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Can Consumption Predict Expected Return?

- Evidence from Korea –

소비는 기대수익률을 예측할 수 있는가?
–한국 시장에서의 실증 연구–

2021년 2월

서울대학교 대학원

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지도교수 고 봉 찬

이 논문을 원 영 웅 석사 학위논문으로 제출함

2020년 12월

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경영학과 재무금융전공

원 영 웅

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2020년 12월

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Abstract

Can Consumption Predict Expected Return?

- Evidence from Korea -

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This paper shows the new variable ‘cyclical consumption’, which follows the detrending method of Hamilton (2018), can capture the consumption risk and have predictability for KOSPI expected returns. Specifically, it is found that ‘cyclical consumption’ has statistically significant inverse relationship with KOSPI market return, and the more accumulated (up to 5 years) the market return is, the stronger the relationship is. This relationship implies the empirical evidence for the theory 'External Habit Model', which asserts that when the consumption is higher (lower) than its trend, future expected market return will decrease (increase). ‘Cyclical consumption’ also predicts KOSPI expected return during both the boom and the recession consistently. Moreover, this paper found that the relationship with ‘cyclical consumption’ is also applied significantly to KOSPI-based industry portfolios. Lastly, the result shows that buy-sell trading rule based on ‘cyclical consumption’ generates 9.15% annual return on average historically.

Keywords: cyclical consumption, external habit model, consumption risk, predictability

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Chapter 1. Introduction

This paper follows the way Atanasov, Møller, and Priestley (2020) made 'cyclical consumption' which is consumption-based variable and constructs with the Korean data. This is because this paper tries to identify whether the cyclical consumption can capture the consumption risk, affecting to the variation of the price change in Korea. According to External Habit Model, when the consumption is higher than the trend, the marginal utility for current consumption will decrease, so the investors reduce the consumption today but will increase the investment instead. This leads to the increase of stock prices, but the decrease of future expected return. On the other hand, when the consumption is lower than the trend, the marginal utility for current consumption will decrease, so the investors will increase the consumption at the expense of current investment. Therefore, the stock prices will be decreased but the future expected return will be increased. If this is true, cyclical consumption will have negative relationship with the market expected return. Moreover, the risk premium will be time-varying in this theory, so the risk rooted from the consumption variation could be reflected into the stock prices differently. This type of risk is the case which is slow-moving in a long-term period.

In conclusion, the consumption variation generated in the certain period will be reflected slowly into the following periods, so It is asserted that this type of variable will have predictive property. Therefore, this paper will check the hypothesis whether cyclical consumption captures the variation in consumption resulted from the change of marginal utility, so this variable has certain relationship with the stock market return. Meanwhile, this paper will also test whether KOSPI or KOSDAQ can represent the Korean stock market. Next, we will test whether cyclical consumption can show the relationship with market returns in both the good time and the bad time simultaneously. This is because many previous studies got criticized that predictive variables are occasionally significant in bad time, but insignificant in good time. Therefore, we need to check whether cyclical consumption is significant regardless of the period. In addition, this paper will check whether cyclical consumption has same result even in the specific industry portfolios. Moreover, we will accompany with several robustness tests to determine whether cyclical consumption is better than other methodologies. Lastly, this paper check whether buy-sell trading strategy is profitable depending on cyclical consumption.

In fact, there have been many studies to figure out some variables can capture the risk or variation related to consumption and to connect them to stock market or specific economic components in the field of finance and macroeconomics. Especially, the research verifying whether some variables can be predictable to the corresponding risk have been actively done. Santos and Veronesi (2006) claim that the variable which constructed by the ratio of labor income to consumption varies together when the risk premium varies, so it can capture the consumption risk as well as can have predictive ability for stock returns. Lettau and Ludvigson (2001) show consumption-wealth ratio (cay ratio) which is detrending variable from the relationship between consumption, wealth, and income has powerful predictability for stock returns. Moreover, Bansal, Khatchatrian, and Yaron (2005) assert that the variable called consumption volatility can perform asset valuation as a measure of consumption risk. Especially, they explain that the variation of stock returns can be captured from the variation of consumption risk and the growth rate of cashflow. Cooper and Priestley (2009) assert if the variable can be constructed through the way it captures the residual from the output of total industrial production index by choosing an appropriate detrending method, the variable becomes the proxy of business cycle so that it will have predictability for international stock excess returns or US bond excess returns.

The common part of those studies is that they use predictive regression to verify the predictivity of corresponding variables. However, there have been many critics as well about the econometric issues generated when the study uses the time-series variables on the predictive regression. Kim, J. H. (2014), for example, suggests the improved regression method which can overcome the drawbacks of predictive regression like sample bias or stationarity problem. Moreover, Kostakis, Magdalinos, and Stamatogiannis (2015) also suggests the complement for incomplete inference resulted from the uncertainty related to the integration order of predictive variables by constructing IVX estimation which is robust to the time-series property of employed regressors. Especially, Campbell and Yogo (2006) criticizes that the previous tests clarifying the predictive property about stock returns are uncertain and suggests the pretest that can check whether the t-test involves such problems. Lastly, Hamilton (2018) criticizes that HP filter which has been widely used for predictive regression has serios problem, saying that Hamilton filter is a better alternative.

Meanwhile, similar research has been studied in South Korea. For example, Choi (2011) shows that utility function with the habit formation is more proper to explain return premium in Korea. This paper grants the justification for using the variable cyclical consumption in Korea. Yoo and Kim (2011) asserts that the uncertainty on Korea stock market can affect the uncertainty on the consumption. This paper has implication in a way that the connection between stock returns and the variation in consumption has been verified in Korea. Kang (2013) shows that the variable 'cay' which is suggested by Lettau and Ludvigson (2001) has significant predictability in Korea.

However, there have been no papers that verify the relationship between stock returns and consumption risk related to cyclical consumption in Korea, and the efforts to check whether or not consumption-based predictive variables is related to Korean stock market have been lacked so far. Therefore, this paper makes such a contribution in a way that it verifies the relationship between the Korean stock returns and the cyclical consumption which is unconventional variable supplementing the drawbacks of previous predictive variables. In Chapter 2, this paper explains in detail about External Habit Model and how it related to the cyclical consumption. And in Chapter 3, this paper covers the methodology about the data and how to construct the main variable. In Chapter 4, this paper analyzes the results of empirical tests and the conclusion is followed in Chapter 5.

Chapter 2. Theoretical Context

If the economy gets worse dramatically, the rich person who had lived economically abundant life is hard to reduce the consumption sharply due to previous consumption habit. Conversely, if the poor person who had lived economically insufficient life suddenly becomes rich, then this person is hard to consume excessively due to previous consumption habit. In fact, the utility function with 'the habit formation' reflects this mechanism by considering the habit of investors. Especially, Campbell and Cochrane (1999) assume that this habit formation is determined by the whole history of aggregate consumption rather than that of personal consumption. In this model, it is assumed that identical investors intend to maximize the following utility function,

$$E\sum_{t=0}^{\infty}\delta^{t}\frac{(C_t-X_t)^{1-\gamma}-1}{1-\gamma} \qquad (1)$$

where X_t means the habit, and δ means the subjective time discount factor. The habit X_t is defined indirectly through surplus consumption ratio. To put it another way, X_t is calculated by $S_t \equiv (C_t - X_t)/C_t$. Campbell and Cochrane (1999) assume that log surplus consumption ratio $s_t \equiv \log(S_t)$ follows heteroskedastic AR(1) process,

$$s_t \equiv (1-\varphi)\bar{s} + \varphi s_t^{a} + \lambda(s_t^{a})(c_{t+1}^{a} - c_t^{a} - g) \qquad (2)$$

where φ, g, and $\bar{s}$ are all parameters. $\lambda(s_t^{a})$ is the sensitive function which is nonlinearly and monotonically decreasing and the consumption growth g determines how it affects surplus consumption. In fact, this model asserts the habit is activated as the trend of consumption. In Appendix C of working paper of Wachter (2006), the proof that the first-order approximation around $s_t = \bar{s}$ implies the surplus consumption moves slowly and adjusts to the whole history of current and past consumption with the parameter φ,

$$s_t \approx k + \lambda(\bar{s})\sum_{j=0}^{\infty}\varphi^{j}\Delta c_{t-j} \qquad (3)$$

where k is the constant and it depends on model parameters. Atanasov, Møller, and Priestley (2020) claim there is the connection between surplus consumption and cyclical consumption when k and $\lambda(\bar{s})$ is excluded and $\lambda(\bar{s}) \approx 1$ is assumed.

$$\widehat{s_t} \approx c_t - c_{t-k} \approx cc_t \qquad (4)$$

Subscript k determines the length of time interval which adjusted to the past consumption. The detailed explanation about constructing cyclical consumption will be mentioned in the next chapter. In conclusion, the whole process above is what Atanasov, Møller, and Priestley (2020) claims about the theoretical relationship between the variable cyclical consumption and 'External Habit model'.

Meanwhile, if the excess return of stock market and the consumption growth are jointly and lognormally distributed, the model of Campbell and Cochrane (1999) brings the implication like below,

$$E_t(r_{t+1}) + \frac{1}{2}\sigma_t^2 = \gamma_t cov_t(\gamma_{t+1}, \Delta c_{t+1}) \qquad (5)$$

where γ_t is the state-dependent price of consumption risk defined as $\gamma_t = \gamma(1 + \lambda(s_t))$. Since s_t is clarified to be similar as cyclical consumption in Eq. (4) and $\lambda(s_t)$ is set to be decreasing function in Eq. (2), so that it is obvious to have the inverse relationship between cyclical consumption and s_t by the covariance term. Also, it implies inverse relationship between cyclical consumption and risk premia. This is because the consumption higher than the trend is connected to the decrease of covariance and the consumption lower than the trend is connected to the increase of covariance. Shortly speaking, when the consumption is higher than the trend (the boom), the marginal utility of current consumption will decrease, and it makes the investors reduce current consumption but enhance the investment today. This leads to increase the stock price today, while it decreases the expected return in the future. Conversely, when the consumption is lower than the trend (the recession), the marginal utility of current consumption will increase, and it makes the investors consume more but invest less today. This leads to decrease the stock price today, while it increases the expected return in the future. From now on, this paper introduces how the main variable 'cyclical consumption' is made of and describes the graph of time-series trend of it as well. By doing this, this paper can show how cyclical consumption relates to market excess return in Korea geometrically.

Chapter 3. Data and Methodology

3.1. Cyclical Consumption

First, we will investigate how the variable cyclical consumption is derived. This paper uses aggregate seasonally adjusted personal consumption expenditures (PCE) as a proxy of the consumption data. This data is obtained from the table 10.7.1.2.2 of Economic Statistics System (ECOS), which is real per capita term and quarterly data from 19701Q to 20194Q. In fact, It is different from that Atanasov, Møller, and Priestley (2020) uses aggregate seasonally adjusted consumption expenditures on nondurables and services as a proxy. This is because in the case of Korean stock market, PCE is the most significant variable among others compared to U.S stock market, in the following table that determines which consumption variables explains better.

$$C_t = b_0 + b_1 C_{t-k} + b_2 C_{t-(k+1)} + b_3 C_{t-(k+2)} + b_4 C_{t-(k+3)} + w_t \qquad (6)$$

As it is mentioned before, this paper follows the detrending method of Hamilton (2018) in order to capture the risk of consumption variation from the change of marginal utility. In Eq. (6), we regress four lagged consumption data at $t-k,\ t-(k+1),\ t-(k+2),\ t-(k+3)$ on the consumption data at t. Then the residual part w_t is the cyclical consumption at t (cc_t).

$$cc_t = C_t - \left(\hat{b}_0 + \hat{b}_1 C_{t-k} + \hat{b}_2 C_{t-(k+1)} + \hat{b}_3 C_{t-(k+2)} + \hat{b}_4 C_{t-(k+3)}\right) \qquad (7)$$

Eq. (7) should bring the same result of Eq. (6) by structure. That is, cc_t can be also obtained by subtracting the estimated coefficients away from the left side of Eq (6), which is C_t. According to Hamilton (2018), the variable followed by this method has the following characteristics. First, the forecast error is stationary when the true data generating process is unknown about all available wide class of nonstationary process. And it will not deviate from the characteristic of random walk. Moreover, it will remain the characteristic of time trend purely. Next, it will have stationarity no matter how long the time interval is. Lastly, this method can overcome the previous disadvantages as well as it is simply restricted model in relative term.

Therefore, cc_t which is extracted by Hamilton (2018) will have better explanation power and have less error compared to other methods.

Next, it is important to determine k in subscript of independent variables from the right side of Eq. (6). According to Hamilton (2018), it is recommended to decide k as about five years to capture the long-term shock when the paper consider the dynamic of business cycle. Especially, since this paper sets up the variable which captures the slow-moving and time-varying variation in consumption, it assumes that cc_t will have more explanation power around five years than other periods. The empirical results will be discussed more in the corresponding table later. In conclusion, cc_t has the most fitted outcome in Korea when it is determined as $k = 24$, which is six years in annual term. Following this result, every table behind this section uses cc_t with $k = 24$.

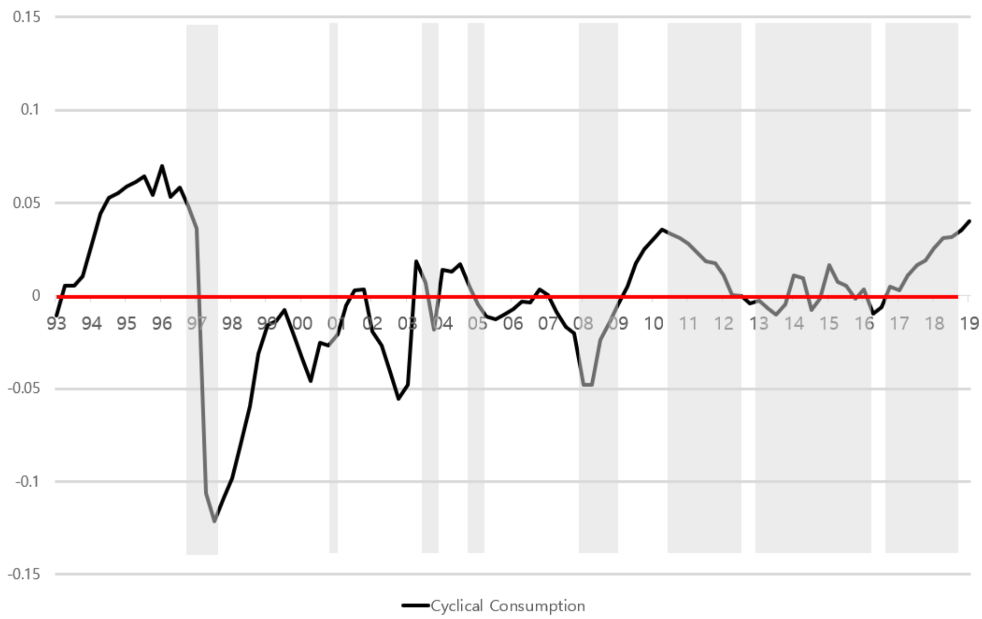

Figure 1. The time-series trend of cc_t

[Figure 1] shows the time-series trend of cc_t to observe the movement of it when $k = 24$. The time period covers from 1993Q4 to 2019Q4. In fact, the period of consumption data is from 1970 and the KOSPI market return is from 1980Q1, while KOSDAQ market return is from 1996Q3. And, the 364-days Monetary Stabilization Bond (MBS) returns as a proxy of risk-free rate is from 1987Q1. Since cc_t is constructed from the lagged data ($k = 24$), the period of data in [Figure 1] is inevitably limited to obtain from 1993Q4 which is lagged by six years from 1987Q4. cc_t is expressed with black line, while the space shaded by darker color represents the bad times by following specific definition. To be more specific, in the time of 1998 Korea IMF crisis, cc_t was in the inflection point that changed to negative domain from positive domain. However, in the time of 2008 Financial crisis, cc_t in Korea had been floated in the negative domain, which is not clearly fitted to the conjecture of this paper. But, during 2011 to 2013, this period was defined as bad times and cc_t was positive in general. Moreover, during 2013 to 2016, in the time of bad times, cc_t was in the positive domain. Finally, during the bad time from 2017 to 2019, it is observed that the trend of cc_t is increased in the positive domain.

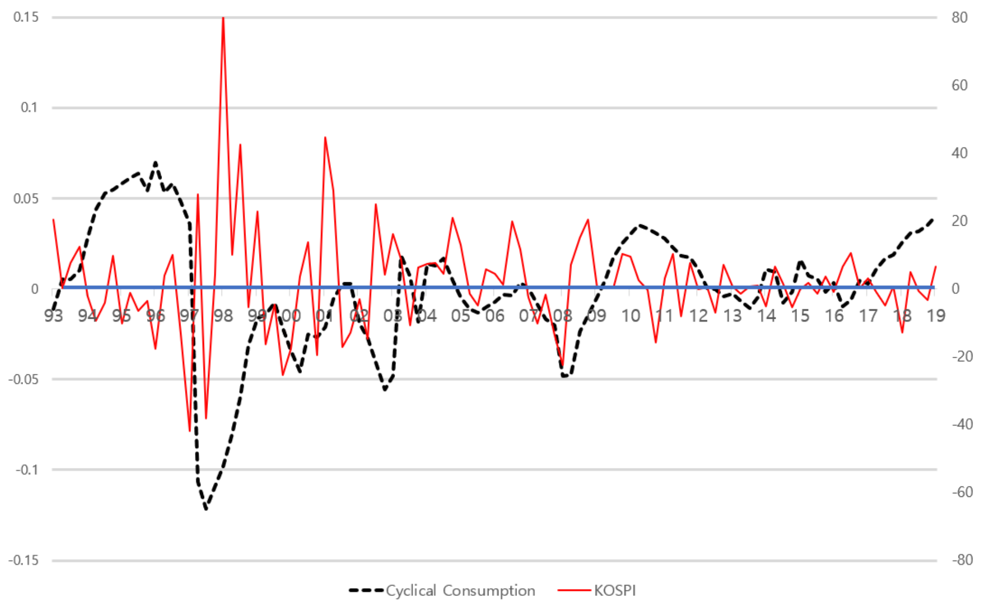

Figure 2. The time-series trend of cc_t and KOSPI market returns

Next, in [Figure 2], the graph represents the comparison between the trend of cc_t and KOSPI market returns. The trend of cc_t is black dotted line while

KOSPI market returns is red straight line. In general, the trend of cc_t had been in the negative domain when KOSPI market returns had been in the positive domain and vice versa. So, we can observe the inverse relationship between the trend of cc_t and KOSPI market returns.

3.2. Predictive Regression

In this section, I will explain how the predictive regression is constructed for determining whether cc_t has predictability about market returns. First, KOSPI and KOSDAQ market returns are used as a proxy of market returns. The period of KOSPI market return data is from 1980Q1 to 2019Q4, and the period of KOSDAQ market return data is from 1996Q3 to 2019Q4. And 364-days MSB returns are used as a proxy of risk-free rate to make it similar in a way that Atanasov, Møller, and Priestley (2020) uses 30-days T-bills as a proxy. In fact, there are several short-term proxies which have more similar properties, but this paper use 364-days MBS returns since it has longer data period. The data period of 364-days MBS returns are from 1987Q1 to 2019Q4. The proxy of risk-free rate is necessary for establishing excess return. Every return data is obtained from FnGuide 5.0. Table 1 compares the form of excess return, nominal return, and real return at the same time. Nominal return is literally the raw data of market return itself, and excess return is calculated by subtracting the risk-free rate from nominal return. Real return is calculated by deflating nominal returns using the inflation rate of the aggregate South Korea CPI, which is downloaded from KOSTAT.

$$r_{t,t+h} = \alpha + \beta cc_t + \varepsilon_{t,t+h} \qquad (8)$$

Eq. (8) is the form of the return predictive regression. On the left side, $r_{t,t+h}$ is h-quarter continuously compounded log return. On the right side, cc_t is the variable calculated by Eq. (6). By using this equation, this paper regresses cc_t on $r_{t,t+h}$. The determination of h in $r_{t,t+h}$ follows the way as Atanasov, Møller, and Priestley (2020) shows the cumulative returns in the table from one year to five years. As it is discussed before, the predictive regression contains some econometrical issues when the paper just uses it solely without any consideration. Atanasov, Møller, and Priestley (2020) suggests three methods to overcome those issues. First, it suggests the use of t-value from the robust t-statistics method of Newey-west (1987). It is known that heteroskedasticity- and autocorrelation-robust t-statistic truncated at lag h can eliminate heteroscedasticity and autocorrelation of error term which is easily noticed in time-series data. So, t-statistics become robust by preventing possible distortion and reinforcing the reliability of the test.

And next, it also asserts that the wild-bootstrapped p-values must be accompanied with. This is related to the recommendation from Inoue and Kilian (2005) that the one-sided alternative hypothesis should be used when the predictability of estimated coefficient is judged. Rapach, Ringgenberg, and Zhou (2016) notes that Stambaugh (1999) bias which is the error frequently occurred when many papers determine the predictive property of the variable as well as the overlapping observation bias of accumulated data discovered by Hodrick (1992) should be considered. Since these kinds of bias could lead to the wrong statistical inference in the test, it is claimed that the researchers should not only perform the robust t-statistics followed by Newey and West (1987), but also compute a wild bootstrapped p-value to test null hypothesis (b=0) against alternative hypothesis (b>0) in order to get corrected statistical inference. This paper will also compute the wild bootstrapped p-value to reinforce the reliability of the test. Lastly, it also argues that IVX-Wald statistics should be used for validity of using coefficient. Atanasov, Møller, and Priestley (2020) insists that this method can overcome the sample bias of the time-series data discovered from long-term predictive regression model or incorrect statistical inference by possible misspecification. The last method is not used in this paper.

Chapter 4. Empirical Result

4.1. The predictive power of cyclical consumption

In this section, this table shows the result of the return predictive regression of cc_t on KOSPI and KOSDAQ market returns. This table tests both of KOSPI and KOSDAQ market returns, which is stated in the first column. And how many quarters the returns are accumulated is stated from the second column to seventh column. cc_t is constructed by aggregate seasonally adjusted personal consumption expenditure (PCE), because PCE explains better empirically than other consumption data in Korea. In addition, $k = 24$ is determined since it explains better than in another period in Korea. The empirical results about those are explained in the following table later.

Table 1. The Predictive Power of Cyclical Consumption

This table reports the result of the return predictive regression which regresses cc_t on KOSPI and KOSDAQ market returns. Panel A shows the form of excess return by subtracting risk-free rate from each market return. Panel B is the nominal return itself. Panel C is the real return which is calculated by deflating nominal returns using the inflation rate of the aggregate South Korea CPI. The data period of Panel A is from 1987Q1 to 2019Q4 because of the data period of risk-free rate. The period of Panel B is from 1980Q1 to 2019Q4 and that of Panel C is from 1997Q3 to 2019Q4. The parentheses represent the robust t-value by using wild bootstrapped p-value, and a square bracket represents the adjusted R-square. * as 10%, ** as 5%, and *** indicates 1% of significance level.

	h=1	h=4	h=8	h=12	h=16	h=20
			Panel A: Excess Market Returns			
KOSPI	-1.03	-5.14	-4.92	-4.89	-5.91	-6.13
	(-2.66)***	(-5.81)***	(-2.34)**	(-2.09)**	(-2.99)***	(-2.54)**
	[6.08]	[34.65]	[22.32]	[17.13]	[20.39]	[25.95]
KOSDAQ	-0.06	-0.07	-0.59	-0.35	-2.44	1.61
	(-0.09)	(-0.03)	(-0.35)	(-0.27)	(-0.97)	(0.70)
	[0.00]	[0.00]	[0.20]	[0.04]	[3.13]	[1.41]
			Panel B: Nominal Market Returns			
KOSPI	-0.82	-3.24	-3.18	-2.47	-3.07	-3.40
	(-3.31)***	(-3.70)***	(-2.50)**	(-1.53)	(-2.50)**	(-3.24)***
	[6.19]	[23.89]	[16.11]	[9.01]	[13.61]	[17.77]
KOSDAQ	-0.08	-0.05	-0.19	0.00	-2.10	1.88
	(-0.12)	(-0.02)	(-0.11)	(-0.00)	(-0.82)	(0.84)
	[0.00]	[0.00]	[0.10]	[0.00]	[3.37]	[1.47]
			Panel C: Real Market Returns			
KOSPI	-0.71	-3.27	-2.97	-2.15	-2.71	-2.99
	(-3.16)***	(-3.48)***	(-2.26)***	(-1.20)	(-1.70)*	(-2.00)**
	[4.57]	[22.91]	[13.68]	[6.41]	[9.36]	[11.73]
KOSDAQ	-0.07	-0.04	-0.42	-0.13	-2.39	1.47
	(-0.10)	(-0.02)	(-0.23)	(-0.09)	(-0.99)	(0.73)
	[0.00]	[0.00]	[0.00]	[0.00]	[2.29]	[1.91]

According to Panel A, KOSPI market excess returns have negative coefficient in every period, and the absolute value of coefficient is higher when the return is more accumulated. This means that cc_t has inverse relationship with the market returns once the consumption risk can be captured. In fact, t-values in the most periods indicate the coefficient is significant in 1% significance level. T-value in h=8 and h=20 is -2.34 and -2.54 for each period, which is covered in 5% significance level. The most distinguished period is when h=4, estimated coefficient is -5.14, and t-value is -5.81 with 34.65 of adjusted R-square. It is different from the result of Atanasov, Møller, and Priestley (2020), which shows that the absolute value of coefficient is getting increased when the market returns are more accumulated as well as t-value and adjusted R-square are. This implies that the consumption risk in Korean stock market is accumulated strongly until fourth quarters, but it is relieved (it does not mean it is diminished at all) after a year. On the other hand, KOSDAQ market excess returns in Panel A shows negative value of estimated coefficients but it changed to positive value (1.61) when h=20. However, in every period, the null hypothesis (estimated coefficients is indifferent from 0) cannot be rejected since every t-value is trivial. Therefore, the inverse relationship between cc_t and KOSDAQ market returns cannot be defined well.

In Panel B, it shows the result of the form as nominal return. Nominal returns of KOSPI have negative estimated coefficients in every period, but the absolute value of them are lower than those of Panel A in every period. Also, most of t-value indicate that estimated coefficients are statistically significant in 1% significance level, but t-value is -1.53 when h=12. So, the estimated coefficients when h=12 is statistically insignificant. On the other hand, nominal return of KOSDAQ has negative estimated coefficient in the most period but has positive one when h=20 like it is in Panel A. And most estimated coefficients are statistically insignificant because of low t-value. Moreover, adjusted R-squares converge to almost zero until h=8, so this means that this panel is not fitted well to the model. Finally, Panel C shows the result of the form as real return. The real return of KOSPI has the lowest absolute value of estimated coefficients compared to other panels. Specifically, the estimated coefficients when h=16 is statistically insignificant (-1.70), Adjusted R-square indicates similar result since it is the lowest value compared to other panels in every period. In the case of KOSDAQ, the estimated coefficient when h=20 is positive but insignificant. Generally, t-value in most periods is low so the estimated coefficients are not statistically significant.

In conclusion, KOSPI market returns have statistically significant inverse relationship with cc_t in every form of the excess, nominal, and real return. In general, the more the market returns accumulated, the stronger the relationship is. However, KOSDAQ market returns shows no consistent result about the relationship between market returns and cc_t, and the estimated coefficients is statistically insignificant. Therefore, KOSPI market return is the representative Korean stock market, and cc_t can capture the consumption risk affecting to the variation of stock price changes in Korea.

4.2. The Predictive Power of Cyclical Consumption over Good Time and Bad Time

Table 2 examines whether cyclical consumption can have predictability even during both booms and recessions. This is because many previous studies have often showed the result that the predictive variables worked well in bad times but not in good times. In addition, in order to show that the variable is highly related to External habit model, it should have consistent relationship with future expected returns regardless of the boom or the recession. Atanasov, Møller, and Priestley (2020) found that cyclical consumption has significant predictability in both good times and bad times. The determinant of how to divide the boom (the good times) and the recession (the bad times) is also important in this section. Atanasov, Møller, and Priestley (2020) used four different ways. First, according to Rapach, Strauss, and Zhou (2010) and Henkel, Martin, and Nardari (2011), NBER-dated recessions to proxy for bad states is used. Second, according to Rapach, Strauss, and Zhou (2010), the bad time (the recession) is defined as the period where real GDP growth rate is under the one-third bottom. Fourth, according to Berge and Jorda (2011), the recession is defined as Purchasing Managers Index (PMI) is under 44.48 which is threshold value. Finally, the recession is defined by cyclical consumption where it is more than one standard deviation below its mean.

However, since Korea has no NBER-dated recession data like the first method, this paper used Composite Economic Index (CEI) in Korea as a proxy of it. According to KDI, CEI is the comprehensive economy index combined with the employment, production, consumption, investment, and finance index together. Especially, the business cycle is defined as the boom if the circulated variation of Coincident Composite Index of it is above 100, or the recession if not. By considering this, Panel A of Table 2 defines the recession when the circulated variation of Coincident Composite Index of it is under 100. Panel B defines the recession as the period where real GDP growth rate is under the one-third bottom followed by Rapach, Strauss, and Zhou (2010). Finally, Panel C defines the recession where cyclical consumption is more than one standard deviation below its mean, followed by Atanasov, Møller, and Priestley (2020).

$$r_{t,t+h} = \alpha + \beta_{bad} I_{bad} cc_t + \beta_{good}\left(1 - I_{good}\right) cc_t + \varepsilon_{t,t+h} \qquad (9)$$

In order to examine above, we followed Eq. (4) where indicator function has the value 1 when it is the recession (the bad times) and has the value 0 when it is the boom (the good times). This paper testifies the hypothesis that every estimated coefficient for both β_{bad} and β_{good} will be negative and whether all they are statistically significant.

In Panel A, all the estimated coefficients in both good times and bad times are negative when we use CEI as the criterion. Especially, when it is the boom (the good times), the estimated coefficients are statistically significant in 5% (h=4, 12) or 1% significance level, except when h=1. Rather, there is the case the estimated coefficients are insignificant in bad times, where the t-value is -1.60 (h=20). Except when h=1 and h=20 from bad times, the predictability of cyclical consumption exists even in both good times and bad times.

In Panel B, every estimated coefficient is negative and is more statistically significant compared to other panels. Except the t-value is -1.40 when h=8 from good times, most of the estimated coefficients are statistically significant in 1% or 5% significance level. In Panel C, every estimated coefficient is negative and is statistically significant except the case where h=1 from bad times, which t-value is -

1.23. In conclusion, among all the panel in each different definition of good times and bad times, cyclical consumption has inverse relationship with market excess return as well as the predictability of it still exists except few periods.

Table 2. The Predictive Power of Cyclical Consumption over Good Time and Bad Time

This table reports the result of the return predictive regression which followed by Eq. (9), $r_{t,t+h} = \alpha + \beta_{bad} I_{bad} cc_t + \beta_{good}(1 - I_{good}) cc_t + \varepsilon_{t,t+h}$. Panel A defines the bad times the recession when the circulated variation of Coincident Composite Index of it is under 100. Panel B defines the recession as the period where real GDP growth rate is under the one-third bottom followed by Rapach, Strauss, and Zhou (2010). Panel C defines the recession where cyclical consumption is more than one standard deviation below its mean. The data period of every panel is from 1987Q1 to 2019Q4 because every dependent variable is KOSPI excess return. The parentheses represent the robust t-value by using wild bootstrapped p-value, and a square bracket represents the adjusted R-square. * as 10%, ** as 5%, and *** indicates 1% of significance level.

	h=1	h=4	h=8	h=12	h=16	h=20
	Panel A: CEI (Composite Economic Index) Index					
β (Good)	-0.98	-4.94	-7.84	-8.48	-8.75	-11.05
	(-1.67)*	(-2.58)**	(-2.62)***	(-2.30)**	(-5.29)***	(-4.54)***
β (Bad)	-1.07	-5.28	-2.80	-2.30	-3.86	-2.58
	(-1.33)	(-6.15)***	(-1.81)*	(-1.74)*	(-1.73)*	(-1.60)
	[6.13]	[35.01]	[26.98]	[22.52]	[23.23]	[35.52]
	Panel B: Real GDP Growth					
β (Good)	-1.21	-5.03	-5.15	-6.96	-6.74	-9.07
	(-2.64)***	(-2.84)***	(-1.40)	(-1.96)*	(-2.38)**	(-2.60)**
β (Bad)	-0.87	-5.23	-4.69	-2.80	-5.08	-3.12
	(-1.20)	(-4.73)***	(-4.74)***	(-2.42)**	(-3.83)***	(-2.95)***
	[6.28]	[34.99]	[22.58]	[20.29]	[20.99]	[32.09]
	Panel C: Cyclical Consumption					
β (Good)	-1.09	-4.60	-6.65	-7.43	-8.62	-11.03
	(-2.22)**	(-2.42)**	(-2.14)**	(-2.06)**	(-4.86)***	(-4.41)***
β (Bad)	-0.98	-5.60	-3.50	-2.82	-3.69	-2.12
	(-1.23)	(-6.51)***	(-2.57)**	(-2.13)**	(-1.89)*	(-1.70)*
	[6.14]	[35.23]	[24.38]	[20.41]	[23.46]	[37.24]

4.3. The Predictive Power of Cyclical Consumption over Industry Portfolios

In Table 3, this paper examines whether cyclical consumption has also inverse relationship with all industries consisting of the stock market as well as has predictive properties. Atanasov, Møller, and Priestley (2020) divides industries into Nondurable Goods (NON), Durable Goods (DUR), Manufacturing (MAN), Energy (ENG), Hi-Tech Business Equipment (HT), Telephone and Television Transmission (TEL), Wholesale and Retail (SHOPS), Healthcare and Medical Equipment (HLTH), Utilities (UTILS), and Other industry categories (OTHER). In fact, there are KOSPI-based industry portfolios in Korea, so this paper examines for all 22 industry portfolios. This table also sorts the industries into larger-scale categories, which are Non-durable goods (NON), Durable goods (DUR), Manufacturing (MAN), Energy (ENG), Telecommunication (TEL), Healthcare and Medical Equipment (HLTH), Utilities (UTILS), and Others.

In conclusion, the estimated coefficients in most industries are statistically significant. Especially, several main industries have the most powerful relationship compared to other industries. For example, the industries which the estimated coefficients have statistically significant are KOSPI Non-metal mineral, Metal mineral, Manufacturing, Electric/Electro, and Chemistry. The estimated coefficients of Manufacturing are -7.03 and corresponding t-value is -3.09, which implies it has statistically significant coefficient in 1% significance level. And every periods of this industry have the estimated coefficients which are significant in 5% or 1% significance level. This is reasonable because manufacturing industry provides the product and the service which is highly related to household consumption expenditures. On the other hand, the industries which shows predictability and inverse relationship between cyclical consumption, even though not all the estimated coefficients are statistically insignificant, are KOSPI Beverage, Transportation, Warehouse, Utility, Construction, Finance, Bank, Insurance and Security.

Table 3. The Predictive Power of Cyclical Consumption over Industry Portfolios

This table reports the result of the return predictive regression which regresses cc_t on the excess returns of KOSPI-based industry portfolios. For the categories, they are sorted into Non-durable goods, Durable goods, Manufacturing, Energy, Telecommunication, Healthcare and Medical Equipment, Utilities, and Others. This paper examines all of 22 industry portfolios and the data is downloaded from Dataguide5.0. The data period of most industries is from 1988Q1 to 2019Q4, but few industries are from 2000Q1 to 2019Q4, such as Precision Medicine, Electric/Gas, Telecommunication, and service industry. The parentheses represent the robust t-value by using wild bootstrapped p-value, and a square bracket represents the adjusted R-square. * as 10%, ** as 5%, and *** indicates 1% of significance level.
(Notes: Transp.: Transportation, Machine.: Machinery, Manuf.: Manufacturing, Telecom.: Telecommunication, Chem.: Chemistry, and Construct.: Construction for abbreviation)

		h=1	h=4	h=8	h=12	h=16	h=20
NON	Beverage	-0.83	-3.79	-2.12	-2.68	-4.50	-5.00
		(-2.34)**	(-3.12)***	(-1.01)	(-1.26)	(-1.89)*	(-1.79)*
		[3.73]	[18.33]	[4.63]	[5.65]	[11.74]	[16.61]
	Textile/ Garment	-0.53	-3.11	-1.82	-2.48	-1.65	-1.07
		(-1.36)	(-1.88)*	(-0.57)	(-0.65)	(-0.32)	(-0.16)
		[0.95]	[7.70]	[1.43]	[1.67]	[0.56]	[0.19]
	Paper/ Wood	-0.55	-2.94	-1.57	-3.19	-6.21	-6.56
		(-1.47)	(-1.68)*	(-0.42)	(-0.73)	(-1.14)	(-1.00)
		[1.12]	[8.07]	[1.57]	[3.83]	[9.73]	[9.42]
DUR	Nonmetal Mineral	-1.16	-5.42	-5.40	-6.64	-7.53	-7.67
		(-2.69)***	(-3.20)***	(-1.78)*	(-2.15)**	(-2.49)**	(-2.37)**
		[4.04]	[22.57]	[15.77]	[15.54]	[15.03]	[16.28]
	Metal Mineral	-1.09	-5.01	-4.11	-5.00	-6.64	-6.85
		(-2.41)**	(-6.55)***	(-2.26)**	(-2.55)**	(-3.07)***	(-2.85)***
		[5.28]	[30.05]	[13.76]	[13.99]	[18.32]	[17.63]
	Transp.	-0.88	-4.26	-6.06	-10.13	-12.44	-13.12
		(-1.68)*	(-2.81)***	(-1.59)	(-2.57)**	(-2.68)***	(-2.67)***
		[2.92]	[16.33]	[17.58]	[28.44]	[30.56]	[29.85]
	Warehouse	-1.45	-6.06	-4.83	-5.86	-9.86	-12.70
		(-3.01)***	(-3.71)***	(-1.18)	(-1.31)	(-2.01)**	(-2.37)**
		[6.24]	[22.92]	[9.52]	[9.39]	[19.07]	[26.99]
	Machine.	-0.83	-3.20	-2.73	-5.79	-8.82	-10.91
		(-1.60)	(-2.22)**	(-0.71)	(-1.39)	(-1.58)	(-1.85)*
		[2.52]	[9.13]	[3.71]	[9.15]	[14.88]	[18.08]
MAN	Manuf.	-0.98	-5.01	-5.16	-5.43	-6.76	-7.03
		(-2.29)**	(-6.94)***	(-2.51)**	(-2.21)**	(-3.40)***	(-3.09)***
		[4.83]	[32.65]	[25.13]	[20.66]	[26.22]	[32.08]
ENG	Electric/ Electro	-0.98	-5.29	-5.12	-3.81	-4.63	-4.46
		(-1.87)*	(-5.65)***	(-3.31)***	(-1.67)*	(-4.20)***	(-3.90)***
		[3.49]	[28.23]	[20.87]	[11.01]	[18.18]	[22.19]
	Electric/ Gas	-0.48	-1.23	0.56	2.58	-0.07	0.47
		(-0.85)	(-0.80)	(0.18)	(0.64)	(-0.01)	(0.11)
		[0.78]	[1.35]	[0.12]	[1.66]	[0.00]	[0.05]
TEL	Telecom.	-0.14	0.36	3.58	6.64	5.38	4.44
		(-0.25)	(0.28)	(1.93)*	(2.67)***	(2.02)**	(1.67)
		[0.06]	[0.11]	[9.86]	[21.71]	[13.46]	[8.31]
HLTH	Medical/ Medicine	0.01	-2.11	-3.29	-4.68	-5.30	-5.33
		(0.03)	(-1.78)	(-1.30)	(-1.47)	(-1.37)	(-1.26)
		[0.00]	[4.82]	[7.95]	[9.20]	[8.63]	[7.98]
	Precision Medicine	-2.12	-2.44	-0.16	-0.61	-2.62	-1.30
		(-1.89)	(-0.72)	(-0.05)	(-0.17)	(-0.57)	(-0.35)
		[3.32]	[1.19]	[0.00]	[0.04]	[0.87]	[0.15]
UTILS	Utility	-1.07	-5.50	-4.46	-6.40	-8.34	-8.45
		(-2.22)**	(-3.98)***	(-1.42)	(-2.05)**	(-2.59)**	(-2.03)**
		[3.95]	[25.50]	[12.72]	[17.70]	[21.51]	[22.56]
OTHER	Chem.	-1.32	-6.00	-5.77	-6.49	-7.84	-8.10

	(-3.19)***	(-6.07)***	(-2.08)**	(-2.28)**	(-2.80)***	(-2.64)***
	[7.62]	[33.92]	[22.64]	[21.18]	[23.83]	[28.56]
Construct.	-1.21	-5.47	-5.06	-8.15	-10.95	-13.60
	(-2.46)**	(-2.33)**	(-1.03)	(-1.54)	(-1.67)*	(-1.87)*
	[4.23]	[16.15]	[8.18]	[12.39]	[15.60]	[20.84]
Finance	-1.16	-5.32	-5.09	-7.80	-9.43	-9.22
	(-2.35)**	(-2.95)***	(-1.43)	(-2.21)**	(-2.38)**	(-1.95)*
	[4.77]	[22.99]	[13.60]	[21.82]	[22.76]	[21.96]
Bank	-0.93	-5.34	-5.97	-9.22	-11.33	-10.74
	(-1.47)	(-2.91)***	(-1.56)	(-2.27)**	(-2.62)***	(-2.17)**
	[2.67]	[14.19]	[4.51]	[14.45]	[21.62]	[19.03]
Insurance	-0.93	-4.11	-2.68	-5.32	-7.86	-7.75
	(-1.69)*	(-2.40)**	(-0.86)	(-2.20)**	(-2.81)***	(-2.10)**
	[2.77]	[22.21]	[16.15]	[26.69]	[29.75]	[25.64]
Security	-1.88	-6.55	-4.54	-4.59	-4.50	-4.14
	(-2.74)***	(-3.12)***	(-1.65)	(-1.77)*	(-2.03)**	(-1.44)
	[7.03]	[21.23]	[7.92]	[6.66]	[5.50]	[5.84]
Service	-0.56	-1.13	-1.03	-1.01	-4.28	-3.54
	(-0.94)	(-0.68)	(-0.29)	(-0.33)	(-1.42)	(-2.05)
	[0.66]	[0.62]	[0.46]	[0.27]	[6.53]	[4.85]

In fact, this paper expected most of the industries in Nondurable (NON) category to have significant result, but they are not. To be specific, Textile/Garment and Paper/Wood industries in Nondurable (NON) category has inverse relationship with cyclical consumption with insignificant coefficients. However, the industries in Durable category (DUR) show the significant result about predictive property and inverse relationship with cyclical consumption except Machinery industry. Moreover, the industries in Telecommunication (TEL) and Healthcare and Medical Equipment (HLTH) category show no significant results at all. In case of Telecommunication industry, the estimated coefficient is 4.44 which is positive relationship with cyclical consumption when h=20. Especially, the estimated coefficients are positive and statistically significant when h=16 and h=20, so that this implies no relationship with cyclical consumption. In addition, Medical/Medicine and Precision Medicine industry show inverse relationship with cyclical consumption but the estimated coefficients are statistically insignificant. However, there is limitation because Precision Medicine and Telecommunication industry was included into KOSPI-based industry portfolio after 2000, so these industries should be tested afterwards.

Overall, 8 industries (out of 22) have no significant coefficients even though there is inverse relationship between cyclical consumption and sometimes there are few industries which has positive relationship in certain periods. However, four industries among them, which are Precision Medicine, Electric/Gas, Telecommunication, and Service Industry, was included into KOSPI-based industry portfolio after 2000, so that they should be studied later due to the weak reliability of the result. Shortly speaking, one of three industries in 'NON' (Beverage), two of five industries in 'DUR' (Transportation and Warehouse), one of one industry in 'UTILS' (Utility), and five of seven industries in 'OTHERS' (Construction, Finance, Bank, Insurance, and Security) have relatively imperfect relationship with cyclical consumption. And another two of five industries in 'DUR' (Non-metal Mineral and Metal Mineral), one of one industry in 'MAN' (Manufacturing), one of two industries in 'ENG' (Electric/Electro), and one of seven industries in 'OTHERS' (chemistry) have significant relationship in every period with cyclical consumption. Therefore, 5 industries (out of 14 remained industries), which are Non-metal Mineral, Metal Mineral, Manufacturing, Electric/Electro, and Chemistry industries lead the clear and strong negative relationship with cyclical consumption in every period as well as the estimated coefficients are all statistically significant. Other 9 industries have inverse relationship with it but weaker, so this is different from prior assumption that every industry in Korean market will have the relationship with cyclical consumption.

4.4. Alternative Methods for Constructing Cyclical Consumption

In Table 4, this paper will show the result of the alternative methods for constructing cyclical consumption by comparing with the method followed by Hamilton (2018). This is because there has been no theoretical background for constructing cyclical consumption, and that is why this paper empirically examines which method is better. There are five representative alternative method. Among all, the first one assumes a secular linear upward trend in consumption.

$$C_t = d_0 + d_1 t + w_t \qquad (10)$$

$$C_t = \begin{cases} d_0 + d_1 t + w_t & for\ t \leq t_1 \\ d_0 + d_1 t + d_1(t - t_1) + w_t & for\ t > t_1 \end{cases} \qquad (11)$$

According to Eq. (10), cyclical consumption can be defined as the residual where the time 't' itself is regressed on proxy data of consumption at t (C_t). This is the way which assumes the increasing trend in consumption linearly. Eq. (11)

allows linear trend formulation to allow for a breakpoint. This is the method to capture the risk more accurately by considering the time when there was huge financial crisis in stock market. Atanasov, Møller, and Priestley (2020) designated the breakpoint at 1992Q1 in order to reflect the economic shock in U.S. stock market. This paper will designate the breakpoint at 1997Q4 which was the biggest economic shock in Korean stock market.

$$C_t = d_0 + d_1 t + d_2 t^2 + w_t \qquad (12)$$

$$C_t = d_0 + d_1 t + d_2 t^2 + d_3 t^3 + w_t \qquad (13)$$

Next, the third and fourth method consider high degree of polynomial. The third one expands to second degree, and the fourth one expands to third degree in order to reflect the slow-moving shock which cannot be captured in linear relationship. And lastly, this paper constructs ‘stochastically detrended’ consumption series according to Campbell (1991) and Hodrick (1992). This is the way which regress the backward-looking moving average of five years (20 quarters) for log consumption data on consumption at date t. In Table 4, ‘Linear’ and ‘Break’ methods show that t-values are small which cannot be even included in 10% level, so that the corresponding estimated coefficients are statistically insignificant. Therefore, these two alternatives hardly capture the consumption variation in Korean stock market. Next, ‘Quadratic’ method shows good result until h=8 such that the estimated coefficient is -3.00 and the t-value is -2.09 when h=8, but there are no statistically significant coefficients after h=12. So, this alternative is also restricted to capture the consumption risk in Korean stock market. On the other hand, ‘Cubic’ method shows estimated coefficients in every period have negative values and statistically significant in 1% level except t-value is -2.54 when h=12. However, the absolute value of every estimated coefficients is smaller than Hamilton (2018) method. Lastly, ‘Stochastic’ method shows negative estimated coefficients in every period and corresponding t-values are all significant in 5% or 1% level. But the absolute value of coefficients and the degree of fitting to model is comparatively lower than Hamilton (2018) method. In conclusion, cyclical consumption followed by Hamilton (2018) method shows the most significant estimated coefficients among all alternatives except that ‘Cubic’ or ‘Stochastic’ methods show similar result.

Table 4. Alternative Methods for Constructing Cyclical Consumption

This table reports the result of the return predictive regression which regresses five different ways of cc_t on the KOSPI excess returns. 'Linear' method follows Eq. (10), which assumes the increasing trend in consumption linearly. 'Break' method analyses the result of piecewise OLS regression by separating the breakpoint at 1997Q4, which there was IMF financial crisis in Korea. 'Quadratic' and 'Cubic' methods expand the linear time trend model to second and third degree of polynomials. Lastly, 'Stochastic' method follows Campbell (1991) and Hodrick (1992) in order to assume stochastically detrended time model. The data period is from 1987Q1 to 2019Q4. The parentheses represent the robust t-value by using wild bootstrapped p-value, and a square bracket represents the adjusted R-square. * as 10%, ** as 5%, and *** indicates 1% of significance level.

	h=1	h=4	h=8	h=12	h=16	h=20
Linear	-0.06	-0.34	-0.49	-0.67	-0.80	-0.70
	(-0.93)	(-1.40)	(-1.11)	(-1.24)	(-1.30)	(-0.97)
	[0.59]	[4.26]	[5.38]	[6.71]	[6.52]	[4.89]
Break	-0.19	-1.10	-0.57	0.06	0.79	0.99
	(-1.09)	(-1.41)	(-0.58)	(0.05)	(0.49)	(0.51)
	[0.84]	[6.40]	[1.03]	[0.00]	[0.86]	[1.30]
Quadratic	-0.64	-3.03	-3.00	-2.96	-2.99	-2.86
	(-3.19)***	(-3.42)***	(-2.09)**	(-1.63)	(-1.79)*	(-1.36)
	[5.00]	[25.72]	[17.78]	[12.93]	[10.04]	[10.21]
Cubic	-0.76	-3.32	-4.04	-4.35	-4.50	-4.16
	(-4.37)***	(-4.76)***	(-3.69)***	(-2.54)**	(-3.26)***	(-2.91)***
	[7.73]	[33.21]	[33.33]	[29.44]	[25.72]	[26.04]
Stochastic	-0.61	-3.07	-3.58	-3.88	-4.15	-3.64
	(-2.97)**	(-3.58)***	(-3.13)***	(-2.22)**	(-2.30)**	(-2.00)**
	[4.88]	[28.61]	[27.84]	[25.03]	[22.62]	[19.97]

4.5. Alternative Methods for Using Consumption Proxy Data

In Table 5, this paper compares some alternatives for aggregate seasonally adjusted personal consumption expenditures (PCE) as a proxy of consumption data to construct cyclical consumption. In fact, Atanasov, Møller, and Priestley (2020) uses aggregate seasonally adjusted consumption expenditures on nondurables and services (NON+SERV). This is because there has been no theoretical background for which proxy should be used, so the method with the most significant result must be used among all alternatives through empirical verification. This paper compares six different alternatives as follows. 'DUR' includes only durable goods, 'NON' includes only nondurable goods, 'SERV' includes only service, 'NON+SERV' includes only nondurable goods and service, and 'PCE' includes every category from aggregate seasonally adjusted consumption expenditures of GDP. Empirically, 'DUR' shows every estimated coefficient is negative but it is just around 0 to -1.5, which are comparatively weaker absolute values. Especially, when h=1, the estimated coefficient is -0.25 and t-value is -1.75 which is statistically significant in 10% level. However, 'NON' shows all estimated coefficients are negative and high t-values implies most coefficients are statistically significant in 1% level. The lowest t-value is -2.36 which implies the estimated coefficient is statistically significant in 5% level when h=1.

However, 'SERV' shows negative coefficients until h=4 and positive coefficients after, so that this alternative cannot explain the relationship. Of course, t-values in every period are very small, so that the absolute value of coefficients has no meaning statistically. This is different from U.S. stock market in Atanasov, Møller, and Priestley (2020) where 'SERV' shows comparatively weak absolute value but it is statistically significant. Next, 'NON+SERV' shows statistically significant negative coefficients in every period except the t-value is -1.79 and -1.76 when h=1 and h=12, which is significant in 10% level. Lastly, 'PCE' shows statistically significant negative coefficients in every period in 5% or 1% level. Therefore, 'PCE' is the most robust proxy data for explaining the relationship between cyclical consumption and expected market return among all others. As it is showed, there are some differences compared to data from U.S. GDP. In fact, the average proportion of each category in Korea data is 4.50% for 'DUR', 34.00% for 'NON', 51.56% for 'SERV' in last 50 years while it is 8.67% for 'DUR', 22.73% for 'NON', 37.21% for 'SERV' in U.S. data during last 80 years. This implies that even though 'SERV' takes a half of aggregate seasonally adjusted personal consumption expenditures, the sole category itself cannot hold the relationship. Moreover, the reason 'DUR' shows weakest absolute value of estimated coefficients in Korea is because the proportion is very small in Korea.

Table 5. Alternative Methods for Using Consumption Proxy Data

This table reports the result of the return predictive regression which regresses cc_t depending on six different consumption proxy data on the KOSPI excess returns. 'DUR' includes only durable goods, 'NON' includes only nondurable goods, 'SERV' includes only service, 'NON+SERV' includes only nondurable goods and service, and 'PCE' includes every category. The data period is from 1987Q1 to 2019Q4. The parentheses represent the robust t-value by using wild bootstrapped p-value, and a square bracket represents the adjusted R-square. * as 10%, ** as 5%, and *** indicates 1% of significance level.

	h=1	h=4	h=8	h=12	h=16	h=20
DUR	-0.25	-1.31	-1.18	-1.11	-1.54	-1.31
	(-1.75)*	(-4.02)***	(-2.82)***	(-1.98)**	(-2.96)***	(-2.45)**
	[3.93]	[25.66]	[15.07]	[10.35]	[16.28]	[13.63]
NON	-0.53	-2.75	-3.92	-4.98	-6.61	-6.76
	(-2.36)**	(-2.78)***	(-2.82)***	(-2.56)**	(-3.81)***	(-3.59)***
	[3.01]	[17.93]	[21.63]	[23.17]	[30.87]	[36.03]
SERV	-0.35	-2.69	1.13	4.36	5.25	4.45
	(-0.60)	(-1.01)	(0.47)	(1.55)	(1.15)	(1.35)
	[0.36]	[5.09]	[0.64]	[7.44]	[8.52]	[7.03]
GOODS	-0.39	-2.06	-2.88	-3.60	-4.75	-4.60
	(-2.48)**	(-3.23)***	(-3.22)***	(-2.82)***	(-3.81)***	(-4.23)***
	[3.18]	[19.83]	[26.31]	[30.18]	[41.76]	[44.77]
NON+SERV	-1.26	-7.53	-6.68	-5.76	-7.26	-7.09
	(-1.79)*	(-5.05)***	(-2.08)**	(-1.76)*	(-2.81)***	(-2.04)**
	[3.70]	[29.97]	[15.57]	[8.90]	[11.52]	[13.04]
PCE	-1.03	-5.14	-4.92	-4.89	-5.91	-6.13
	(-2.66)***	(-5.81)***	(-2.34)**	(-2.09)**	(-2.99)***	(-2.54)**
	[6.08]	[34.65]	[22.32]	[17.13]	[20.39]	[25.95]

4.6. Decision of K

Table 6 shows which period k is the most optimal period to capture the cyclical consumption referred to Hamilton (2018). As it is mentioned before, Hamilton (2018) recommends determining k to be about five years of horizon in order to capture long-term shock in business cycle. This paper assumes that period k will have better explanation power when it is around 20 quarters (five years), since the variable is set to capture the time-varying consumption risk in a long-term horizon. Atanasov, Møller, and Priestley (2020) shows that the explanation power of cyclical consumption is better when period k is 24 (six years) in the table from online index. In order to decide which period k has better result in Korean stock market, this paper checks the period from 4 to 44 (1 year to 11 years).

In summary, the table shows that cyclical consumption has the most robust result when period k is 24 as well. When k is 24 (six years), all estimated coefficients are negative in every period like it is shown in Table 1, and high t-value implies the coefficients are all statistically significant in 1% level. Moreover, it shows also similar result when k is 20, but t-value during h=12 is -1.56, so that the corresponding coefficient is statistically insignificant. Except during h=12, most coefficients are statistically significant in 5% level. Even though there are some periods which is fitted to the model better, but when over h=12, they are not. And most absolute values of coefficients are smaller relatively. Meanwhile, other periods show smaller t-value except few period h, so that the most estimated coefficients are statistically insignificant. Therefore, this table confirms that it has the most robust result when k is 24 (six years) to construct cyclical consumption among all other periods.

Table 6. Decision of K

This table reports the result of the return predictive regression which regresses cc_t which regressed on all different period k on the KOSPI excess returns. This table covers period k from 4 to 44 (1 year to 11 years). The data period is from 1987Q1 to 2019Q4. The parentheses represent the robust t-value by using wild bootstrapped p-value, and a square bracket represents the adjusted R-square. * as 10%, ** as 5%, and *** indicates 1% of significance level.

	h=1	h=4	h=8	h=12	h=16	h=20
k=4	-0.72	-4.98	-4.88	-4.23	-4.14	-2.91
	(-1.46)	(-8.37)***	(-3.65)***	(-1.84)*	(-2.81)***	(-1.93)*
	[3.42]	[38.40]	[26.51]	[15.47]	[12.06]	[7.05]
k=8	-0.69	-3.02	-2.65	-1.94	-1.04	-1.05
	(-2.29)**	(-3.60)***	(-1.57)	(-1.25)	(-0.72)	(-0.61)
	[5.19]	[22.82]	[12.57]	[5.24]	[1.22]	[1.48]
k=12	-0.66	-2.81	-1.99	-0.90	-0.72	-1.14
	(-2.18)**	(-2.28)**	(-1.23)	(-0.60)	(-0.44)	(-0.60)
	[4.75]	[20.25]	[7.23]	[1.13]	[0.60]	[1.77]
k=16	-0.69	-3.00	-1.69	-1.32	-1.57	-2.80
	(-1.80)*	(-1.86)*	(-0.85)	(-0.60)	(-0.68)	(-1.14)
	[3.74]	[16.39]	[3.66]	[1.73]	[1.98]	[7.54]
k=20	-0.86	-4.39	-3.70	-3.53	-4.44	-5.78
	(-2.19)**	(-3.67)***	(-1.72)*	(-1.56)	(-2.29)**	(-2.42)**
	[4.23]	[25.45]	[12.67]	[8.87]	[11.44]	[23.02]
k=24	-1.03	-5.14	-4.92	-4.89	-5.91	-6.13
	(-2.66)***	(-5.81)***	(-2.34)**	(-2.09)**	(-2.99)***	(-2.54)**
	[6.08]	[34.65]	[22.32]	[17.13]	[20.39]	[25.95]
k=28	-1.11	-4.93	-4.86	-4.99	-4.59	-4.57
	(-3.41)***	(-5.93)***	(-2.66)***	(-2.50)**	(-3.04)***	(-2.50)**
	[8.40]	[38.13]	[26.34]	[21.55]	[14.83]	[17.38]
k=32	-1.02	-4.69	-4.69	-3.74	-3.09	-3.56
	(-3.31)***	(-5.53)***	(-2.92)***	(-2.24)**	(-2.18)**	(-2.08)**
	[7.65]	[37.66]	[26.76]	[13.13]	[7.28]	[11.50]
k=36	-1.10	-4.75	-3.61	-2.35	-1.86	-2.80
	(-3.69)***	(-5.67)***	(-2.24)**	(-1.35)	(-1.11)	(-1.41)
	[8.64]	[37.26]	[15.15]	[4.94]	[2.54]	[6.79]
k=40	-0.96	-4.42	-2.86	-1.44	-0.86	-2.00
	(-2.68)***	(-3.78)***	(-1.47)	(-0.80)	(-0.36)	(-0.79)
	[5.56]	[27.31]	[8.10]	[1.60]	[0.45]	[2.94]
k=44	-0.95	-4.60	-2.91	-1.35	-0.70	-1.46
	(-2.50)**	(-3.71)***	(-1.62)	(-0.81)	(-0.26)	(-0.55)
	[5.18]	[28.26]	[8.06]	[1.33]	[0.28]	[1.51]

4.7. Economic Power of Cyclical Consumption

In Table 7, this paper examines the profitability when the buy-sell pricing strategy is established based on cyclical consumption if it really has inverse relationship with KOSPI excess return and predictability to future market return. This table refers to table 2 from Kho, B. C. (1996) which examines the profitability of moving average trading rule. This paper found the future expected return will increase when cyclical consumption is negative while future expected return will decrease when cyclical consumption is nonnegative. Therefore, the buy signal is when cyclical consumption is negative, and the sell signal is when cyclical consumption is positive. Next, the position based on signal remains for next one quarter, one year, two years, three years, four years, and five years of accumulated log excess return separately. In addition, if cyclical consumption floats in the 1% band around zero (in other words, the value is indifferent from 0), then the position is neutral so that there is no position for trading. Since the unit of signal is quarterly, this paper uses quarterly return data in advance. However, this paper also uses monthly return data because the number of observations for quarterly return data is not enough to have statistical reliability.

Every mean returns in column 3 of Panel A, B and C is annualized. At first, panel A shows the result of quarterly return data, so that the number of observations for each trading signal is only close to 50. Small number of observations implies statistically low reliability. To be specific, the mean returns from buy signal in six different accumulated returns are positive, while the mean returns from sell signal in all time period are negative. However, most of mean returns of buy signal are statistically insignificant until three-years accumulated return. For the case of buy-sell strategy in Panel A, one-quarter accumulated return shows 8.13% annualized return, but it is statistically insignificant since the t-value is 0.88. And one-year accumulated return shows 13.11% annualized return, and it is statistically significant in 1% level since the t-value is 2.70. From two-years to five-years accumulated return, these show about 7.00% to 10.00%, which are statistically significant in 1% or 5% (two and three-years accumulated return) level.

Table 7. Economic Power of Cyclical Consumption

This table reports the result of mean return for accumulated return in five different period after buy-sell signal is determined by cyclical consumption. Column 1 shows the number of observations for each signal and column 2 shows the standard deviation of mean return. Column 3 shows the mean return of buy, sell, and buy-sell strategy. Panel A indicates the result of quarterly return data, while panel B indicates the result of monthly return data. Every mean returns in column 3 is annualized. Returns are winsorized at 5% level. The data period is from 1987Q1 to 2019Q4. The parentheses represent the robust t-value by using wild bootstrapped p-value, and a square bracket represents the adjusted R-square. * as 10%, ** as 5%, and *** indicates 1% of significance level.

	Obs.		Std. dev.		Mean Return		
	Buy	Sell	Buy	Sell	Buy	Sell	Buy-Sell
	Panel A: Quarterly Data						
(1/4 Yr) Acc.Ret	49	53	0.13	0.10	2.21%	-5.92%	8.13%
(1 Yr) Acc.Ret	49	52	0.26	0.22	4.74%	-8.37%***	13.11%***
(2 Yr) Acc.Ret	49	48	0.30	0.34	2.16%	-5.33%**	7.48%**
(3 Yr) Acc.Ret	49	44	0.33	0.40	1.95%	-4.09%**	6.04%**
(4 Yr) Acc.Ret	47	42	0.40	0.52	3.66%***	-5.48%***	9.13%***
(5 Yr) Acc.Ret	46	39	0.38	0.48	3.38%***	-3.89%***	7.28%***
	Panel B: Monthly Data						
(1/4 Yr) Acc.Ret	147	164	0.13	0.10	4.88%	-7.80%**	12.68%**
(1 Yr) Acc.Ret	147	155	0.25	0.22	4.98%**	-7.94%***	12.92%***
(2 Yr) Acc.Ret	147	143	0.28	0.34	1.88%*	-4.87%***	6.74%***
(3 Yr) Acc.Ret	147	131	0.30	0.40	2.17%***	-4.47%***	6.64%***
(4 Yr) Acc.Ret	140	126	0.34	0.42	3.56%***	-5.05%***	8.60%***
(5 Yr) Acc.Ret	137	117	0.36	0.48	3.38%***	-3.96%***	7.35%***
	Panel C: Monthly Data (One-month skip)						
(1/4 Yr) Acc.Ret	147	157	0.12	0.10	5.84%	-9.32%**	15.16%***
(1 Yr) Acc.Ret	147	157	0.25	0.23	4.39%**	-8.76%***	13.15%***
(2 Yr) Acc.Ret	147	143	0.28	0.34	1.62%	-4.79%***	6.41%***
(3 Yr) Acc.Ret	147	131	0.30	0.40	2.33%***	-4.75%***	7.09%***
(4 Yr) Acc.Ret	140	126	0.35	0.41	3.26%***	-4.70%***	7.95%***
(5 Yr) Acc.Ret	137	117	0.37	0.48	3.28%***	-3.72%***	7.01%***

On the other hand, panel B is set to reinforce the reliability of test by using monthly return data while other environments are equal. The number of observations for each signal is more than 100. For the case of buy-sell strategy in Panel B, one-year accumulated return shows 12.92% annualized return and it is statistically significant in 1% level. From two-years to five-years accumulated return, these also show about 6.00% to 9.00% annualized return and most are statistically significant in 1% level. In Panel C, this paper examines one-month skip strategy which follows the signal one month after it is revealed on public. The result is shown to be indifferent to the result of panel B.

In conclusion, if the buy-sell pricing strategy is established by cyclical consumption, it gains average 9.15% annualized return. This one revisits the result of Table 1, which implies that cyclical consumption captures consumption variation affected to Korean stock market and has predictive property of it. And the absolute value of estimated coefficients when h=4 is the highest in Table 1, this is consistent with the result of pricing strategy in a way that one-year accumulated return has the highest mean return. In other words, unlike U.S. stock market, the degree of relationship is strongest when the return is accumulated for one year, while it is similar that the more accumulated the return is, the stronger the relationship is. Overall, the pricing strategy based on cyclical consumption has economic power in stock market and this result implies that investors in Korea can gain significant positive return by capturing the variation of consumption risk in business cycle.

Chapter 5. Conclusion

In this paper, I construct the variable cyclical consumption which captures consumption variation followed by Atanasov, Møller, and Priestley (2020) and examine whether cyclical consumption have inverse relationship with future expected return of Korean stock market as well as have predictive property. In summary, this paper found that cyclical consumption based on Korean data has inverse relationship with KOSPI market return, and the more accumulated the return is (one-quarter to five-years), the stronger the relationship is. This implies cyclical consumption has predictability about expected return in Korea. Secondly, the relationship between cyclical consumption and future expected return is consistent regardless of good times (boom) or bad times (recession). Thirdly, I develop hypothesis that the relationship should be captured in the industry level, since the relationship is captured in the market level.

Empirically, the relationship is not significant in all industries, but more than 60% of industries captures the significant relationship with cyclical consumption. To be specific, I found that the five industries which lead the relationship mainly are Non-metal Mineral, Metal Mineral, Manufacturing, Electric/Electro, and Chemistry industries. Fourthly, it is found that the way cyclical consumption is constructed in this paper is the most robust method among all alternatives. Specifically, it is robust when PCE is used as a proxy of consumption data for constructing cyclical consumption, when Hamilton (2018) is used to extract the residual term as cyclical consumption, and when the determination of h in Hamilton (2018) method is 24 compared to all other periods. Lastly, this paper confirms the significant profitability of pricing test based on cyclical consumption as buy-sell signal, which is about 11% annualized return on average for six different time periods of accumulated return.

Indeed, this paper has several contributions. First, it is the first trial to clarify the empirical relationship between cyclical consumption and external habit model in Korean stock market. Especially, this paper found that consumption risk affects Korean stock market on the basis of cyclical consumption, so that the related studies can be developed by using the new consumption-based variable cyclical consumption. Moreover, this paper elaborates the relationship between cyclical consumption and future expected market return not only in terms of Economics, but also in terms of Finance by raising a question whether the profitability of pricing strategy based on cyclical consumption is related to mispricing of consumption risk or some types of unknown factor model. Meanwhile, there is obvious limitation since the number of observations for Korean data is almost three times less than U.S. data. However, this paper can apparently lead to many of new approaches especially for consumption-based studies in Korea later.

Reference

Atanasov, V., Møller, S. V., & Priestley, R. (2020). Consumption fluctuations and expected returns. The Journal of Finance, 75(3), 1677-1713.

Campbell, J. Y., & Cochrane, J. H. (1999). By force of habit, A consumption-based explanation of aggregate stock market behavior. Journal of political Economy, 107(2), 205-251.

Campbell, J. Y., & Yogo, M. (2006). Efficient tests of stock return predictability. Journal of financial economics, 81(1), 27-60.

Dangl, T., & Halling, M. (2012). Predictive regressions with time-varying coefficients. Journal of Financial Economics, 106(1), 157-181.

Golez, B., & Koudijs, P. (2018). Four centuries of return predictability. Journal of Financial Economics, 127(2), 248-263.

Hamilton, J. D. (2018). Why you should never use the Hodrick-Prescott filter. Review of Economics and Statistics, 100(5), 831-843.

Henkel, S. J., Martin, J. S., & Nardari, F. (2011). Time-varying short-horizon predictability. Journal of financial economics, 99(3), 560-580.

Inoue, A., & Kilian, L. (2005). In-sample or out-of-sample tests of predictability: Which one should we use?. Econometric Reviews, 23(4), 371-402.

Kho, B. C. (1996). Time-varying risk premia, volatility, and technical trading rule profits Evidence from foreign currency futures markets. Journal of Financial Economics, 41(2), 249-290.

Kim, J. H. (2014). Predictive regression: An improved augmented regression method. Journal of Empirical Finance, 26, 13-25.

Kostakis, A., Magdalinos, T., & Stamatogiannis, M. P. (2015). Robust econometric inference for stock return predictability. The Review of Financial Studies, 28(5), 1506-1553.

Lettau, M., & Ludvigson, S. (2001). Consumption, aggregate wealth, and expected stock returns. the Journal of Finance, 56(3), 815-849.

Rapach, D. E., Ringgenberg, M. C., & Zhou, G. (2016). Short interest and aggregate stock returns. Journal of Financial Economics, 121(1), 46-65.

Rapach, D. E., Strauss, J. K., & Zhou, G. (2010). Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. The Review of Financial Studies, 23(2), 821-862.

Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. The Review of Financial Studies, 21(4), 1455-1508.

Won Ho Choi (2011). The Habit Formation and the Equity Premium Puzzle in case of Korea. THE KOREAN JOURNAL OF FINANCIAL STUDIES, 40(2), 261-285.

Won Kang. (2013). A Study on the Explanatory Power for Future Stock Returns of Changes in Consumption-Wealth Ratio: In Case of Korean Economy. THE KOREAN JOURNAL OF FINANCIAL MANAGEMENT, 30(3), 69-99.

Yoo, Han-Soo, Kim, Byoung-Joon (2011). The Lead-Lag Relationship between Stock Price Index Volatility and Consumption Volatility. THE KOREAN JOURNAL OF BUSINESS ADMINISTRATION, 24(5), 3097-3112.

국문 초록

소비는 기대수익률을 예측할 수 있는가?

-한국 시장에서의 실증 연구-

서울대학교 대학원

경영학과 재무금융전공

원영웅

본 연구는 Hamilton (2018)의 추세제거 방식을 따른 주기적 소비 (cyclical consumption)라는 새로운 변수가 소비 위험을 포착할 수 있고 KOSPI 기대수익률에 대해 예측성을 가질 수 있다는 것을 보여준다. 구체적으로, 주기적 소비 변수는 KOSPI 시장 수익률에 대해 통계적으로 유의한 반비례 관계를 가지며, 시장 수익률이 더 누적될수록(최대 5년), 관계는 더 강해진다는 것을 발견했다. 이 관계는 외부 소비 습관부 모형 이론에 대한 실증적 증거를 제공한다. 이 모형은 소비가 추세보다 더 높을 때(낮을 때), 미래 시장 기대수익률은 감소한다(증가한다)고 주장한다. 또한, 주기적 소비 변수는 호황과 불황일 때 모두 KOSPI 기대 수익률을 예측한다. 이 논문은 주기적 소비라는 변수가 KOSPI 기반 산업 포트폴리오들에 대해서도 유의미하게 관계를 보여준다는 것을 밝혔다. 마지막으로, 주기적 소비라는 변수를 기반으로 한 buy-sell 거래 전략을 구성하면 역사적으로 약 연 9.15%의 연수익률을 창출한다는 것을 밝혔다.

주요어: 주기적 소비, 외부 소비 습관부 모형, 소비 위험, 예측성

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