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Cyclical Consumption and Expected Stock Returns: Evidence from the Korean Capital Market

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ABSTRACT

Purpose: In this study, we empirically demonstrate how the new variable of ‘cyclical consumption’ can capture consumption risk and predict expected stock returns, which relationship is stronger and should be considered as the primary macro indicator for stock markets between KOSPI and KOSDAQ, and which specific industries exhibit stronger or weaker relationship with cyclical consumption in the Korean capital market.

Design/methodology/approach: The basic research design is composed of three approaches as follows: After testing the predictability of ‘cyclical consumption’ for the overall market returns, we examine whether or not there are differential characteristics in return predictability between two capital markets in Korea, KOSPI and KOSDAQ. Then, we analyze which specific industries have stronger or weaker relationship with the consumption. To explore these main issues, we apply such models as return predictive regressions, alternative detrending methods, external habit model, and others. Hamilton(2018)’s detrending method plays a key role in constructing the appropriate cyclical consumption and in running return predictive regressions.

Findings: First, cyclical consumption has a statistically significant inverse relationship with market returns; moreover, the more accumulated the market returns(up to five years), the stronger the relationship, and the result holds during both boom and recession periods. Second, cyclical consumption has stronger inverse relationship with KOSPI than KOSDAQ market and only KOSPI market shows statistical significance. Third, the relationship with cyclical consumption can also be applied to almost 11 industry portfolios for KOSPI, such as finance, manufacturing, electronics, and other 8 industries among 22 sample industries.

Research limitations/implications: The results from this study can be widely used by investors, policy makers and other market participants in constructing investment strategies and in designing macroeconomic policies and market micro structures. In particular, investors can utilize the results in constructing individual portfolios for some industries. The shortage of data for the various consumption variables in Korea is the limitation of this study.

Originality/value: This is the first paper to prove the relationship between the ‘cyclical’ consumption and stock returns in Korea. The differential characteristics between KOSPI and KOSDAQ and among industries are newly added value. In addition, this study can stimulate further research in other countries for enhancing the generality of the results.

Keywords: cyclical consumption (cc), External Habit Model (EHM), consumption risk, return predictability, detrending method, KOSPI and KOSDAQ, industry portfolio

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I. Introduction

The purpose of this paper is to test the inverse relationship between aggregate consumption and market returns in order to derive meaningful implications for investors, policymakers, regulators, and other interested parties. For this purpose, we employed the macro-economic variable of ‘cyclical consumption’ (cc)—a consumption-based variable designed by Atanasov, Møller, and Priestley (2020)—and collected data from the Korean capital market to conduct empirical tests. In other words, this paper seeks to identify whether cyclical consumption can capture consumption risks affecting variations in stock price changes in Korea. According to the External Habit Model (EHM), the marginal utility of current consumption is low when consumption is higher than its trend, forcing investors to reduce consumption today while increasing their investment instead. This leads to an increase in stock prices and a simultaneous decrease in future expected returns. If this scenario is true, cyclical consumption will have a negative relationship with market expected returns. Moreover, in this theory, the risk premium will be time-varying; thus, the risk that arises from variations in consumption could be reflected in stock prices differently.

The consumption variations generated in a certain time period will be reflected slowly in subsequent periods, implying that this type of variable can have predictive power. Therefore, this paper will examine the hypothesis that cyclical consumption captures consumption variations resulting from changes in marginal utility, suggesting that this consumption variable has a certain relationship with stock market returns. Moreover, this paper will also test whether KOSPI or KOSDAQ can represent the Korean stock markets.¹⁾ In particular, we will examine which relationship is stronger and which should be considered as the primary macro indicator for stock markets between KOSPI and KOSDAQ. An examination will

be conducted regarding whether cyclical consumption can show the relationship with market returns in both good times (boom periods) and bad times (recession periods) simultaneously. Many previous studies have been criticized for presenting predictive variables as being occasionally significant during bad times only. Therefore, we must evaluate whether cyclical consumption is significant regardless of economic conditions. Additionally, this paper will examine whether cyclical consumption can provide the same results even across a variety of specific industry portfolios. In other words, we will test which specific industries exhibit stronger or weaker relationship with cyclical consumption in the Korean capital market. Finally, this study will examine whether the buy-sell trading strategy is profitable when employing the cyclical consumption variable.

The rest of this paper is organized as follows. In Section II, we review previous studies regarding how stock returns are related to cyclical consumption in depth. Section III presents the study’s data and research methodology for constructing the main variable. In Section IV, we analyze the results of the study’s empirical tests. Finally, Section V discusses the results and concludes the paper.

II. Literature Review

Many studies have been conducted to identify variables that can capture consumption-related risks and/or variations and to relate them to the stock market or specific economic components in the field of finance and macroeconomics. In particular, research verifying that some variables can predict the corresponding risk has been actively done. Santos and Veronesi (2006) claim that the variable constructed by the ratio of labor income to consumption varies when the risk premium varies; hence, it can capture the consumption risk while also serving a predictive function for stock returns. Lettau and Ludvigson (2001) show that the consumption-wealth ratio (cay ratio) - the detrending variable derived from the relationship

1) KOSPI: Korea Sock Price Index, KOSDAQ: Korea Securities Dealers Automated Quotation.

between consumption, wealth, and income—has powerful predictive abilities regarding stock returns. Moreover, Bansal, Khatchatrian, and Yaron (2005) assert that consumption volatility can perform asset valuation as a measure of consumption risk. The authors explain that stock return variation can be captured from consumption risk variation and cash flow growth rate. Cooper and Priestley (2009) assert that if a variable can be constructed through the way it captures the residual from the output of the total industrial production index by employing an appropriate detrending method, that variable can become a proxy for the business cycle. In other words, it will have a predictive function for international stock excess returns and US bond excess returns.

A common feature of prior studies is that they use predictive regression to verify the predictability of corresponding variables. However, these studies have also received criticism regarding econometric issues—such as sample bias or stationarity—generated when time-series variables are used for predictive regression. In order to overcome these drawbacks, Kim (2014) suggested an improved regression method. Kostakis, Magdalinos, and Stamatogiannis (2015) also suggested a IVX estimation method for the long-horizon predictability tests, which is robust when it comes to the time-series property of employed regressors. Campbell and Yogo (2006) criticized previous tests that were used to clarify predictability regarding stock returns as uncertain, suggesting a pretest that can evaluate whether or not the t-test in question has this problem. Lastly, Hamilton (2018) argues that the Hodrick and Prescott’s (1997) filter (the so-called *HP filter*), which has been widely used for predictive regression, has serious problems and that the Hamilton filter is a relatively better alternative.

Meanwhile, research along similar lines has been conducted in Korea. For example, Choi (2011) shows that utility function along with habit formation is appropriate for explaining return premiums. Choi’s paper thus justifies the use of the cyclical consumption variable in Korea. Yoo and Kim (2011) assert that uncertainty in the Korean stock market can affect uncertainty in consumption. The authors demonstrate

that the connection between stock returns and consumption variations has been verified. Kang (2013) also shows that the ‘cay’²⁾ variable, suggested by Lettau and Ludvigson (2001), holds significant predictability.

However, no research has been done to verify the relationship between stock returns and consumption risks related to cyclical consumption in Korea. Thus, it has been challenging to find studies focused on whether a consumption-based predictive variable might be related to the Korean stock market. Given this knowledge gap, the present paper seeks to contribute to existing research by verifying the relationship between Korean stock returns and cyclical consumption, which is an unconventional variable used to overcome the drawbacks of previous predictive variables.

If the economy takes a dramatic downturn, it is difficult to reduce consumption sharply due to the consumption habits of wealthy individuals who have previously lived economically abundant lives. Conversely, if less wealthy individuals who are used to living economically limited lifestyles suddenly become rich, it is challenging for them to consume excessively due to their previous consumption habits. In fact, the utility function with ‘habit formation’ reflects this mechanism by considering investors’ habits. In particular, Campbell and Cochrane (1999) assume that this habit formation is determined by the whole history of aggregate consumption rather than by personal consumption. The authors’ model assumes that identical investors intend to maximize the following utility function:

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

where X_t and δ refer to habit and subjective time discount factor, respectively. The habit X_t is defined indirectly by the surplus consumption ratio. In other words, X_t is calculated by $S_t \equiv (C_t - X_t)/C_t$. Campbell and Cochrane (1999) assume that the log surplus

2) $cay_t \equiv c_t - \beta_a a_t - \beta_y y_t$, where c_t = consumption, a_t = asset wealth, and y_t = labor income.

consumption ratio, $s_t \equiv \log(S_t)$, follows the heteroskedastic AR(1) process,

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

where φ , g , and \bar{s} are all parameters. $\lambda(s_t^a)$ is a sensitive function that is nonlinearly and monotonically decreasing and g is a consumption growth rate affecting surplus consumption. In fact, this model asserts that habits are activated by consumption trends. Wachter (2006) has proven that in the first-order approximation around $s_t = \bar{s}$, surplus consumption moves slowly and adjusts to the whole history of current and past consumption with the parameter φ ,

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

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

$$\hat{s}_t \approx c_t - c_{t-k} \approx \alpha c_t. \quad (4)$$

In equation (4), subscript k determines the length of time interval that is adjusted based on past consumption. The next section of this paper will provide a more detailed explanation regarding construction of cyclical consumption. In sum, the whole process laid out above represents Atanasov, Møller, and Priestley's (2020) claims about the theoretical relationship between the cyclical consumption variable and the External Habit Model (EHM).

Meanwhile, if stock market excess returns and consumption growth are jointly and lognormally distributed, Campbell and Cochrane's (1999) model posits the following implication:

$$E_t(r_{t+1}) + \frac{1}{2}\sigma_t^2 = \gamma_t \text{cov}_t(\gamma_{t+1}, \Delta c_{t+1}) \quad (5)$$

where γ_t is the state-dependent price of consumption

risk defined as $\gamma_t = \gamma(1 + \lambda(s_t))$. Since s_t is similar to cyclical consumption in equation (4), and $\lambda(s_t)$ is set to be the decreasing function in equation (2), it is obvious that there is an inverse relationship between cyclical consumption and s_t by the covariance term. This also implies an inverse relationship between cyclical consumption and risk premium. This is because consumption that is higher (lower) than the trend is related to a decrease (increase) of covariance. In other words, when consumption is higher than the trend (i.e., during boom periods), the marginal utility of current consumption decreases, making investors reduce current consumption while enhancing investments today. This leads to an increase in stock prices today while decreasing expected returns in the future. Conversely, when consumption is lower than the trend (i.e., during recession periods), the marginal utility of current consumption increases, leading investors to consume more but invest less today. This leads to a decrease in stock prices today while also increasing expected returns in the future.

In the next section, this paper introduces how the main variable of cyclical consumption can be established and offers a time-series trend graph of the variable. In doing so, the paper demonstrates how cyclical consumption is related to market excess returns in Korea geometrically.

III. Data and Methodology

A. Cyclical Consumption

First, we investigate how the cyclical consumption variable is derived. This paper uses aggregate seasonally-adjusted personal consumption expenditures (PCE) as a proxy for consumption data. The data were obtained from Table 10.7.1.2.2 of the Bank of Korea's Economic Statistics System (ECOS), which features real per-capita terms and quarterly data from 19701Q to 20194Q. In fact, these data differ from those offered by Atanasov, Møller, and Priestley (2020), who use aggregate seasonally-adjusted consumption expenditures

on nondurables and services as a proxy. This difference is because, compared to the U.S. stock market, PCE is the most significant variable in the Korean stock market. Using the following equation, we examined which consumption variable would be most useful:

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

As mentioned previously, this paper follows Hamilton’s (2018) detrending method in order to capture the consumption variation risk from changes in marginal utility. In equation (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 represents cyclical consumption (cc_t) at t .

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

Structurally, equation (7) should produce the same result as equation (6). That is, cc_t can also be obtained by subtracting the estimated coefficients from the left-hand side of equation (6), which is C_t . The cc_t , extracted from Hamilton’s (2018) method, will feature superior explanation power and fewer errors

compared to other methods.

Next, it is important to determine the subscript k for independent variables on the right-hand side of equation (6). Hamilton (2018) recommends for k to be set as approximately five years to capture long-term shocks when considering the dynamics of the business cycle. In particular, since this paper sets up a variable that captures slow-moving and time-varying consumption variations, it assumes that cc_t will have greater explanation power for a five-year period than for other periods. The study’s empirical results, which will be discussed in detail in the corresponding tables, actually show that cc_t has the most fitted outcome in Korea when k is equal to 24. Utilizing this finding, we use cc_t with $k = 24$ in this paper.

Figure 1 displays the time-series trend of cc_t when $k = 24$. This time period covers 1993Q4 to 2019Q4. In fact, the consumption data period is from 1970, the KOSPI market return is from 1980Q1, and the KOSDAQ market return is from 1996Q3. Additionally, the 364-day Monetary Stabilization Bond (MSB) returns as a proxy for risk-free rates are from 1987Q1. Since cc_t is constructed from the lagged data ($k = 24$), the data period in Figure 1 inevitably starts in 1993Q4, which is lagged for six years beginning in 1987Q4. A bold line is used to represent cc_t , while the spaces

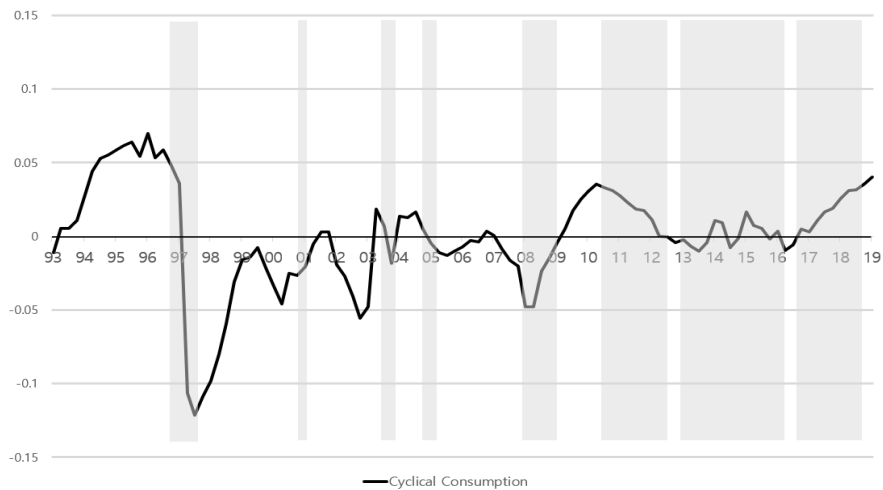


Figure 1. Time-series Trend of cc_t

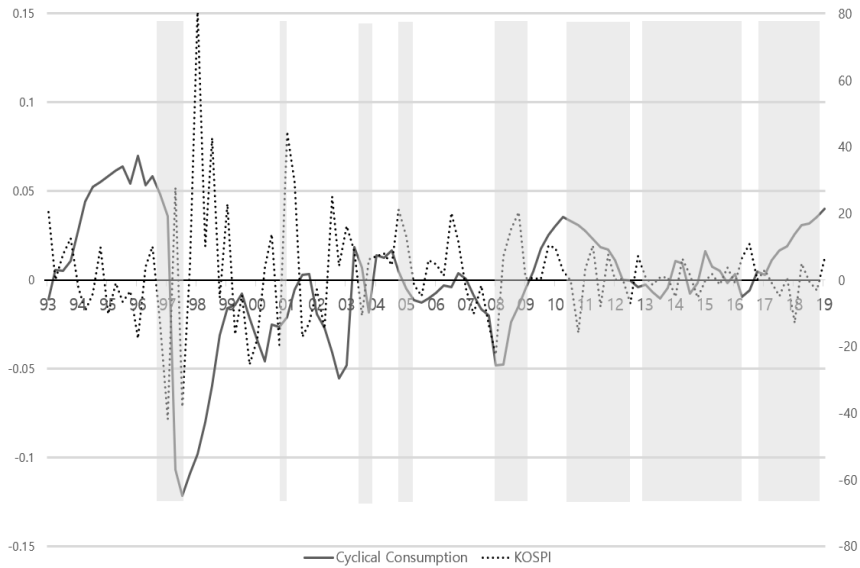


Figure 2. Time-series Trend of cc_t and KOSPI Market Returns

shaded by a darker color represent bad economic times according to certain definitions. More specifically, during the 1998 financial crisis in Korea, cc_t was at the inflection point where the positive value changed to a negative value. However, during the 2008 global financial crisis, cc_t in Korea hovered above the negative value, which is not clearly fitted to this paper's conjecture. From 2011 to 2013, even though this was defined as a poor period of time economically speaking, cc_t was positive. Moreover, from 2013 to 2016, during poor economic times, cc_t was also in the positive. Finally, during poor times from 2017 to 2019, the trend of cc_t was also observed to be positive.

Next, Figure 2 represents a comparison between cc_t (straight line) and KOSPI market returns (dotted line). In general, cc_t had been in the negative while KOSPI market returns had been in the positive, and vice versa. Thus, we can observe the inverse relationship between cc_t and KOSPI market returns.

B. Predictive Regression

This section explains how predictive regression

was constructed to evaluate the predictive power of cc_t regarding market returns. First, KOSPI and KOSDAQ market returns were used as a proxy for market returns. The KOSPI market return data are from 1980Q1 to 2019Q4, while the KOSDAQ market return data are from 1996Q3 to 2019Q4. Moreover, 364-day MSB returns were used as a proxy for risk-free rates. Although Atanasov, Møller, and Priestley (2020) employ 30-day T-bill rates as a proxy for risk-free rates, we used 364-day MSB returns since a longer data period is available for MSB in the market. The data period for 364-day MSB returns is from 1987Q1 to 2019Q4. A proxy for risk-free rates is necessary to establish excess returns. All return data were obtained from FnGuide 5.0. Table 1 compares excess returns, nominal returns, and real returns simultaneously. Nominal returns refer to the raw data of market returns themselves, while excess returns are calculated by subtracting the risk-free rate from nominal returns. Meanwhile, real returns are calculated by deflating nominal returns using the inflation rate of the aggregate South Korea CPI, which was downloaded from KOSTAT.³⁾ The following is this study's return

3) KOSTAT: national database by Korean government agency,

predictive regression:

$$r_{t,t+h} = \alpha + \beta \alpha_t + \varepsilon_{t,t+h}. \quad (8)$$

The left side of equation (8), $r_{t,t+h}$, represents an h-quarter continuously compounded log return. On the right side, α_t is the cyclical consumption variable calculated by equation (7). The determination of h in $r_{t,t+h}$ follows Atanasov, Møller, and Priestley's (2020) approach using cumulative returns spanning 1-5 years in the table. As discussed before, predictive regression can be vulnerable to some econometrical issues when it is used without any further consideration. Thus, Atanasov, Møller, and Priestley (2020) suggest three methods for overcoming these potential issues. First, they suggest employing the t-value from Newey-West's (1987) robust t-statistics method. Heteroskedasticity- and autocorrelation-robust t-statistics truncated at lag h have been proven to eliminate both the heteroscedasticity and autocorrelation of error terms that can be easily noticed in time-series data. Therefore, t-statistics become robust by preventing possible distortion and reinforcing the test's reliability. Second, the authors also assert that the wild-bootstrapped p-values must be analyzed also. This is in line with Inoue and Kilian's (2005) recommendation that a one-sided alternative hypothesis should be used when judging the predictability of an estimated coefficient. Moreover, Rapach, Ringgenberg, and Zhou (2016) note that the bias identified by Stambaugh (1999)—which is the error that frequently occurs when determining a variable's predictive properties—and the overlapping observation bias of accumulated data discovered by Hodrick (1992) should be considered. Since these biases could produce an inaccurate statistical inference through the test, the abovementioned authors claim that researchers should not only perform the robust t-statistics as recommended by Newey and West (1987) but also compute a wild bootstrapped p-value to test the null hypothesis ($b=0$) against an alternative hypothesis ($b>0$) to derive an accurate statistical inference. Thus, the present study computed a wild

bootstrapped p-value to reinforce the test's reliability. Third, the authors also argue that IVX-Wald statistics should be used for validity regarding the use of a coefficient. Atanasov, Møller, and Priestley (2020) insist that this method can overcome the sample bias of time-series data, which can be discovered through the long-term predictive regression models or the presence of an incorrect statistical inference via possible misspecification.

IV. Empirical Results

A. Predictive Power of Cyclical Consumption

This section presents the results of the return predictive regression of α_t on KOSPI and KOSDAQ market returns. We tested both KOSPI and KOSDAQ market returns, which are displayed on the Panel A, B, and C of Table 1. The regression results for $h=1$ to $h=20$ are presented on the second to seventh columns. α_t was constructed using aggregate seasonally-adjusted personal consumption expenditure (PCE) because, for Korea, PCE generally offers a better explanation than other consumption data. The empirical results for economic boom and recession are explained in the following Panel D, E and F of Table 1 as well.

According to Panel A of Table 1, KOSPI market excess returns have negative coefficients in every period, and a coefficient's absolute value is higher when the return is more accumulated. This means that α_t has an inverse relationship with market returns once consumption risk can be captured.

In fact, t-values for most periods indicate that coefficients are significant at the 1% significance level. T-values for $h=8$ and $h=20$ are -2.34 and -2.54, respectively, and they are significant at the 5% level. The most interesting period is $h=4$, which has an estimated coefficient of -5.14 and a t-value of -5.81 with an adjusted R-square value of 34.65. These results differ somewhat from those of Atanasov, Møller, and Priestley (2020), demonstrating that the

National Statistical Office.

Table 1. Predictive Power of Cyclical Consumption

	h=1	h=4	h=8	h=12	h=16	h=20
Panel A: Excess Market Returns						
KOSPI	-1.03 (-2.66)*** [6.08]	-5.14 (-5.81)*** [34.65]	-4.92 (-2.34)** [22.32]	-4.89 (-2.09)** [17.13]	-5.91 (-2.99)*** [20.39]	-6.13 (-2.54)** [25.95]
KOSDAQ	-0.06 (-0.09) [0.00]	-0.07 (-0.03) [0.00]	-0.59 (-0.35) [0.20]	-0.35 (-0.27) [0.04]	-2.44 (-0.97) [3.13]	1.61 (0.70) [1.41]
Panel B: Nominal Market Returns						
KOSPI	-0.82 (-3.31)*** [6.19]	-3.24 (-3.70)*** [23.89]	-3.18 (-2.50)** [16.11]	-2.47 (-1.53) [9.01]	-3.07 (-2.50)** [13.61]	-3.40 (-3.24)*** [17.77]
KOSDAQ	-0.08 (-0.12) [0.00]	-0.05 (-0.02) [0.00]	-0.19 (-0.11) [0.10]	0.00 (-0.00) [0.00]	-2.10 (-0.82) [3.37]	1.88 (0.84) [1.47]
Panel C: Real Market Returns						
KOSPI	-0.71 (-3.16)*** [4.57]	-3.27 (-3.48)*** [22.91]	-2.97 (-2.26)*** [13.68]	-2.15 (-1.20) [6.41]	-2.71 (-1.70)* [9.36]	-2.99 (-2.00)** [11.73]
KOSDAQ	-0.07 (-0.10) [0.00]	-0.04 (-0.02) [0.00]	-0.42 (-0.23) [0.00]	-0.13 (-0.09) [0.00]	-2.39 (-0.99) [2.29]	1.47 (0.73) [1.91]
Panel D: CEI (Composite Economic Index)						
β (Good)	-0.98 (-1.67)* [6.13]	-4.94 (-2.58)** [35.01]	-7.84 (-2.62)*** [26.98]	-8.48 (-2.30)** [22.52]	-8.75 (-5.29)*** [23.23]	-11.05 (-4.54)*** [35.52]
β (Bad)	-1.07 (-1.33) [6.13]	-5.28 (-6.15)*** [35.01]	-2.80 (-1.81)* [26.98]	-2.30 (-1.74)* [22.52]	-3.86 (-1.73)* [23.23]	-2.58 (-1.60) [35.52]
Panel E: Real GDP Growth						
β (Good)	-1.21 (-2.64)*** [6.28]	-5.03 (-2.84)*** [34.99]	-5.15 (-1.40) [22.58]	-6.96 (-1.96)* [20.29]	-6.74 (-2.38)** [20.99]	-9.07 (-2.60)** [32.09]
β (Bad)	-0.87 (-1.20) [6.28]	-5.23 (-4.73)*** [34.99]	-4.69 (-4.74)*** [22.58]	-2.80 (-2.42)** [20.29]	-5.08 (-3.83)*** [20.99]	-3.12 (-2.95)*** [32.09]
Panel F: Cyclical Consumption						
β (Good)	-1.09 (-2.22)** [6.14]	-4.60 (-2.42)** [35.23]	-6.65 (-2.14)** [24.38]	-7.43 (-2.06)** [20.41]	-8.62 (-4.86)*** [23.46]	-11.03 (-4.41)*** [37.24]
β (Bad)	-0.98 (-1.23) [6.14]	-5.60 (-6.51)*** [35.23]	-3.50 (-2.57)** [24.38]	-2.82 (-2.13)** [20.41]	-3.69 (-1.89)* [23.46]	-2.12 (-1.70)* [37.24]

* Note: The parentheses represent the robust t-values by wild bootstrapped p-values, while square brackets represent the adjusted R-squares. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

absolute values of coefficients, t-values, and adjusted R-squares tend to increase when market returns are more accumulated. This implies that the consumption risk in the Korean stock market is accumulated strongly until the fourth quarter on an annual basis, but it is then relieved (though it is not at all diminished). On the other hand, the KOSDAQ market excess returns in Panel A exhibit negative values for estimated coefficients, which shift to positive values (1.61) during $h=20$. However, in every period, the null hypothesis (i.e., the estimated coefficient is indifferent from 0) cannot be rejected since every t-value is trivial. Therefore, an inverse relationship between cc_t and KOSDAQ market returns is not well-supported by the evidence.

Panel B of Table 1 presents the results for nominal returns. KOSPI nominal returns have negative estimated coefficients for every period, but their absolute values are lower than those of Panel A for every period as well. Moreover, most t-values indicate that the estimated coefficients are statistically significant at the 1% level except for the case when $h=12$. On the other hand, KOSDAQ nominal returns have negative estimated coefficients for most periods, except for a positive one when $h=20$ (as in Panel A). Most estimated coefficients are statistically insignificant due to low t-values. Moreover, adjusted R-squares converged to almost zero until $h=8$, meaning that this panel is not well-fitted to the model.

Panel C of Table 1 presents the results for real returns. KOSPI real returns have the lowest estimated coefficient absolute values out of all panels. Specifically, the estimated coefficient when $h=16$ is statistically insignificant (-1.70), and the adjusted R-square indicates a similar result. For KOSDAQ real returns, the estimated coefficient when $h=20$ is positive but insignificant. Generally, the t-values for most periods are relatively low, implying that the estimated coefficients are not statistically significant. In summary, Panel A to C of Table 1 consistently show two important results: First, cyclical consumption has an inverse relationship with market returns and predictive power. Second, the relationship is statistically significant only for KOSPI and not the case for KOSDAQ. We will

analyze the reasons in detail in the following section.

In addition, Panel D, E, and F of Table 1 examine whether cyclical consumption can be used for predictive purposes during *economic booms and recessions*. This examination was conducted because many previous studies have argued that predictive variables work well during poor economic times but not during booms. Atanasov, Møller, and Priestley (2020) employ NBER-dated recessions as a proxy for poor times and Rapach, Strauss, and Zhou's (2010) define bad times (i.e., recessions) as times when real GDP growth rate is under the bottom one-third. Since Korea has no data equivalent to the NBER-dated recessions in the first method mentioned above, we employed the Composite Economic Index (CEI) in Korea as a proxy for this kind of data. According to the Korea Development Institute (KDI), one of the Korean government's major economic institutes, CEI is an index constructed by combining employment, production, consumption, investment, and finance indexes. In particular, the business cycle is categorized as a boom if the circulated variation of the CEI is above 100; otherwise, it is categorized as a recession. Taking this into consideration, Panel D of Table 1 defines "recession" as a period where the circulated variation of the CEI is under 100. Panel E defines "recession" as a period when real GDP growth rate falls below the bottom one-third, following Rapach, Strauss, and Zhou's (2010) framework. Finally, Panel F defines "recession" as a period when cyclical consumption is one standard deviation less than its mean, following Atanasov, Møller, and Priestley's (2020) framework. In order to examine the predictive power of cyclical consumption for the business cycle, we constructed the following equation:

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

In equation (9), the indicator function I_{bad} has the value of 1 when it is a period of economic recession (i.e., bad times) and the value of 0 when it is a period of economic boom (i.e., good times). This paper tests the hypothesis that both estimated coefficients, β_{bad} and β_{good} , are significantly negative.

As Panel D of Table 1 shows, all estimated coefficients for both good and bad times are negative when we use CEI as the criterion. Specifically, during an economic boom, the estimated coefficients are statistically significant at the 5% ($h=4, 12$) or 1% significance level, except for $h=1$. In contrast, there are two cases during economic recession where the estimated coefficients are insignificant when $h=1$ and $h=20$. Except for the cases where $h=1$ and $h=20$ during bad times, this study was able to verify the predictive power of cyclical consumption during both good and bad economic times. Panel E of Table 1 shows that every estimated coefficient is negative and more statistically significant compared to other panels. Except for the case where $h=8$ during good times, most of the estimated coefficients are statistically significant at the 1% or 5% significance level. Panel F of Table 1 demonstrates that every estimated coefficient is negative and statistically significant except for the case where $h=1$ during poor times.

In sum, two important results can be derived from Table 1. First, in Korean capital markets, cyclical consumption has an inverse relationship with market excess returns regardless of the definition of “economic boom” (i.e., good times) and “economic recession” (i.e., bad times). Second, cyclical consumption has predictive power for market returns except for a few time periods. These results imply that we can use cyclical consumption as a useful variable to predict market stock returns regardless of economic conditions, such as boom and recession.

B. Differential Predictive Power of Cyclical Consumption between KOSPI and KOSDAQ

One of the main results of Table 1 is that the predictive power of cyclical consumption for KOSPI is different from that of KOSDAQ. In this section, we examine the reasons of differential predictive power in detail.

The Korea Exchange (KRX) is responsible for operating the Korean stock market and has 3 market

divisions, such as KOSPI, KOSDAQ and derivatives. Since derivatives market is not our interest in this paper, we focus only on KOSPI and KOSDAQ market. KOSPI is considered the representative list of companies publicly traded companies in Korea, while the KOSDAQ has small and medium sized businesses and start-ups listed on it. KOSDAQ is considered much more risky than KOSPI and often compared to NASDAQ in the US.⁴⁾

According to results from Table 1, KOSPI market returns have a statistically significant inverse relationship with cc_t in every form of return (excess, nominal, and real). In general, the more the market returns accumulate, the stronger the relationship. However, KOSDAQ market returns show no consistent results in terms of the relationship between market returns and cc_t , and all of the estimated coefficients for these returns are statistically insignificant. To explore the reasons of the difference between KOSPI and KOSDAQ, we additionally test the correlation coefficients between cyclical consumption and KOSPI and KOSDAQ returns. The results in Table 2 show that nominal, excess, and real KOSPI returns have negative and significant relations with nominal, excess, and real cc , while KOSDAQ does not have significant relations with any cc , which implies that cyclical consumption variable has predictive power only for the KOSPI market. This result can be conjectured from the fact that most of the listed companies on KOSPI represent most of the major companies supplying consumption goods or services in Korea, while most of the registered companies on KOSDAQ represent most of the small and startup firms focused mostly on IT and production related goods or services rather than consumption goods or services.

We can infer other reasons of the differential effect of KOSPI and KOSDAQ from the recent results by Cho and Ko (2015) and Kim et al. (2019). Cho and Ko (2015) examined 602 KOSPI firms and 224 KOSDAQ firms in order to analyze the accurate valuation of firms, showing that KOSPI firms are

4) As of June 30, 2021, there are 803 companies listed on the KOSPI and 1,485 companies on KOSDAQ.

Table 2 . Correlation between Cyclical Consumption and KOSPI and KOSDAQ returns

	cc	cc_{excess}	cc_{real}	KOSPI	KOSDAQ	KOSPI (excess)	KOSDAQ (excess)	KOSPI (real)	KOSDAQ (real)
cc	1.00								
cc_{excess}	0.85 (0.00)***	1.00							
cc_{real}	0.99 (0.00)***	0.86 (0.00)***	1.00						
KOSPI	-0.25 (0.00)***	-0.26 (0.01)***	-0.26 (0.00)***	1.00					
KOSDAQ	-0.04 (0.71)	-0.06 (0.57)	-0.04 (0.72)	0.71 (0.00)***	1.00				
KOSPI (excess)	-0.27 (0.00)***	-0.26 (0.01)***	-0.27 (0.00)***	0.99 (0.00)***	0.71 (0.00)***	1.00			
KOSDAQ (excess)	-0.04 (0.51)	-0.05 (0.60)	-0.04 (0.33)	0.71 (0.54)	0.99 (0.49)	0.71 (0.00)***	1.00		
KOSPI (real)	-0.26 (0.00)***	-0.26 (0.01)***	-0.26 (0.00)***	0.99 (0.00)***	0.71 (0.00)***	0.99 (0.00)***	0.71 (0.00)***	1.00	
KOSDAQ (real)	-0.04 (0.71)	-0.05 (0.60)	-0.04 (0.71)	0.70 (0.00)***	0.99 (0.00)***	0.70 (0.00)***	0.99 (0.00)***	0.71 (0.00)***	1.00

* Note: The parentheses represents p-values. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively. cc_{excess} and cc_{real} means cc which matches to the period of excess and real KOSPI, KOSDAQ market returns, respectively; KOSPI(excess) (or KOSDAQ(excess)) KOSPI(real) (or KOSDAQ(real)) means KOSPI (KOSDAQ) market returns subtracted by risk-free rates and KOSPI (KOSDAQ) market returns calculated by deflating nominal returns using the inflation rate of the aggregate Korea CPI.

more accurately valued than KOSDAQ firms. That is, the market values of KOSDAQ firms are less reliable than those of KOSPI firms, implying that the KOSDAQ related data are relatively unstable and the results of KOSDAQ analyses can change depending on valuation methods. In addition, Kim et al. (2019) analyzed 4,446 firms listed on KOSPI and KOSDAQ to find out the direction of information flows between KOSPI and KOSDAQ, suggesting that KOSPI is a more informationally efficient market than KOSDAQ, implying that KOSPI can give us more accurate information than KOSDAQ. These recent studies indirectly explain why there is differential predictive power between KOSPI and KOSDAQ.

Furthermore, as we will see from the results of Table 3 (KOSPI) and 4 (KOSDAQ), cyclical consumption has differential predictive power for some individual industry portfolios between KOSPI and KOSDAQ.

From these results, we conclude that cc_t can more accurately and significantly capture the consumption risks affecting stock price variations in KOSPI than in KOSDAQ.

C. Predictive Power of Cyclical Consumption for Industry Portfolios

This section examines whether cyclical consumption also has an inverse relationship with specific industries and predictive properties. Atanasov, Møller, and Priestley (2020) categorize 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 (OTHER).

Table 3. Predictive Power of Cyclical Consumption for Industry Portfolios: KOSPI

		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]

Table 3. Continued

		h=1	h=4	h=8	h=12	h=16	h=20
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]

* Note: 1. The following abbreviations are used above. Transp.: Transportation, Machine.: Machinery, Manuf.: Manufacturing, Telecom.: Telecommunication, Chem.: Chemistry, and Construct.: Construction.
 2. The parentheses represent the robust t-values by wild bootstrapped p-values, while square brackets represent the adjusted R-squares. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

In Korea, there are 22 KOSPI-based industry portfolios, which we employed for the study’s analyses. We also sorted these 22 industries into eight larger-scale categories: Non-durable Goods (NON), Durable Goods (DUR), Manufacturing (MAN), Energy (ENG), Telecommunication (TEL), Healthcare and Medical Equipment (HLTH), Utilities (UTILS), and Others.

The major results presented in Table 3 can be summarized as follows. The estimated coefficients for most industries are statistically significant. In particular, a number of main industries have the most powerful relationships compared to other industries. The industries with statistically significant coefficients are KOSPI Non-metal Minerals, Metal Minerals,

Manufacturing, Electric/Electro, and Chemistry. The estimated coefficient for Manufacturing is -7.03 with a t-value of -3.09, which is statistically significant at the 1% significance level. For every period of this industry, the estimated coefficients are significant at the 5% or 1% significance level. This seems natural because the manufacturing industry provides products and services highly related to household consumption expenditures. In contrast, the industries that exhibit predictability and an inverse relationship with cyclical consumption are KOSPI Beverages, Transportation, Warehouses, Utilities, Construction, Finance, Banks, Insurance and Security.

Although we expected most of the industries under

the Nondurable (NON) category to be significant, they were actually not. More specifically, the Textile/Garment and Paper/Wood industries under the Nondurable (NON) category turned out to have an inverse relationship with cyclical consumption, but their coefficients were not significant. However, the industries under the Durable category (DUR)—with the exception of Machinery—exhibited significant results for predictive power and an inverse relationship with cyclical consumption. Moreover, the industries categorized under Telecommunication (TEL) and Healthcare and Medical Equipment (HLTH) showed no significant results at all. In the case of Telecommunication, the estimated coefficient is 4.44, which implies a positive relationship with cyclical consumption when $h=20$. In particular, the estimated coefficients were found to be positive and statistically significant when $h=16$ and $h=20$, implying no relationship with cyclical consumption. The Medical/Medicine and Precision Medicine industry exhibited an inverse relationship with cyclical consumption, but its estimated coefficients were not statistically significant. However, our results for Precision Medicine and Telecommunication are somewhat limited because these industries have a short history in the markets; they were introduced into the KOSPI-based industry portfolio after 2000.

Overall, eight out of the 22 examined industries have no significant coefficients even though the study did find an inverse relationship between these industries and cyclical consumption. In addition, one of the three industries under ‘NON’ (Beverages), two of the five industries under ‘DUR’ (Transportation and Warehouses), the single industry under ‘UTILS’ (Utilities), and five of the seven industries under ‘OTHERS’ (Construction, Finance, Banks, Insurance, and Security) were found to have a relatively imperfect relationship with cyclical consumption. Two of the five industries under ‘DUR’ (Non-metal Minerals and Metal Minerals), the single industry under ‘MAN’ (Manufacturing), one of the two industries under ‘ENG’ (Electric/Electro), and one of the seven industries under ‘OTHERS’ (Chemistry) were found to have a significant relationship with cyclical consumption in every period. Therefore, five industries (out of

the 14 remaining industries)—Non-metal Minerals, Metal Minerals, Manufacturing, Electric/Electro, and Chemistry—were found to have a strong negative relationship with cyclical consumption in every period, with estimated coefficients that were all statistically significant. The other nine industries were found to have an inverse, though weaker, relationship with cyclical consumption. In sum, these findings diverge somewhat from our expectation that every industry in the Korean market will have a negative relationship with cyclical consumption.

In addition, we analyze 20 KOSDAQ-based industry portfolios using the same methodology as KOSPI. The major results in Table 4 show that except for 1 Non-durable, 2 Durables, and 1 Health industry portfolio, all other portfolios do not have significant relations with cyclical consumption. In addition, only one portfolio (Transportation and Parts) out of four significant portfolios shows inverse relation with cyclical consumption. In summary, we find the results that cyclical consumption also has predictive power for 14 industry portfolios based on KOSPI, and these results are generally consistent with the results of previous studies.

D. Cyclical Consumption and Investment Strategy

This section examines the profitability of the investment strategies based on cyclical consumption, if cyclical consumption really has an inverse relationship with KOSPI excess returns and predictive power regarding future market returns. We find that future expected returns increase when cyclical consumption is negative, and future expected returns decrease when cyclical consumption is nonnegative.

In our investment strategy, the ‘buy’ (‘sell’) signal is exercised when cyclical consumption is ‘negative’ (‘positive’). Then, the investment position based on the selected signal remains the same for the following quarter, year, two years, three years, four years, and five years while accumulated log excess returns are calculated separately. Additionally, if cyclical consumption

Table 4. Predictive Power of Cyclical Consumption for Industry Portfolios: KOSDAQ

		h=1	h=4	h=8	h=12	h=16	h=20
NON	Bevera	1.69	-0.30	-2.45	1.81	-1.26	5.64
		(0.40)	(-0.07)	(-0.74)	(0.48)	(-0.31)	(1.01)
		[0.73]	[0.02]	[0.83]	[0.42]	[0.20]	[5.40]
	Textile/ Garment	4.27	3.99	-0.36	0.46	1.05	10.39
		(1.03)	(0.71)	(-0.06)	(0.08)	(0.16)	(1.68)*
		[3.72]	[1.51]	[0.01]	[0.01]	[0.06]	[7.63]
	Paper/ Wood	2.52	-2.04	-5.75	1.52	4.36	14.39
		(0.59)	(-0.42)	(-1.31)	(0.25)	(0.44)	(1.31)
		[1.21]	[0.35]	[1.66]	[0.09]	[0.62]	[7.60]
DUR	Nonmetal Mineral	-0.83	0.25	-0.29	-0.01	4.06	2.86
		(-0.70)	(0.09)	(-0.08)	(0.00)	(1.17)	(1.25)
		[0.17]	[0.01]	[0.01]	[0.00]	[2.91]	[1.88]
	Metal Mineral	2.37	0.23	1.57	6.13	-0.57	7.71
		(0.55)	(0.05)	(0.28)	(0.93)	(-0.08)	(1.02)
		[1.30]	[0.01]	[0.18]	[1.94]	[0.01]	[3.05]
	Transp.	1.24	3.39	-0.93	-0.97	1.86	-2.40
		(1.22)	(1.11)	(-0.31)	(-0.28)	(0.46)	(-0.67)
		[0.38]	[1.71]	[0.08]	[0.08]	[0.31]	[0.61]
	Transp./ Parts	2.75	0.86	-2.32	-0.26	-4.68	3.39
		(0.65)	(0.17)	(-0.48)	(-0.06)	(-1.62)*	(0.58)
		[1.83]	[0.11]	[0.54]	[0.01]	[2.28]	[1.55]
	Furnitur	3.57	4.71	3.86	12.69	8.40	2.76
		(1.30)	(1.29)	(0.60)	(1.27)	(1.29)	(0.50)
		[3.03]	[1.28]	[0.53]	[6.88]	[4.75]	[0.64]
Publicat	-0.54	0.29	1.57	10.66	10.41	5.52	
	(-0.47)	(0.08)	(0.22)	(1.29)	(1.24)	(0.60)	
	[0.06]	[0.01]	[0.16]	[5.96]	[7.64]	[2.11]	
Machine.	-0.68	-0.38	-2.37	2.90	5.69	3.99	
	(-0.70)	(-0.17)	(-0.69)	(0.65)	(1.83)*	(1.41)	
	[0.12]	[0.03]	[0.78]	[1.10]	[7.48]	[4.70]	
MAN	Manuf.	1.71	-2.40	-3.05	0.33	-2.27	6.83
		(0.40)	(-0.45)	(-0.77)	(0.08)	(-0.49)	(1.15)
		[0.68]	[0.73]	[0.90]	[0.01]	[0.33]	[3.93]
IT	IT (total)	0.68	-2.53	-0.86	0.38	-2.18	6.33
		(0.15)	(-0.47)	(-0.20)	(0.09)	(-0.48)	(0.99)
		[0.11]	[0.84]	[0.08]	[0.01]	[0.36]	[3.65]
	IT (venture)	1.41	-7.26	-6.64	-1.03	-6.29	10.73
		(0.21)	(-0.73)	(-0.85)	(-0.12)	(-0.89)	(1.49)
		[0.25]	[3.92]	[3.08]	[0.05]	[1.84]	[8.11]
ENG	Electric/ Electro	0.25	-4.82	-4.47	-0.28	-2.17	7.49
		(0.05)	(-0.81)	(-1.07)	(-0.05)	(-0.32)	(0.96)
		[0.01]	[2.78]	[1.88]	[0.01]	[0.27]	[3.61]

Table 4. Continued

		h=1	h=4	h=8	h=12	h=16	h=20
TEL	Telecom.	1.54 (0.35) [0.63]	-0.38 (-0.09) [0.02]	2.27 (0.49) [0.48]	4.61 (1.07) [1.77]	0.34 (0.06) [0.01]	7.64 (0.96) [4.41]
HLTH	Medical/Med dicin	1.30 (0.90) [0.38]	5.54 (1.25) [3.25]	2.15 (0.49) [0.39]	13.63 (1.82)* [14.88]	6.42 (1.67)* [6.80]	5.93 (1.29) [6.92]
	Precisi Medicin	0.65 (0.47) [0.11]	2.48 (0.97) [0.97]	-0.16 (-0.03) [0.00]	3.76 (0.48) [1.06]	3.91 (0.50) [1.33]	-2.69 (-0.35) [0.71]
UTILS	Utility	-1.59 (-0.81) [0.59]	-3.70 (-0.89) [1.88]	-2.73 (-0.49) [0.69]	-3.20 (-0.55) [0.76]	-2.05 (-0.28) [0.26]	0.92 (0.16) [0.10]
OTHER	Chem.	1.33 (0.30) [0.40]	-1.35 (-0.26) [0.25]	-1.75 (-0.40) [0.31]	0.23 (0.05) [0.00]	-2.46 (-0.62) [0.45]	6.33 (1.26) [4.51]
	Constru.	4.63 (1.21) [5.39]	4.73 (1.24) [2.66]	6.27 (1.03) [2.58]	10.27 (1.57) [5.19]	7.11 (0.85) [1.98]	13.59 (1.26) [7.53]
	Finance	1.93 (0.46) [0.96]	2.72 (0.71) [1.09]	4.53 (1.18) [1.96]	6.35 (1.63)* [3.41]	4.21 (0.79) [1.27]	11.90 (1.80)* [11.24]

* Note: 1. The following abbreviations are used above. Transp.: Transportation, Machine.: Machinery, Manuf.: Manufacturing, Telecom.: Telecommunication, Chem.: Chemistry, and Construct.: Construction.)

2. The parentheses represent the robust t-values by wild bootstrapped p-values, while square brackets represent the adjusted R-squares. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

hovers in the 1% band around zero (in other words, the value is indifferent from 0), then the position is neutral and there is therefore no position for trading. Since the time unit for each signal is quarterly, this paper adopts quarterly return data in advance. Furthermore, this study utilizes monthly return data because the number of observations for quarterly return data is not sufficient to guarantee statistical reliability.

Every mean return in columns 6, 7, and 8 of Panels A and B in Table 5 is annualized. The main results presented in Table 5 can be summarized as follows. First, Panel A shows the results of quarterly return data; for this, the mean returns for the buy and sell signal in each six different period are 3.02% and 5.51% on average, respectively. Whereas most of mean returns of buy signal are statistically insignificant

until three-years accumulated return, all mean returns of sell signal are statistically significant at both 5% and 1% level. Second, Panel B was constructed to reinforce the test's reliability by using monthly return data. The number of observations for each signal is over 100. As we can see from Panel B, the annual mean returns from buy and sell signal in each six different period are 3.47% and 5.68% on average. All mean returns of buy signal are statistically significant at least at 10% level, except for a quarter of accumulated log excess returns. On the other hand, mean returns of sell signal are statistically significant at 1% level, while a quarter of accumulated log excess returns are at 5% level. Third, the average of annual mean returns for the sell signal shows about 2% higher than that of buy signal.

In sum, if the investment strategy based on cyclical

Table 5. Cyclical Consumption and Investment Strategy

	Obs.		Std. Dev		Annual Mean Return (%)		
	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	
(1 Yr) Acc.Ret	49	52	0.26	0.22	4.74	8.37***	
(2 Yr) Acc.Ret	49	48	0.30	0.34	2.16	5.33**	
(3 Yr) Acc.Ret	49	44	0.33	0.40	1.95	4.09**	
(4 Yr) Acc.Ret	47	42	0.40	0.52	3.66***	5.48***	
(5 Yr) Acc.Ret	46	39	0.38	0.48	3.38***	3.89***	
Average returns (%)					3.02	5.51	4.26
Panel B: Monthly data							
(1/4 Yr) Acc.Ret	147	164	0.13	0.10	4.88	7.80**	
(1 Yr) Acc.Ret	147	155	0.25	0.22	4.98**	7.94***	
(2 Yr) Acc.Ret	147	143	0.28	0.34	1.88*	4.87***	
(3 Yr) Acc.Ret	147	131	0.30	0.40	2.17***	4.47***	
(4 Yr) Acc.Ret	140	126	0.34	0.42	3.56***	5.05***	
(5 Yr) Acc.Ret	137	117	0.36	0.48	3.38***	3.96***	
Average returns (%)					3.47	5.68	4.58

* Note: The parentheses represent the robust t-values by wild bootstrapped p-values, while square brackets represent the adjusted R-squares. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

consumption is applied, the strategy can realize on average a 4.58% annualized return. This finding confirms the results of Table 1, implying that cyclical consumption can capture and predict consumption variations influencing the Korean stock market. Since the absolute values of estimated coefficients are highest when h=4 in Table 1, this is consistent with the results of our investment strategy because the one-year accumulated return features the highest mean return. In other words, unlike the results derived from the U.S. stock market, the degree of relationship is the strongest when returns are accumulated for one year in Korea. However, in both the U.S. and Korean stock markets, there is a clear and common phenomenon: the more accumulated the return, the stronger the relationship. Overall, this study shows that investment strategies based on cyclical consumption have economic power in stock markets, implying that investors in Korea can realize significant positive returns by capturing consumption risk variations in the business cycle.

V. Discussion and Conclusion

This study constructed the variable of ‘cyclical consumption’ to capture consumption variations following Atanasov, Møller, and Priestley (2020) in order to examine whether cyclical consumption has predictive power over and/or an inverse relationship with future expected returns in the Korean stock market. This section discusses the study’s findings and concludes.

First, cyclical consumption using Korean data has an inverse relationship with KOSPI market returns. Namely, the more accumulated a return is (one quarter to five years), the stronger the relationship is as well. This implies that cyclical consumption has predictive power regarding expected returns in Korea. These findings can be used to generalize this relationship in other parts of the world. In addition, the relationship between cyclical consumption and future expected returns is consistent regardless of good economic times (booms) or poor economic times (recessions).

Second, the predictive power of cyclical consumption is different between KOSPI and KOSDAQ. The External Habit Model used by previous studies, correlation coefficient analysis, and industry portfolio approach consistently show that cyclical consumption has predictive power only for the KOSPI market. The main reasons of the result can be conjectured from the fact that most of the consumption in Korea comes from the major companies listed on KOSPI and KOSPI is more informationally efficient than KOSDAQ. The results from the analyses of correlation coefficients support the reasoning indirectly.

Third, we empirically verify the study's hypothesis and find that this relationship can be captured not only at the overall market industry level but also at the individual industry level. Out of 22 industry sample portfolios from the KOSPI, 14 industry portfolios show significant predictive power, indicating that we can utilize cyclical consumption variable to predict future returns of some industry portfolios. But, 20 sample industry portfolios from KOSDAQ do not show any significant and meaningful results.

Fourth, this study confirms the significant profitability of a buy-and-sell investment strategy based on cyclical consumption, which yields an annual return of approximately 4.58% on average for the sample periods. This result gives useful implication for investors when they construct future investment portfolios because publicly available consumption data can be effectively used in their investment decisions.

This research offers both practical and academic contributions. *First*, to our knowledge, this is the first study to clarify the empirical relationship between cyclical consumption and the External Habit Model in the Korean stock market. More specifically, this paper demonstrates that consumption risk affects the Korean stock market on the basis of cyclical consumption; thus, we expect related studies to be conducted employing this new consumption-based variable of 'cyclical consumption' in the context of Korean markets. *Second*, this paper elaborates on the relationship between cyclical consumption and future expected market returns through the lens of not only macroeconomics but also financial economics by raising the question of

whether the profitability of an investment strategy based on cyclical consumption arises due to a mispricing of consumption risk or other types of unknown factors. *Third*, this paper offers implications relevant for investors, policymakers, and other interested parties; namely, that we can predict future expected returns in the markets using macroeconomic data rather than micro-firm data. Generally speaking, public macro-data are more accessible to the public than micro-firm data; therefore, this paper provides a convenient and useful method for the prediction of market prices and returns. *Finally*, by demonstrating the relationship in question employing data from Korean markets, this study contributes to the generalization of previous findings from other countries.

References

- Atanasov, V., Møller, S. V., & Priestley, R. (2020). Consumption fluctuations and expected returns. *Journal of Finance*, 75(3), 1677-1713.
- Bansal, R., Khatchatrian, V., & Yaron, A. (2005). Interpretable Asset Markets?. *European Economic Review*, 49(3), 531-560.
- Berge, T. J., & Jordà, Ò. (2011). Evaluating the classification of economic activity into recessions and expansions. *American Economic Journal: Macroeconomics*, 3, 246-277.
- 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.
- Cho, K. H., & Ko, C. R. (2015). Comparison of the valuation of technology firms in KOSPI and KOSDAQ. *Asian Journal of Innovation and Policy*, 4(1), 35-54.
- Choi, W. H. (2011). The habit formation and the equity premium puzzle in case of Korea. *Korean Journal of Financial Studies*, 40(2), 261-285.
- Cooper, I., & Priestley, R. (2009). Time-varying risk premiums and the output gap. *Review of Financial Studies*, 22, 2801-2833.
- 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.
- Hodrick, R. J. (1992). Dividend yields and expected stock returns: Alternative procedures for inference and measurement. *Review of Financial Studies*, 5, 357-386.
- Hodrick, R. J., & Prescott, E. C. (1997). Postwar US business cycles: An Empirical investigation. *Journal of Money, Credit and Banking*, 29, 1-16.
- 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.
- Kang, W. (2013). A study on the explanatory power for future stock returns of changes in consumption-wealth ratio: In case of Korean economy. *Korean Journal of Financial Management*, 30(3), 69-99.
- Kim, J. H. (2014). Predictive regression: An improved augmented regression method. *Journal of Empirical Finance*, 26, 13-25.
- Kim, J. C., Hwang, S. S., Kim, K. H., & Shin, S. I. (2019). A study on information transmission effect between KOSPI and KOSDAQ markets. *Regional Industry Review*, 42(3), 209-230.
- Kostakis, A., Magdalinos, T., & Stamatogiannis, M. P. (2015). Robust econometric inference for stock return predictability. *Review of Financial Studies*, 28(5), 1506-1553.
- Lettau, M., & Ludvigson, S. (2001). Consumption, aggregate wealth, and expected stock returns. *Journal of Finance*, 56(3), 815-849.
- Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55(3), 703-708. <https://doi.org/10.2307/1913610>
- 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. *Review of Financial Studies*, 23(2), 821-862.
- Santos, T., & Veronesi, P. (2006). Labor-income and predictable stock returns. *Review of Financial Studies*, 19, 1-44.
- Stambaugh, R. F. (1999). Predictive regressions. *Journal of Financial Economics*, 54, 375-421.
- Wachter, J. A. (2006). A consumption-based model of the term structure of interest rates. *Journal of Financial Economics*, 79, 365-399.
- Yoo, H. S., & Kim, B. J. (2011). The lead-lag relationship between stock price index volatility and consumption volatility. *Korean Journal of Business Administration*, 24(5), 3097-3112.