Care	34,918
SWKS	SKYWORKS SOLUTIONS INC	Information Technology	19,855
MANH	MANHATTAN ASSOCIATES INC	Information Technology	5,613
XLNX	XILINX INC	Information Technology	22,418
AMD	ADVANCED MICRO DEVICES	Information Technology	63,000
MRK	MERCK & CO	Health Care	203,738
MPWR	MONOLITHIC POWER SYSTEMS INC	Information Technology	9,379
EXEL	EXELIXIS INC	Health Care	7,556
VMW	VMWARE INC -CL A	Information Technology	65,522
PODD	INSULET CORP	Health Care	11,891
ON	ON SEMICONDUCTOR CORP	Information Technology	6,761

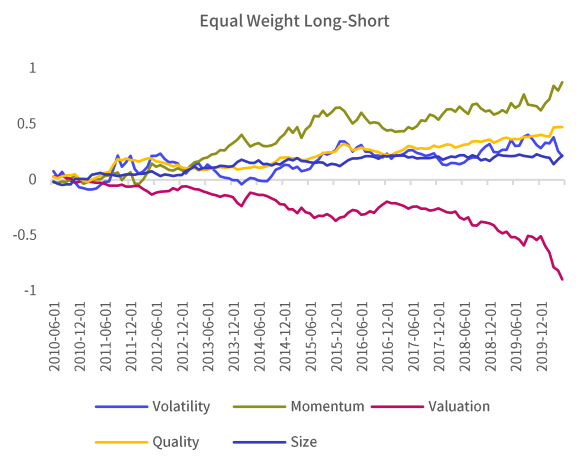
Short Stock			
Ticker	Name	Sector	Market Cap($:MM)
MLM	MARTIN MARIETTA MATERIALS	Materials	11,948
WRK	WESTROCK CO	Materials	7,273
AMT	AMERICAN TOWER CORP	Real Estate	114,455
L	LOEWS CORP	Financials	9,355
WY	WEYERHAEUSER CO	Real Estate	15,066
RIO	RIO TINTO GROUP	Materials	87,412
DEO	DIAGEO PLC	Consumer Staples	83,276
WSO	WATSCO INC	Industrials	6,824
LIN	LINDE PLC	Materials	106,262
BHP	BHP GROUP LTD	Materials	119,086
CCI	CROWN CASTLE INTL CORP	Real Estate	71,791
SBUX	STARBUCKS CORP	Consumer Discretionary	91,100
SU	SUNCOR ENERGY INC	Energy	31,614
TLK	TELEKOMUNIKASI INDONESIA	Communication Services	21,150
OXY	OCCIDENTAL PETROLEUM CORP	Energy	11,655
VOD	VODAFONE GROUP PLC	Communication Services	44,957
TAP.A	MOLSON COORS BEVERAGE CO	Consumer Staples	11,350
TECK	TECK RESOURCES LTD	Materials	6,076
DISH	DISH NETWORK CORP	Communication Services	16,564
INFO	IHS MARKIT LTD	Industrials	27,708

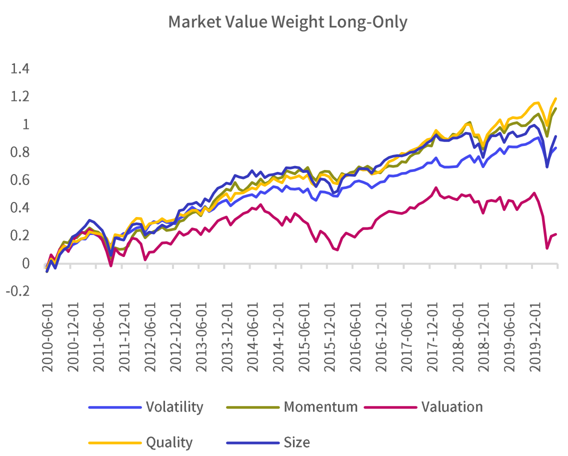
Appendix

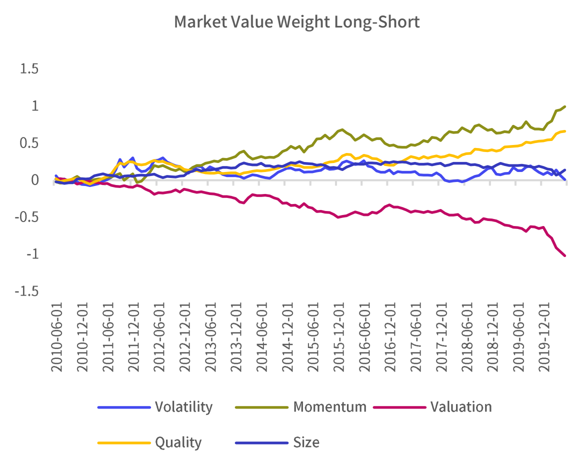
Factor Performance

(1) Volatility : Reciprocal Number of Volatility of 36 months Return
(2) Size : Reciprocal Number of Market Value
(3) Value : Arithmetic Mean(PER(Price Earning Ratio), PBR(Price Book-value Ratio), PCR(Price Cashflow Ratio))
(4) Momentum : Δ12-1m Return
(5) Quality : Arithmetic Mean(ROE(Returns on Equity), ROA(Returns on Asset), GPA(Gross Profits to Asset))
- Data Period : last 10 year
- Long only indicates performance of portfolio of stocks
- Long only indicates performance of portfolio which is composed by highest quintile factor value and Long-Short indicates performance of portfolio which is composed by highest quintile minus lowest quintile.









Source: Qraft Technologies, Compustat

Appendix

QRAFT AI ETF Performance Tracker

1. QRAFT AI-Enhanced US Large Cap ETF(QRFT)

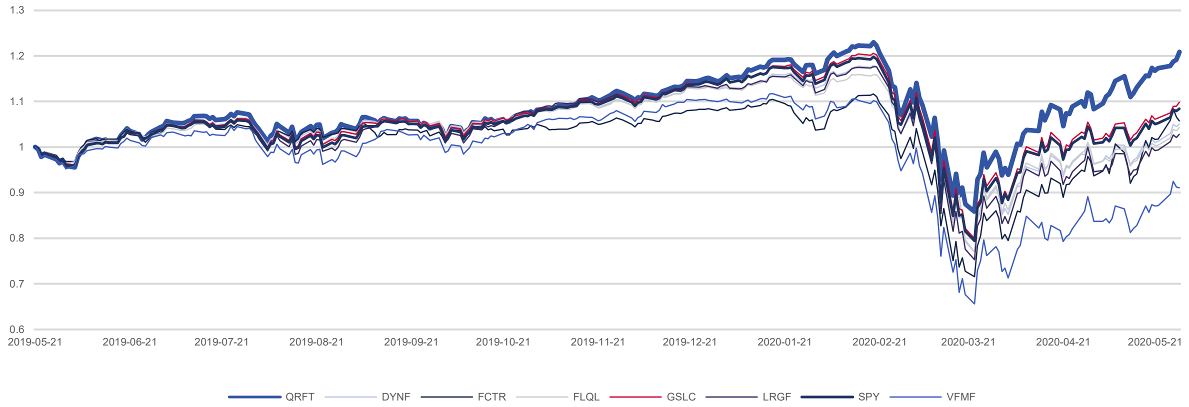


Table 5. US Large Cap Multi-Factor ETF Comparison (from 2019-05-21 to 2020-05-29)

Name	Ticker	Total Return(%)
Qraft AI Enhanced US Large Cap ETF	**QRFT**	**20.85%**
Goldman Sachs ActiveBeta US Large Cap Equity	GSLC	9.82%
SPDR S&P500 ETF Trust (Benchmark)	SPY	8.42%
Blackrock US Equity Factor Rotation ETF	DYNF	5.03%
Franklin LibertyQ US Equity ETF	FLQL	4.27%
iShares Edge MSCI Multifactor USA ETF	LRGF	2.82%
First Trust Lunt US Factor Rotation ETF	FCTR	5.74%
Vanguard US Multifactor ETF	VFMF	(8.91%)

2. QRAFT AI-Enhanced US Large Cap Momentum ETF(AMOM)

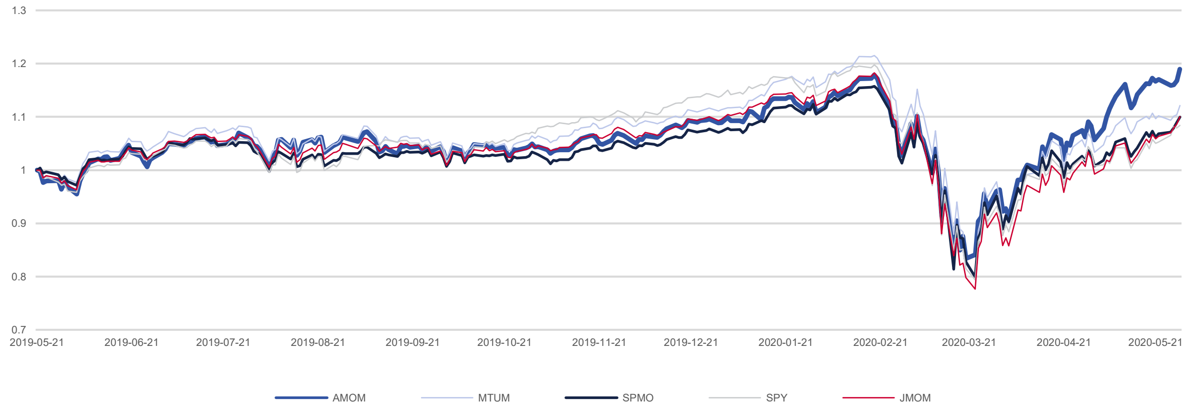


Table 6. US Large Cap Momentum ETF Comparison (from 2019-05-21 to 2020-05-29)

Name	Ticker	Total Return(%)
QRAFT AI-Enhanced U.S. Large Cap Momentum ETF	AMOM	**18.97%**
iShares Edge MSCI USA Momentum Factor ETF	MTUM	12.14%
Invesco S&P500 Momentum ETF (Benchmark)	SPMO	9.98%
SPDR S&P500 ETF Trust	SPY	8.42%
JP Morgan US Momentum Factor ETF	JMOM	10.03%