Understanding BOXPI – Industry Portfolio Perspectives

Myeong Hyeon Kim*
Young Min Kim†
Kisung Yang‡

Abstract

"BOXPI" is an acronym for the boxed KOSPI. Uniquely, KOSPI has remained within an extremely narrow range during 2012–2016 despite global liquidity expansion. This study develops a continuous-time model to describe sector rotation and interprets the BOXPI phenomenon from industry portfolio perspectives. We find that the upper bound of the BOXPI can be interpreted as a consequence of the rotations from cyclical to defensive sectors during that period. Furthermore, a Bayesian variable selection analysis shows that the lower bound of the BOXPI can be regarded as a result of low price-to-book ratio of the KOSPI in the BOXPI period.

JEL Classification: G11, G12, G14

Keywords: BOXPI; Korean stock market; Sector rotation; Bayesian variable selection

Declarations of interest: none

*Formerly, Department of Business Administration, Seoul National University of Science and Technology, Seoul, South Korea. E-mail: mhkim@seoultech.ac.kr. He is in the heaven now.

†Department of International Trade, Jeonbuk National University, Jeonju, South Korea. E-mail:kimym@jbnu.ac.kr

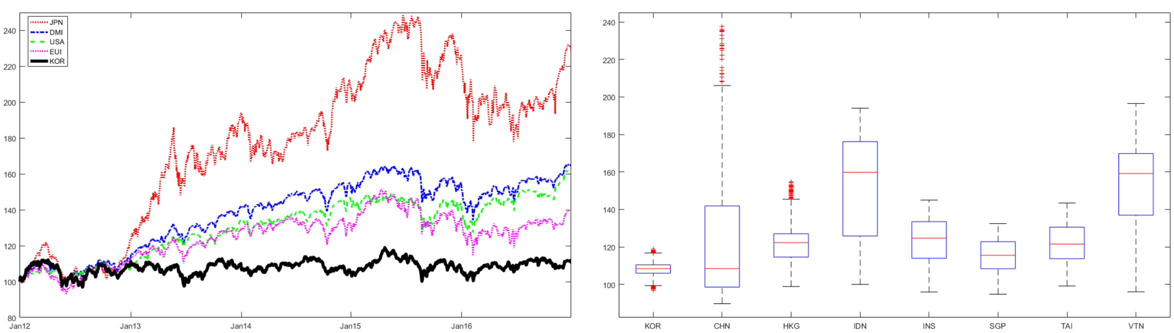
‡*Corresponding author.* School of Finance, Soongsil University, Seoul, South Korea. E-mail: ksyang@ssu.ac.kr

1 Introduction

> "More than \$3.5 billion of foreign outflows in 2015 helped keep the benchmark KOSPI stuck in its five-year range between 1,800 and 2,200 points, a corridor referred to locally as "BOXPI" ... Consumer staples, such as cosmetics, foods, beverage and daily necessities are promising sectors."
> — quotes from Bloomberg

The Korea Composite Stock Price Index (KOSPI) has been stagnant for the five years before 2017 compared to main global stock market indices (Figure 1-(a)) hovering around 2,000 points. It has also displayed the least movement in Asian stock markets, gaining just approximately 20% from its lowest to highest between 2012 and 2016 (Figure 1-(b)). The prolonged lack of movement has led Korean investors to adopt the acronym "BOXPI", which means boxed KOSPI. Figure 1 illustrates the BOXPI at a glance.

Figure 1: Comparison of the Korean Stock Market with Others.



(a) Korean vs. Developed stock markets (b) Korean vs. Asian stock markets

Note. *Figure 1-(a) depicts the time-series of NIKKEI225 (JPN), Morgan Stanley Capital International (MSCI) Developed Market Index (DMI), Dow Jones Industrial Average Index (USA), MSCI European Union Index (EUI), and KOSPI (KOR). Figure 1-(b) exhibits the box plot of the composite stock price indices of Korea and other Asian countries - China (CHN), Hong Kong (HKG), India (IDN), Indonesia (INS), Singapore (SGP), Taiwan (TAI), and Vietnam (VTN). The samples are obtained on a weekly basis from January 2012 to December 2016 and normalized at 100 as of 2012/01/04 for both figures.*

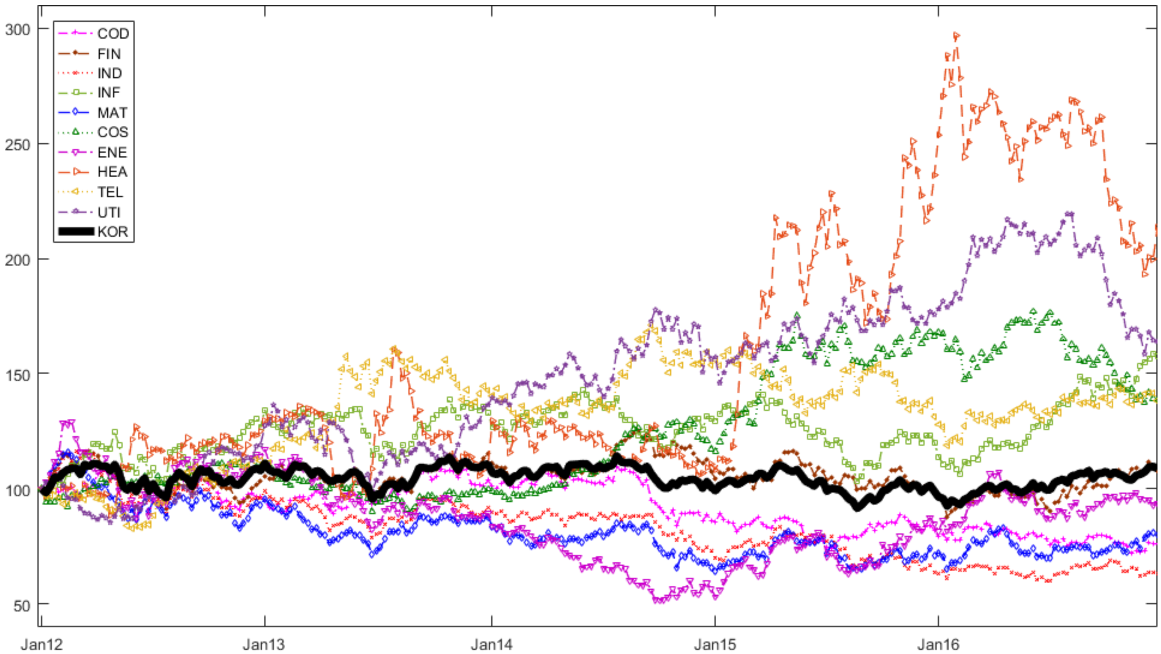
This observation is intriguing because a substantial amount of liquidity from the quantitative easing policies by major central banks, such as the US Federal Reserve System, the European Central Bank, and the Bank of Japan, was injected into all asset classes, including stock markets around the globe, at that time. The developed markets' indices presented in Figure 1-(a) have increased significantly, corresponding to the policy actions. The liquidity supply from advanced economies should be a positive sign for the Korean stock market too, as the South Korean economy heavily depends on its trade with developed countries and the Korean financial market has long been interconnected with them. Therefore, it is rather strange that the KOSPI has been boxed in for the five years from 2012. However, this phenomenon is yet to be investigated in the literature.

This study aims to interpret the BOXPI between 2012 and 2016 (hereafter referred to as the BOXPI period) from industry portfolio perspectives. Note that the industry portfolio indices of the Korean stock market are not boxed in during the BOXPI period contrary to the market portfolio index, as shown in Figure 2. A plausible explanation for this observation is sector rotation, which is naturally associated with industry portfolios. Jacobsen, Stangl, and Visaltanachoti (2011) prove that allocating between industry sectors over different stages of business cycles outperforms the market. Seeking to invest in sectors showing the strongest performance over a specific time-frame is also closely associated with momentum (Jegadeesh and Titman, 1993) and industry momentum (Moskowitz and Grinblatt, 1999). Some industries take on positive momentum while others are simultaneously contrarian. Thus, the multiple industry portfolio indices could cancel each other out, leading to the potential boxed market index, as exemplified in Figure 2.

The other theoretical background of this study is the heterogeneity of different industry sectors. There is ample evidence that industries exhibit heterogeneous patterns. For instance, Petersen and Strongin (1996) report that durable goods industries are three times more cyclical than non-durable goods industries and that the proportions of variable and fixed factor inputs, market concentration, and labor hoarding are important determinants of the cyclical behaviors of durable goods industries. Gomes, Kogan, and Yogo (2009) argue that owing to the heterogeneous sensitivities of different industries to economic conditions, time variations of expected returns should be different across industries.[1] Muller and Verschoor (2009) report that trade and service industries are

[1]The rationale is that the demand for durable goods is more cyclical than that for non-durable goods and services. Consequently, the cash flows and stock returns of durable goods producers are more exposed to the systematic risk.

Figure 2: Market and Industry Portfolio Indices of the Korean Stock Market.



Note. *This figure illustrates the weekly series of the MSCI Korea Index and its inherited sector price indices in Korean won (KRW). There are 10 sectors are in total: Consumer Discretionary (COD), Financials (FIN), Industrials (IND), Information Technology (INF), Materials (MAT), Consumer Staples (COS), Energy (ENE), Health Care (HEA), Telecommunication Services (TEL), and Utilities (UTI). The thick black line denotes the market index. All series are normalized at 100 as of 2012/01/04.*

more sensitive to exchange rate conditions for US multinationals. Similarly, Hutson and O'Driscoll (2010) state that industries are influenced differently by exchange rate sensitivity.

In this study, we derive the stochastic dynamics of the sector index to describe sector rotation by assuming a mean reverting process of the spread between the sector and market index return. We postulate that industry portfolio indices do not drift apart from the market index. Our proposed modeling is different from the conventional sector rotation strategies. Unlike utilizing conditional information, such as a set of lagged macroeconomic variables according to Chordia and Shivakumar (2002) and Jacobsen et al. (2011), lagged common risk factors (Du and Denning, 2005), monetary policy shifts (Conover, Jensen, Johnson, and Mercer, 2008), or slow diffusion of information across industries (Rapach, Strauss, Tu, and Zhou, 2015), we base our model on the *distance* between the sector and market index return. We provide an interpretation about the BOXPI in terms of sector rotation using the proposed model. Moreover, we apply a Bayesian variable selection method to examine how the sector portfolios have reacted differently to global common, local common, and sector-specific variables across sub-periods including the BOXPI period.

As a result of the empirical analysis, we establish that sector rotations have progressed in the Korean stock market according to the stages of economic scenarios, that is, the global financial crisis (GFC), the recovery from the crisis, BOXPI, and the upward escape from the BOXPI. During the BOXPI period, the sector rotation from cyclical to defensive sectors repeats twice, which restricts the rise of the market index since the cyclical sectors account for approximately 80% of the Korean stock market. The Bayesian variable selection analysis confirms the heterogeneities of different sectors. It shows that the importance probabilities of the key determinants of returns and the sensitivities of returns to them are different across sectors and sub-periods. It also finds that the lower bound of the BOXPI is related to low valuation, that is, low price-to-book ratio (PBR) of the KOSPI.

The contributions of this study are as follows. First, we develop a novel continuous-time model describing sector rotation. To the best of our knowledge, this is the first continuous time modeling for sector rotation. Second, we find empirical evidence of sector rotation in the Korean stock market. Lastly, we provide an interpretation about the BOXPI as a consequence of the sector rotation in the Korean stock market and KOSPI's low valuation.

The structure of this paper is as follows: In Section 2, we explain the sector classification used in the current study. Section 3 derives the theoretical model for sector rotation and discuss the estimated results. Section 4 briefly explains the Bayesian variable selection method and discuss the empirical results. Lastly, Section 5 concludes.

Table 1: Summary Statistics of the Portfolio returns of the 10 Sectors.

Statistic	Cyclical					Defensive				
	COD	FIN	IND	INF	MAT	COS	ENE	HEA	TEL	UTI
Mean	0.88%	0.46%	0.69%	0.85%	0.90%	1.21%	1.00%	1.18%	-0.25%	0.26%
Stdev	7.00%	7.97%	8.40%	7.41%	7.33%	4.98%	9.46%	7.77%	5.92%	6.49%
Skew	-0.21	-0.486	-0.628	-0.235	-0.392	-0.099	-0.224	0.083	0.028	-0.298
Kurt	4.73	6.845	5.801	3.836	3.931	3.134	4.195	4.214	3.535	3.320
Beta	0.884	1.150	1.235	1.035	1.069	0.467	1.178	0.650	0.428	0.446
Weight	14.2%	15.0%	13.7%	26.1%	9.7%	5.5%	3.2%	2.4%	6.3%	3.9%
ρ^{MSCI}	0.934	0.997	0.972	0.984	0.985	0.909	0.885	0.743	0.969	0.987

Note. *This table presents the sector classification of the Korean stock market used in this study - Consumer Discretionary (COD), Financials (FIN), Industrials (IND), Information Technology (INF), Materials (MAT), Consumer Staples (COS), Energy (ENE), Health Care (HEA), Telecommunication Services (TEL), and Utilities (UTI) - and the summary statistics of the monthly log return of each sector portfolio. The sample period is from January 2001 to April 2018. "Beta" is the average of the betas from the 3-year rolling window estimations of Sharpe's (1963) single index model. "Weight" is the weight of each sector in the market portfolio calculated as the average over the sample period. "*ρ^{MSCI}*" is the Spearman's correlation between the returns of the sector indices made by FnGuide and MSCI, showing the similarity of the two providers' indices.*

2 Sector Classification and Data

Choosing the sector portfolios requires a subtle approach due to the industry classification issue. The industry classification rule inherited in the KOSPI Industry Group Indices by the Korea Exchange (KRX) is inconsistent with the industry classification rules generally accepted in financial industries, such as the Global Industry Classification Standard (GICS); thus, it has been criticized by local investors.[2] To avoid this issue, we use MKF500 and MKF sector indices, developed by FnGuide, which is the most dominant local index provider in the Korean financial market, rather than the KOSPI and its sector indices, respectively. The MKF sector indices have 10 sectors, that is, COD, FIN, IND, INF, MAT, COS, ENE, HEA, TEL, and UTI, based on their classification rule similar to the GICS.[3]

[2] The KRX now publishes the Korean version of the GICS for its listed domestic companies. However, the historical data based on the new classification rule start from 2010, which makes them restrictive to our study.

[3] The MKF500 index has a near-perfect correlation with KOSPI for various calculation windows and similar risk–return profile to KOSPI. Furthermore, the MKF sector indices are very similar to MSCI Korea sector indices for each sector, as shown by ρ^{MSCI} in Table 1.

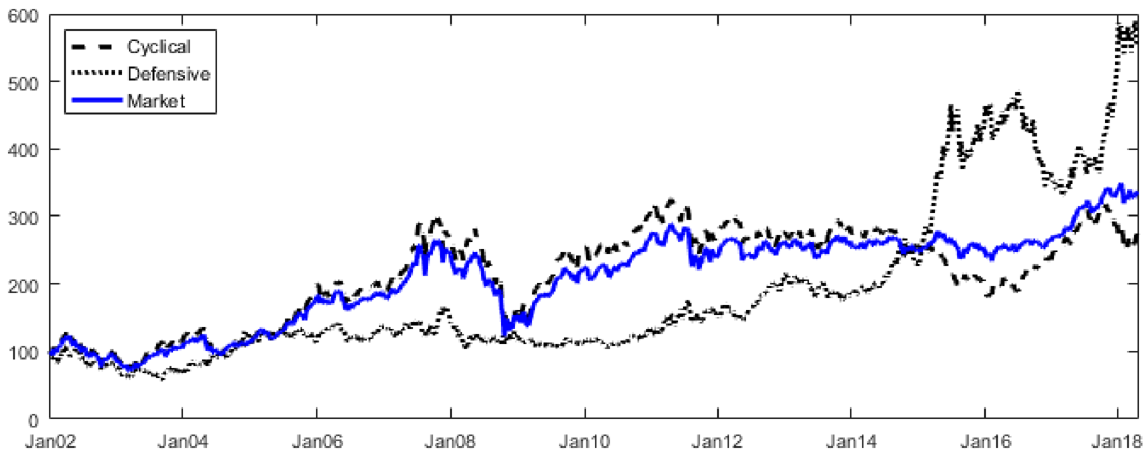
Table 1 summarizes the descriptive statistics of the monthly log returns of the 10 sector indices from January 2001 to April 2018. The cyclical and defensive sectors show distinctive features. The cyclical sectors generally exhibit a smaller mean, larger standard deviation and kurtosis, and more negative skew than the defensive ones. Furthermore, the cyclical sectors generally have market betas greater than 1 whereas the defensive secors' betas are smaller than 1. Lastly, the aggregated weight of the cyclical sectors is 78.7%, which is three times more than that of the defensive sectors. This is because the Korean economy heavily depends on exports and has the characteristic of a small open economy. Thus, if the cyclical sectors perform poorly, the rise of the market index will inevitably be limited. The largest weight of INF results from Samsung Electronics, whose market capitalization accounts for approximately 30% in the KOSPI as of 2018.

To elucidate our discussion, we investigate sector rotation between the two "grouped sectors", i.e., the *cyclical* and *defensive* sectors. According to the GICS, COD, FIN, IND, INF, and MAT are considered cyclical whose prices move more sensitively to the overall state of financial market. However, the remaining five sectors — COS, ENE, HEA, TEL, and UTI — are considered defensive as they have a smaller correlation with the overall direction of the market.[4] We construct the value-weighted indices for the two grouped sectors — the Cyclical (CYC) and Defensive (DEF) sectors — using the indices and market capitalizations of the respective five sectors of each.

Figure 3 shows the series of the market and grouped sector indices. The two grouped sector indices move up and down with the market index between them. For example, during the GFC in 2008, the CYC index goes down together with the market index and its distance form market becomes closer. However, in 2009, CYC bounds up along with the market, thereby extending the distance from the market. During the BOXPI period between 2012 and 2016, the DEF index gradually approaches the market index and eventually becomes larger than the market, whereas the CYC index drops below the market. Our sector rotation modeling to be introduced in the next section is based

[4]Morningstar also provides the three sector classification rule named "Super Sectors." It consists of Cyclical (COD, FIN, MAT), Defensive (COS, HEA, UTI), and Sensitive (IND, INF, ENE, TEL) sectors.

Figure 3: The Grouped Sector Indices: Cyclical vs. Defensive.



Note. *This figure describes the weekly series of the market and the grouped sector indices of the Korean stock market used in this study. Each grouped sector index is calculated as the value weighted average of its sub-indices. "Cyclical" includes the sector indices for COD, FIN, IND, INF, and MAT. "Defensive" covers COS, ENE, HEA, TEL, and UTI. The sample period spans from January 2002 to April 2018 when the time-varying parameters in Section 3.2 are estimated. All series are normalized at 100 as of 2002/01/04.*

on the intuition from these observations.

3 Sector Rotation Analysis

3.1 Continuous-time model

We assume the existence of a set of factors which drives all payoffs as well as prices of risk in the economy. These factors contain the information about uncertainties driven by the total factor productivity shock and the sector-specific productivity shocks. All prices of financial instruments are functions of these state variables.

Let $S_{i,t}$ and M_t denote the index of sector i and the market index at time t, respectively. We assume that the market index M_t follows the geometric Brownian motion:

$$\frac{dM_t}{M_t} = \mu_M dt + \sigma_M dB_t^M \,, \tag{1}$$

where μ_M and σ_M are the drift and the volatility, respectively, and B_t^M is the standard

Brownian motion proxy for aggregated shocks.[5]

We further postulate the spread between the sector and the market index. Our spread modeling approach is motivated by the existence of two heterogeneous investors, namely passive and active investors. As shown by Sassetti and Tani (2006), sector shifting can be profitable only in a medium term, and investing in market indices is more profitable in a long-term horizon while the ability of investors to rotate funds profitably from one sector to another would be questioned as pointed out by Tiwari and Vijh (2005). Based on this, we assume that there are heterogeneous investors investing in the market as passive investors as well as in sector rotations as active investors. We suppose that the return spread $X_{i,t} = \log(S_{i,t}/S_{i,t-\ell}) - \log(M_t/M_{t-\ell})$ between sector i and the market index follows the Ornstein–Uhlenbeck process:

$$dX_{i,t} = \kappa_i \left(\theta_i - X_{i,t}\right) dt + \sigma_i dB_t^i \tag{2}$$

for a fixed time interval ℓ and $i \in \{\text{CYC, DEF}\}$, where $\kappa_i(\theta_i - X_{i,t})$ is the expected instantaneous change of the spread at time t, θ_i is the long run equilibrium level to which the spread reverts, and B_t^i is the standard Brownian motion proxy for the sector specific productivity shock of sector i. The correlation coefficient between B_t^M and B_t^i is assumed to be $\rho_{M,i}$.

The the sector index dynamic is obtained from equations (1) and (2) by using Ito's lemma as follows:

$$\begin{aligned} \frac{dS_{i,t}}{S_{i,t}} &= \left(\mu_M + \frac{1}{2}{\sigma_i}^2 + \rho_{M,i}\sigma_M\sigma_i + \kappa_i(\theta_i - X_{i,t})\right) dt + \sigma_M dB_t^M + \sigma_i dB_t^i \\ &= \left(\gamma_i - \kappa_i X_{i,t}\right) dt + \tilde{\sigma}_i d\tilde{B}_t^i \,, \end{aligned} \tag{3}$$

where $\gamma_i = \mu_M + \frac{1}{2}{\sigma_i}^2 + \rho_{M,i}\sigma_M\sigma_i + \kappa_i\theta_i$, $\tilde{\sigma}_i = \sqrt{\sigma_M^2 + 2\rho_{M,i}\sigma_M\sigma_i + \sigma_i^2}$, and $\tilde{B}_t^i = \int_0^t \left(\sigma_M dB_s^M + \sigma_i dB_s^i\right) / \tilde{\sigma}_i$ is also a standard Brownian motion. This derivation is consis-

[5] Papanikolaou (2011) derives the stochastic differential equation for the value of the market portfolio $S_{M,t}$ with dividend stream $D_{M,t}$ as

$$\frac{dS_{M,t} + D_{M,t}dt}{S_{M,t}} = E_t\left[\frac{dS_{M,t} + D_{M,t}dt}{S_{M,t}}\right] + \sigma_x dB_t^A + \xi_M(\omega)\sigma_Z dB_t^Z \,,$$

where ω is the variable representing the state of the economy, and B_t^A and B_t^Z are the respective standard Brownian motions for the total factor productivity and investment shocks. Hence, $\sigma_M dB_t^M$ in equation (1) corresponds to the sum of the two Brownian motion terms stated above.

tent with Kogan and Papanikolaou (2010) and Papanikolaou (2011) where the stochastic differential equations for the asset risk premia of investment and consumption goods companies are derived.[6]

In equations (2) and (3), our key interest is the mean reversion captured by the parameter κ_i. If κ_i is positive, the sector index $S_{i,t}$ is expected to revert to the market index on average when it is far away from it. However, it will have the tendency of being away from the market index if κ_i is negative. The mathematical role of κ_i in equations (2) and (3) enables us to interpret κ_i as an indicator of active investors' preference to sector i conditional on $X_{i,t}$, the past performance of sector i over the market. For example, in case of $X_{i,t} < 0$ and $\kappa_i > 0$, we can infer that the sector i, which has recently under-performed the market, will improve and approach to the market index, thereby indicating the investor's increased preference to the sector. We discuss the interpretation of the parameter more comprehensively in the next subsection.

3.2 Discrete-time model

We discretize the continuous-time model in equation (3) by incorporating a time-varying relationship between the sector and the market portfolio's return. We consider a linear regression consistent to equation (3) and allow for gradual changes of regression coefficients over time as follows:

$$\begin{aligned} Y_{i,t} &= \alpha_i + \beta_{i,t} X_{i,t} + e_{i,t}, \quad e_{i,t} \sim i.i.d.\,\mathcal{N}(0, \sigma^2_{e_i}), && (4) \\ \beta_{i,t} &= \beta_{i,t-1} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim i.i.d.\,\mathcal{N}(0, \sigma^2_{\varepsilon_i}), && (5) \end{aligned}$$

[6]Specifically, Papanikolaou (2011) derives the values of the investment goods $S_{I,t}$ and the consumption goods sector $S_{C,t}$ as the stochastic differential equations presented below:

$$\frac{dS_{I,t} + D_{I,t}dt}{S_{I,t}} = E_t\left[\frac{dS_{I,t} + D_{I,t}dt}{S_{I,t}}\right] + \sigma_x dB_t^A + \xi_I(\omega)\sigma_Z dB_t^Z\,,$$

$$\frac{dS_{C,t} + D_{C,t}dt}{S_{C,t}} = E_t\left[\frac{dS_{C,t} + D_{C,t}dt}{S_{C,t}}\right] + \sigma_x dB_t^A + \xi_C(\omega)\sigma_Z dB_t^Z\,.$$

Here, $\xi_I(\omega)$ and $\xi_C(\omega)$ capture the sensitivities to the investment shock. The investment shock (dB_t^Z) affects the value of the investment and the consumption goods firm differently due to the existence of heterogeneous sensitivities in each sector, $\xi_I(\omega)$ and $\xi_C(\omega)$. On the other hand, the total factor productivity shock (dB_t^A) has a symmetric effect on both sectors.

where $Y_{i,t} = \log S_{i,t+h} - \log S_{i,t}$ is the future log return of sector i over the next h–weeks and $X_{i,t} = \log(S_{i,t}/S_{i,t-\ell}) - \log(M_t/M_{t-\ell})$ is the spread between the past log returns of sector i and the market portfolio during the recent ℓ–weeks. We select $\ell = 52$ (i.e., 12 months) and $h = 39$ (i.e., 9 months) as they maximize the average R^2 of the regression equation (4) for $i = 1$ (CYC) and 2 (DEF).[7]

The main objective of the extended discrete model is to estimate the parameters $\{\beta_{i,t}\}_{t=1}^{T}$, the dynamic sensitivity of sector i's return to its deviation from the market. Now, we discuss the interpretation of $\beta_{i,t}$. First, the time-varying linear regression coefficient $\beta_{i,t}$ in equation (4) corresponds to the negative of κ_i in equations (2) and (3). Second, $\beta_{i,t} < 0$ implies the mean reverting property of $X_{i,t}$ in equation (2) and equivalently the market-reverting property of $S_{i,t}$ in equation (3) at time t. Here, if $X_{i,t} < 0$ ($X_{i,t} > 0$), which means a recent lower (higher) return of sector i than the market, we can infer that the index of sector i will go up (down) closer to the market index recovering (losing) active investors' preference. Third, $\beta_{i,t} > 0$, however, suggests that $S_{i,t}$ does not possess the market-reverting property but the tendency of being away from the market index at time t. In this case, the under (over) performance of sector i compared to the overall market during the recent lag period (ℓ) is likely to last for the upcoming holding period (h) still losing (gaining) preference of active investors. Thus, $\beta_{i,t}$ contains information about active investors' conditional preference to a sector relative to the other and consequent sector rotation.

We can infer the current state of sector preferences by interpreting $\beta_{i,t}$ along with $X_{i,t}$, as summarized in Table 2. In Table 2, PP indicates a type of sector momentum since a sector which has recently beaten the market is expected to keep gaining positive returns, while NN means the market reversion of a sector that has recently experienced under-performance relative to the market. In summary, we can interpret PP and NN

[7] Jegadeesh and Titman (1993) construct momentum portfolios based on the past 3-, 6-, 9-, and 12-month ($\ell = 13, 26, 39, 52$) returns and analyze performances over the subsequent 3, 6, 9, and 12 months ($h = 13, 26, 39, 52$) using US stock market data. Moskowitz and Grinblatt (1999) use $\ell = h = 26$ (6 months) to measure momentum profits of industry portfolios in the US stock market. Chui, Titman, and Wei (2010) apply $\ell = h = 26$ (6 months) to compare the performances of momentum strategies across various countries, including Korea. Based on the literature, we have tried all combinations of $\ell = 13, 26, 39, 52$ and $h = 13, 16, 39, 52$ to find the optimal (ℓ, h) with the largest average R^2. The detailed results for this comparison are available upon request.

Table 2: Interpretation of $\beta_{i,t}$ in Equations (4) and (5).

Past performance of sector i relative to the market	Future performance of sector i	
	$\beta_{i,t} > 0$	$\beta_{i,t} < 0$
$X_{i,t} > 0$	[PP] $S_{i,t}$ will increase. (Continuing preference)	[PN] $S_{i,t}$ will decrease. (Losing preference)
$X_{i,t} < 0$	[NP] $S_{i,t}$ will decrease. (Continuing less preference)	[NN] $S_{i,t}$ will increase. (Gaining preference)

Note. *This table summarizes the interpretation of the time-varying parameter $\beta_{i,t}$ in equations (4) and (5). We label each cell as PP (the positive $X_{i,t}$ and the positive $\beta_{i,t}$), PN (the positive $X_{i,t}$ and the negative $\beta_{i,t}$), NP (the negative $X_{i,t}$ and the positive $\beta_{i,t}$), and NN (the negative $X_{i,t}$ and the negative $\beta_{i,t}$) according to the signs of $X_{i,t}$ and $\beta_{i,t}$.*

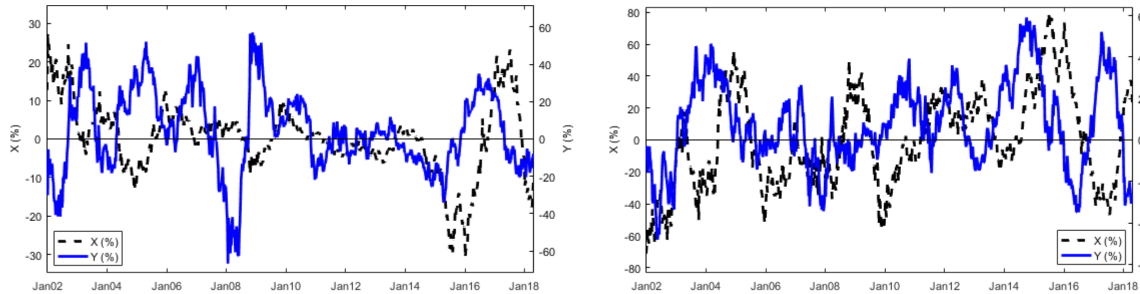
as indicators of preference to a sector by active investors. Conversely, PN and NP have opposite meanings and can be interpreted as signals of less preference to a sector: PN indicates that a past winner sector over the market will lose its returns, whereas NP suggests that a sector which has been less profitable recently than the market will fall down.

Note that the states in the right column ($\beta_{i,t} < 0$) in Table 2 indicate reversions of sector indices to the market index. PN is the downward reversion whereas NN is the upward reversion. Therefore, if one sector is in the state PN while the other is in NN simultaneously, we can in interpret it as a signal of the sector rotation from the former to the latter.

Our reasoning on the sign of $\beta_{i,t}$ is negative on average as we postulate that the market-reversion of a sector index is implemented following equations (2)–(5). Figure 4 captures our reasoning graphically, indicating that our dependent and independent variables in equation (4) do not drift away from each other and individual sectors display heterogeneous time-series patterns.

We estimate the time-varying parameter model in equations (4) and (5) using a conventional Bayesian algorithm. The model can be estimated by maximum likelihood estimation, but it is significantly affected by the initial values in the optimization process. To avoid this issue, a Bayesian Markov chain Monte Carlo (MCMC) algorithm is used to estimate the model parameters $\{\alpha_i, \sigma^2_{e_i}, \sigma^2_{\varepsilon_i}\}$ and $\{\beta_{i,t}\}_{t=1}^{T}$. For a more detailed estimation

Figure 4: Sector and Its Excess Returns over the Market Portfolio.



(a) CYC (b) DEF

Note. *These figures present the series of the dependent and independent variables in equation (4) from January 2002 to April 2018, with the lag periods (ℓ) of 52 weeks (12 months) and the holding periods (h) of 39 weeks (9 months). Figures 4-(a) and (b) are for the cyclical and the defensive sectors, respectively.*

procedure, please refer to Greenberg (2012).

3.3 Empirical results: Dynamic sector rotation

We use the weekly (every Friday) data of the market, CYC, and DEF indices from January 2001 to January 2019 for estimation. Table 3 presents the estimated values of the parameters $\{\alpha_i, \sigma^2_{e_i}, \sigma^2_{\varepsilon_i}\}$ in equations (4) and (5).

In Table 3, CYC shows an evidently larger volatility of return (σ_{e_i}) in the measurement equation than DEF, consistent with the standard deviations and market betas in Table 1. The volatility of beta in the transition equation (σ_{ε_i}) shows a similar pattern but is less clear.[8] Figures 5-(b1) and 5-(b2) confirm that the in-sample estimates $\{\hat{Y}_{i,t}\}_{t=1}^{T}$ generated by equations (4) and (5) with $\{\hat{\alpha}_i, \hat{\sigma}^2_{e_i}, \hat{\sigma}^2_{\varepsilon_i}\}$ in Table 3 track the observed sector returns $\{Y_{i,t}\}_{t=1}^{T}$ successfully.

Based on the time-varying parameter model in equations (4) and (5) along with the parameter estimates in Table 3, we obtain the estimated series of the parameters $\{\hat{\beta}_{i,t}\}_{t=1}^{T}$ for the two grouped sectors from January 2002 to April 2018. Figure 5-(a) illustrates the heterogeneous dynamics of the estimated sensitivities $\{\hat{\beta}_{i,t}\}_{t=1}^{T}$ across the sectors and Table 4 summarizes it. In Table 4, we first find that the unconditional mean of $\hat{\beta}_{i,t}$ during the full period is negative for both sectors, implying that both sector indices on average revert to the market index. Second, the absolute value of the mean is greater for CYC

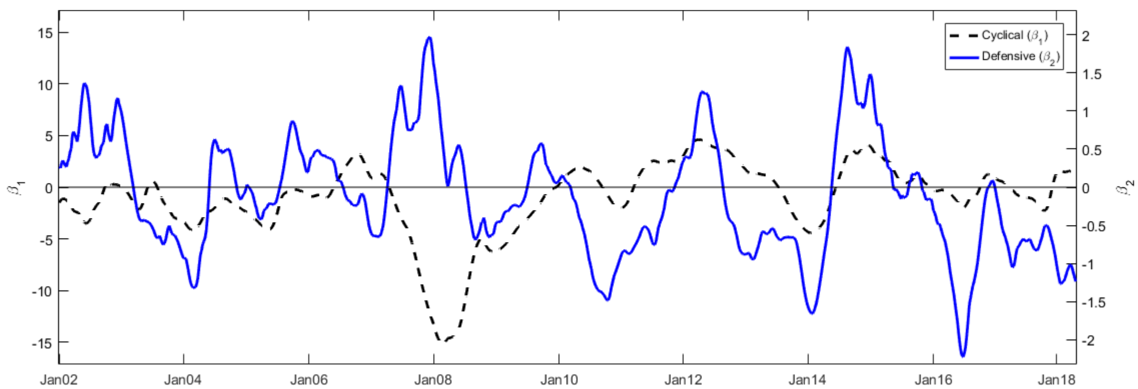
[8]These results are robust for various (ℓ, h)s.

Table 3: Estimated Results of the Time-varying Parameter Models.

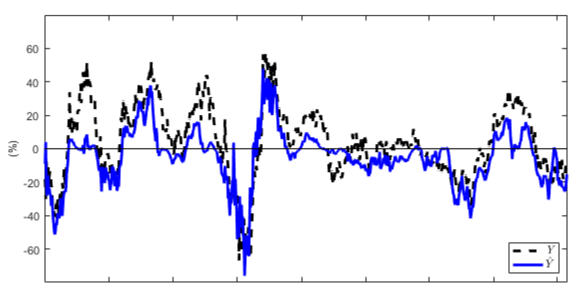
Equation	Parameter	Sector	
		CYC	DEF
Measurement equation	α_i	0.0979	0.0991
		(0.0889)	(0.0913)
	σ_{e_i}	0.4142	0.0850
		(0.0680)	(0.0089)
Transition equation	σ_{ε_i}	0.0355	0.0324
		(0.0128)	(0.0141)
R^2		0.4636	0.6122

Note. *This table displays the estimates of* $\{\alpha_i, \sigma^2_{e_i}, \sigma^2_{\varepsilon_i}\}$ *in the time-varying parameter model in equations (4) and (5). The estimates are the means of the posterior distributions of the parameters obtained from the Bayesian MCMC algorithm. The values in parentheses are the standard deviations of the posterior distributions.*

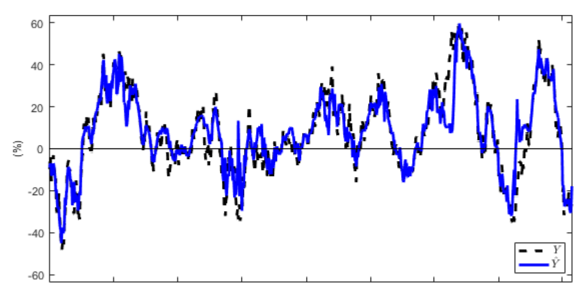
Figure 5: Estimated Results of the Time-varying Parameter Models.



(a) $\hat{\beta}_{1,t}$ and $\hat{\beta}_{2,t}$



(b1) Y_t and $\hat{Y}_t$ of CYC



(b2) Y_t and $\hat{Y}_t$ of DEF

Note. *Figure 5-(a) shows the estimated series of* $\{\beta_{i,t}\}_{t=1}^{T}$ *in equations (4)–(5) for CYC* ($i = 1$) *and DEF* ($i = 2$)*. Figures 5-(b1) and (b2) illustrate the observed and the estimated sector returns for CYC and DEF, respectively.*

Table 4: Summary of the Estimated Time-varying Parameters $\{\hat{\beta}_{i,t}\}_{t=1}^{T}$.

Statistic	Cyclical			Defensive		
	Full period	GFC	BOXPI	Full period	GFC	BOXPI
Mean	-1.0728	-6.7132	0.8841	-0.1276	0.0282	-0.1813
Stdev	3.6842	4.9066	2.4418	0.7742	0.5135	0.9279
Skew	-1.6109	-0.5283	-0.4210	0.2319	0.7963	0.1512

Note. *This table displays the summary statistics of the estimated $\{\beta_{i,t}\}_{t=1}^{T}$ in equation (5) over the full and the sub-periods. Here, "Full period" means the full sample period from January 2002 to April 2018, while "GFC" and "BOXPI" mean the GFC period from October 2007 to June 2009 and the BOXPI period from January 2012 to December 2016, respectively. We select the GFC period based on the US business cycle contraction periods defined by the National Bureau of Economic Research.*

than DEF. Moreover, the sign of skewness is negative for CYC whereas it is positive for DEF. These suggest that CYC has a stronger tendency of market reversion than DEF overall. Third, if we consider the mean and skewness by sub-periods, the market reverting properties of CYC and DEF are strong during the GFC and the BOXPI period, respectively. This suggests that the degrees of market reversion are heterogeneous across sectors and economic conditions, consistent with the results of Petersen and Strongin (1996) and Gomes et al. (2009). Lastly, CYC shows greater variation of $\beta_{i,t}$ than DEF, consistent with the results presented in Tables 1 and 3.

Taking a step further into the time-varying states of the sector preferences, we define an indicator to measure the current degree of investors' preference to sector i, $\Phi_t^i(s)$, by counting the number of each state $s \in \{NN, PP, PN, NP\}$ in Table 2 in a recent time interval $(t-\tau, t]$ as follows:

$$\Phi_t^i(s) = \frac{1}{\tau} \sum_{u=t-(\tau-1)}^{t} I_{\{\phi_u^i = s\}} \tag{6}$$

satisfying $\sum_s \Phi_t^i(s) = 1$ for $i = CYC$ and DEF, where ϕ_u^i is the preference state of sector i at time u. The main inferences from $\Phi_t^i(s)$ are as presented below:

- Case 1: A larger $\Phi_t^i(NN) + \Phi_t^i(PP)$ indicates that investors would favor sector i compared to the other.

- Case 2: Conversely, a greater $\Phi_t^i(PN) + \Phi_t^i(NP)$ implies that investors are likely to be less-preferable to sector i than the other.

- Case 3: The simultaneous rise of $\Phi_t^i(PN)$ and $\Phi_t^j(NN)$ suggests that active investors switch their preference from sector i to j, i.e., a sector rotation from sector i to j.

- Case 4: The rise of $\Phi_t^i(NP)$ and $\Phi_t^j(PP)$ all together following (Case 3) indicates that active investors keep switching their preference from sector i to j, i.e., the continuing sector rotation from sector i to j.

We select the window size τ as 104 weeks (i.e., 24 months) considering that the average lengths of the peak-to-peak and the bottom-to-bottom business cycle of the Korean economy are 52 and 48 months, respectively.[9]

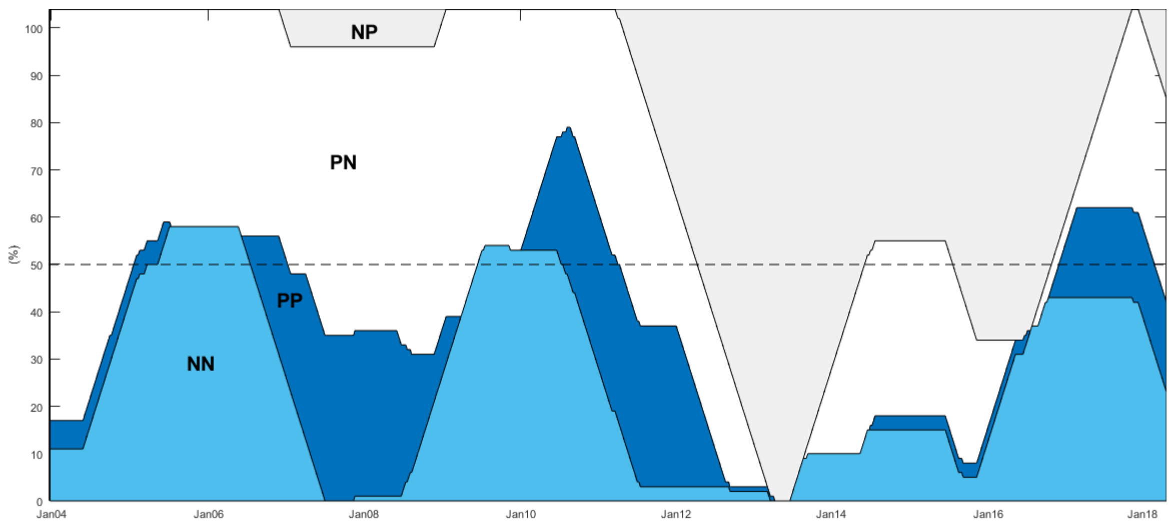
Figure 6 shows the cumulative area graph of the series of $\Phi_t^i(s)$ for each grouped sector. In 2004, both CYC in Figure 6-(a) and DEF in Figure 6-(b) gain preference with $\Phi_t^i(NN) + \Phi_t^i(PP)$ gradually rising to over 50%, indicating an overall boom of the Korean stock market. However, from late 2005 to late 2006, only CYC maintains its status and DEF loses investors' interests with vanishing $\Phi_t^{DEF}(NN)$ and increasing $\Phi_t^{DEF}(PN) + \Phi_t^{DEF}(NP)$.

In 2007, as the GFC takes place, CYC starts to lose investors' preference showing $\Phi_t^{CYC}(PN)$ and $\Phi_t^{CYC}(NP)$ becoming larger leading to $\Phi_t^{CYC}(NN) + \Phi_t^{CYC}(PP)$ below 50%. Meanwhile, $\Phi_t^{DEF}(NN)$ increases although $\Phi_t^{DEF}(NN) + \Phi_t^{DEF}(PP)$ still stays far below 50%. These indicate the beginning of the downturn with a weak sector rotation from CYC to DEF (Case 3). The status continues until late 2008. From late of 2008 to the end of 2009, $\Phi_t^{DEF}(PN)$ leads to vanishing $\Phi_t^{DEF}(PN)$, and $\Phi_t^{CYC}(NN)$ becomes greater simultaneously, which can be interpreted as a sector rotation from DEF to CYC (Case 3). This implies that CYC has led the recovery of the Korean stock market in the late stage of the GFC. In 2010, CYC keeps gaining and DEF recovers the preference with rising $\Phi_t^{CYC}(PP)$[10] and $\Phi_t^{DEF}(NN)$, respectively. This indicates the boom of the

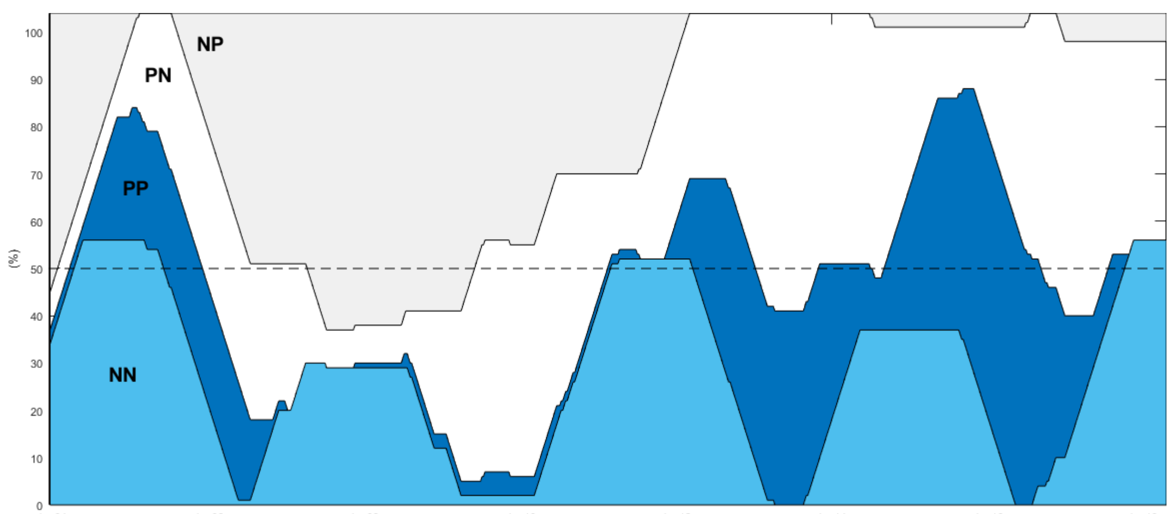
[9] http://kosis.kr/visual/bcc/index/index.do?mb=N

[10] We can interpret this as the momentum after the rebound.

Figure 6: Estimated States of Sector Preference.



(a) Sector preference to CYC



(b) Sector preference to DEF

Note. *Figures 6–(a) and (b) show the series of* $\Phi_t^i(NN)$, $\Phi_t^i(PP)$, $\Phi_t^i(PN)$ *and* $\Phi_t^i(NP)$ *from equation (6) with* $\tau = 24$ *months for* CYC *and* DEF*, respectively.*

Korean stock market after the recovery.

The BOXPI period shows clear signs of sector rotations from CYC to DEF. In 2011, just before the BOXPI period, both $\Phi_t^{CYC}(PN)$ and $\Phi_t^{DEF}(NN)$ increase, which means sector rotation from CYC to DEF (Case 3). The rotation continues in 2012 with $\Phi_t^{CYC}(NP)$ and $\Phi_t^{DEF}(PP)$ rising simultaneously (Case 4). It is quite strong since even $\Phi_t^{CYC}(NN) + \Phi_t^{CYC}(PP)$ vanishes to nearly 0% and $\Phi_t^{DEF}(NN) + \Phi_t^{DEF}(PP)$ goes up to approximately 70%. In the mid BOXPI period, we find an additional sign of the sector rotation from CYC to DEF. From late 2013 to mid 2014, $\Phi_t^{CYC}(PN)$ and $\Phi_t^{DEF}(NN)$ increase simultaneously (Case 3). From mid 2014 to the end of 2015, $\Phi_t^{CYC}(NP)$ increases marginally and $\Phi_t^{DEF}(PP)$ rises[11] with $\Phi_t^{DEF}(NN) + \Phi_t^{DEF}(PP)$ reaching its peak around 90%.

The last year of the BOXPI period shows sector rotation from DEF to CYC. In 2016, $\Phi_t^{DEF}(PN)$ and $\Phi_t^{CYC}(NN)$ rise altogether (Case 3) with $\Phi_t^{DEF}(NN)+\Phi_t^{DEF}(PP)$ below 50% and $\Phi_t^{CYC}(NN)+\Phi_t^{CYC}(PP)$ over 60%. In 2017, when the KOSPI upwardly escapes from its boxed range, CYC maintains $\Phi_t^{CYC}(NN) + \Phi_t^{CYC}(PP)$ over 60% and DEF regains investors' attention with increasing $\Phi_t^{DEF}(NN)$ over 50%, indicating an overall boom of the stock market.

In conclusion, sector rotations have progressed in the Korean stock market according to the stages of economic scenarios and we can understand the BOXPI in this vein. As CYC accounts for approximately 80% of the Korean stock market, as shown in Table 1, the repeating sector rotations from CYC to DEF during the BOXPI period have limited the rise of the KOSPI. However, the box in the BOXPI includes the existence of both lower and upper limits. What drives the lower limit? This motivates us to conduct the second empirical analysis in the next section.

[11] This can be interpreted as the momentum after the rebound, similar to footnote 10.

4 Bayesian Variable Selection Analysis

4.1 Methodology

To determine which variables are relevant to CYC and DEF indices in different subperiods (the GFC and BOXPI), we apply a Bayesian variable selection method. This approach is useful for selecting important variables among a large number of candidates. The linear regression model used in the Bayesian variable selection method is as follows:

$$y_{i,t} = \boldsymbol{\beta}_i' \boldsymbol{x}_t + e_{i,t}, \quad e_{i,t} \sim i.i.d. \mathcal{N}(0, \sigma_i^2 I_T) \tag{7}$$

for i = CYC, DEF and $t = 1, \cdots, T$, where $y_{i,t}$ is the weekly log return of an index. For each sector, we conduct three separate estimations of equation (7) with different types of explanatory variables ($\boldsymbol{x}_t$) — global common, local common, and sector-specific variables. The global common variables consist of short-term interest rate, term spread, trade activity, value of USD, stock market volatility, sovereign default risk, funding liquidity, economic policy uncertainty, and commodity price. The local common variables are comprised of short-term interest rate, term spread, trade activity, value of KRW, stock market volatility, sovereign default risk, funding liquidity, and economic policy uncertainty. The sector specific variables are composed of profitability, value, and foreign investment. The details of the variables are illustrated in Table 5.

This study employs an MCMC algorithm to estimate the model in equation (7). We use the hierarchical prior distribution and set the hyper-parameters for the distribution of each parameter as non-informative to fully reflect the information from data. The sampling algorithm for the posterior distributions can be summarized as follows:

Algorithm: Bayesian variable selection (for each i)
Step 1: Generate $\boldsymbol{\beta}_i$ from $\boldsymbol{\beta}_i | Y_i, X, \sigma_i^2, \Gamma_i$,
Step 2: Generate σ_i^2 from $\sigma_i^2 | Y_i, X, \boldsymbol{\beta}_i, \Gamma_i$,
Step 3: Generate Γ_i from $\gamma_{i,k} | Y_i, X, \boldsymbol{\beta}_i, \sigma_i^2, \Gamma_{i,-k}$ for $k = 1, ..., K$,

where $Y_i = \{y_{i,t}\}_{t=1}^{T}$, $X = \{x_{t,k}\}_{t=1,\,k=1}^{T,\,K}$, $\boldsymbol{\beta}_i = \{\beta_{i,k}\}_{k=1}^{K}$, $\Gamma_i = \{\gamma_{i,k}\}_{k=1}^{K}$, and $\Gamma_{i,-k} = \Gamma_i - \{\gamma_{i,k}\}$ for i = CYC, DEF. Here, $\gamma_{i,k}$ is the variable selection parameter defined as

Table 5: Explanatory Variables for Bayesian Variable Selection Regression

Variable	Data	Scale	Data source
Type A: Global common variables			
Short-term interest rate	US Treasury 3-month yield	Difference	Bloomberg (Ticker: GGR)
Term spread	US Treasury 10-year to 3-month yield	Difference	Bloomberg (Ticker: GGR)
Trade activity*	YoY growth rate of monthly world export volume	Difference	IMF
Value of USD	USD Index calculated by ICE	Log difference	Bloomberg (Ticker: DXY Index)
Stock market volatility	VIX	Difference	Bloomberg (Ticker: VIX Index)
Sovereign default risk	Average of the 5-year CDS spreads of US, Japan, and China	Difference	Bloomberg (Ticker: SOVR)
Funding liquidity	TED spread	Difference	FRED
Economic policy uncertainty*	Baker, Bloom, and Davis (2016)'s global EPU index	Log difference	Bloomberg (Ticker: EPUCGLCP Index)
Commodity price	WTI price	Log difference	Bloomberg (Ticker: USCRWTIC Index)
Type B: Local common variables			
Short-term interest rate	Korea Treasury 3-month yield	Difference	Bloomberg (Ticker: GGR)
Term spread	Korea Treasury 10-year to 3-month yield	Difference	Bloomberg (Ticker: GGR)
Trade activity*	YoY growth rate of monthly Korean export volume	Difference	IMF
Value of KRW	USDKRW spot currency rate	Log difference	Bloomberg (Ticker: USDKRW REGN Curncy)
Stock market volatility	VKOSPI	Difference	Bloomberg (Ticker: VKOSPI Index)
Sovereign default risk	5-year CDS spread of Korea	Difference	Bloomberg (Ticker: SOVR)
Funding liquidity	USDKRW 1-month FX swap point	Difference	Bloomberg (Ticker: KWO1M BGN Curncy)
Economic policy uncertainty*	Baker, Bloom and Davis (2016)'s Korean EPU index	Log difference	Bloomberg (Ticker: EPUCSKOR Index)
Type C: Sector-specific variables			
Profitability	Price-to-Earnings ratio of each sector	Log difference	Data Guide
Value	Price-to-Book ratio of each sector	Log difference	Data Guide
Foreign investment	Proportion of foreign investors' holding in each sector	Log difference	Data Guide

Note. **As the original data are provided on a monthly basis, we apply linear interpolation to obtain the weekly series.*

the Bernoulli variable with the value of 1 when $\beta_{i,k}$ is non-zero. Given a posterior sample of $\gamma_{i,k}$, the corresponding explanatory variablex_k is regarded as an important variable depending on the value of $\gamma_{i,k}$. Therefore, the posterior mean of $\gamma_{i,k}$ is interpreted as the importance probability of x_k for sector i's index. Intuitively, when the estimated $\beta_{i,k}$ differs from zero, x_k is chosen as an important variable. Conversely, when the estimated $\beta_{i,k}$ is close to zero, x_k is treated as non-critical. For a more detailed procedure of each step of the algorithm, please refer to George and McCulloch (1993) and George and McCulloch (1997).

4.2 Estimated results

Table 6 presents the estimated $\beta_{i,k}$'s and importance probabilities of the global common, local common, and sector-specific variables using the full sample (January 2001 – April 2018), GFC (October 2007 – June 2009), and BOXPI (January 2012 – December 2016) periods for each sector. In Panels A and B of Table 6, we find that interest rate related variables, such as "short-term interest rate," "Term spread," and "Funding liquidity," are the key determinants of the both sector indices. However, the two sectors show opposite signs of the estimated $\beta_{i,k}$'s and different importance probabilities in both of the sub-periods. Furthermore, the estimated regression coefficients and their importance probabilities vary considerably across the sub-periods for each sector. Hence, we conclude that the importance of the variables, as well as the sensitivities of returns to them, depends on both sectors and sub-periods. These results support Gomes et al. (2009) stating that the time variations of expected returns should be different across industries due to the heterogeneous sensitivities of different industries to economic conditions.

In Panel C of Table 6, "Value" is selected as the most important variable for DEF especially in the BOXPI period. This indicates that active investors seek low PBR stocks when switching their portfolios from CYC to DEF in the BOXPI period. This result provides a clue to understanding the lower bound of the BOXPI. In Figure 7–(a), KOSPI moves between PBR 1.0× and 1.2×during the BOXPI period and finally decreases to PBR 1.0×. The PBR of a composite stock price index of less than 1 is usually regarded as a relatively apparent sign of overall under-valuation of a stock market as it means

Table 6: Estimated Results of the Bayesian Variable Selection Regression

Variable	Cyclical						Defensive					
	Full period		GFC		BOXPI		Full period		GFC		BOXPI	
	Beta	[Prob.]	Beta	[Prob.]	Beta	[Prob.]	Beta	[Prob.]	Beta	[Prob.]	Beta	[Prob.]
Panel A: Global common variables												
Short-term interest rate	1.810	[99%]	1.391	[95%]	0.235	[83%]	-0.233	[68%]	-0.173	[74%]	-1.409	[91%]
Term spread	0.696	[89%]	0.596	[74%]	0.356	[57%]	0.060	[50%]	-0.963	[81%]	-0.660	[73%]
Trade activity	-0.053	[12%]	0.071	[15%]	-0.043	[13%]	0.043	[14%]	0.264	[30%]	-0.056	[13%]
Value of USD	-0.007	[12%]	-0.012	[14%]	0.008	[13%]	-0.084	[15%]	0.066	[16%]	-0.030	[11%]
Stock market volatility	-0.005	[11%]	0.000	[13%]	0.009	[14%]	-0.014	[14%]	-0.103	[17%]	-0.046	[11%]
Sovereign default risk	0.014	[11%]	0.010	[13%]	0.002	[13%]	-0.026	[13%]	-0.046	[15%]	0.034	[11%]
Funding liquidity	0.936	[95%]	0.572	[73%]	0.242	[83%]	0.041	[59%]	0.467	[69%]	-1.275	[89%]
Economic policy uncertainty	-0.009	[11%]	-0.019	[12%]	-0.003	[12%]	-0.003	[14%]	-0.055	[15%]	-0.027	[11%]
Commodity price	-0.001	[12%]	-0.005	[12%]	0.000	[12%]	0.005	[14%]	-0.027	[14%]	0.003	[11%]
Panel B: Local common variables												
Short-term interest rate	0.179	[54%]	-0.260	[69%]	0.733	[78%]	0.157	[68%]	1.492	[88%]	-0.165	[79%]
Term spread	0.200	[40%]	0.312	[59%]	-0.742	[81%]	-0.957	[91%]	-0.449	[70%]	0.824	[78%]
Trade activity	0.029	[11%]	-0.003	[13%]	0.012	[12%]	-0.043	[14%]	-0.179	[21%]	0.020	[12%]
Value of KRW	-0.078	[13%]	-0.023	[12%]	0.018	[13%]	0.036	[14%]	0.178	[21%]	-0.119	[13%]
Stock market volatility	-0.096	[13%]	-0.076	[14%]	-0.072	[14%]	0.043	[14%]	0.099	[16%]	0.051	[12%]
Sovereign default risk	-0.014	[11%]	-0.008	[12%]	-0.017	[12%]	0.012	[14%]	0.005	[14%]	-0.012	[11%]
Funding liquidity	0.044	[13%]	0.032	[12%]	-0.100	[25%]	0.007	[13%]	0.039	[15%]	-0.080	[40%]
Economic policy uncertainty	-0.003	[12%]	0.001	[12%]	0.000	[13%]	-0.003	[14%]	0.022	[15%]	0.019	[10%]
Panel C: Sector-specific variables												
Profitability	0.004	[11%]	0.086	[14%]	0.205	[21%]	-0.008	[13%]	0.006	[14%]	-0.008	[10%]
Value	0.242	[26%]	0.226	[25%]	0.106	[15%]	0.401	[63%]	0.290	[31%]	0.387	[46%]
Foreign investment	0.121	[15%]	-0.121	[18%]	0.300	[37%]	0.120	[17%]	0.285	[38%]	-0.256	[26%]

Note. *This table displays the estimated results of the Bayesian variable selection regression in equation (7) for each sector. Beta is the posterior mean of the parameter estimate and Prob. is the importance probability of the corresponding explanatory variable.*

the market value of the equity less than the book value in aggregation. A composite stock price index's PBR of less than 1 is generally considered a relatively clear sign of stock market undervaluation, as it means that the sum of the market values of the stock market is less than the sum of its book values. Figure 7–(b) illustrates that the KOSPI and its PBR move differently during the BOXPI period and begin to rise together from 2017 when the market escapes out of the BOXPI. From these observations, we can deduce that the low valuation has prevented the KOSPI from additional falls and PBR 1.0× has played the role as a support level.

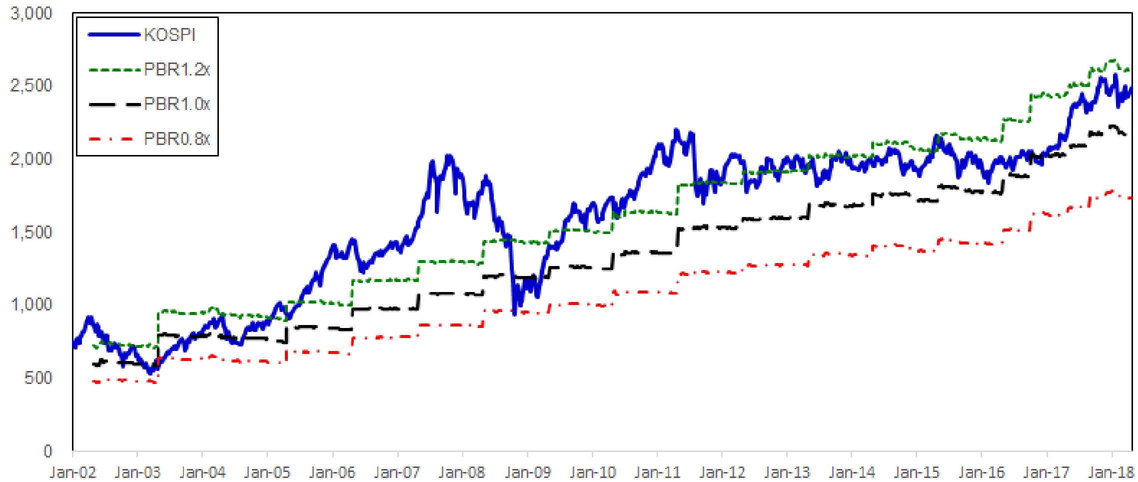
5 Conclusion

The term "BOXPI" was coined for the KOSPI by local investors as the index had been trading in a narrow range during the 2012–2016 period when the liquidity of global stock markets was expanding. This is a unique phenomenon that remains unexplained in the literature. This study employs industry portfolio perspectives to explain the BOXPI phenomenon. We derive a novel continuous-time sector index model by assuming the mean reversion of the spread between sector and market returns, and use it to empirically investigate the sector rotation between the cyclical and defensive sectors in the Korean stock market. We also apply the Bayesian variable selection method to examine the determinants of the portfolio return of each sector.

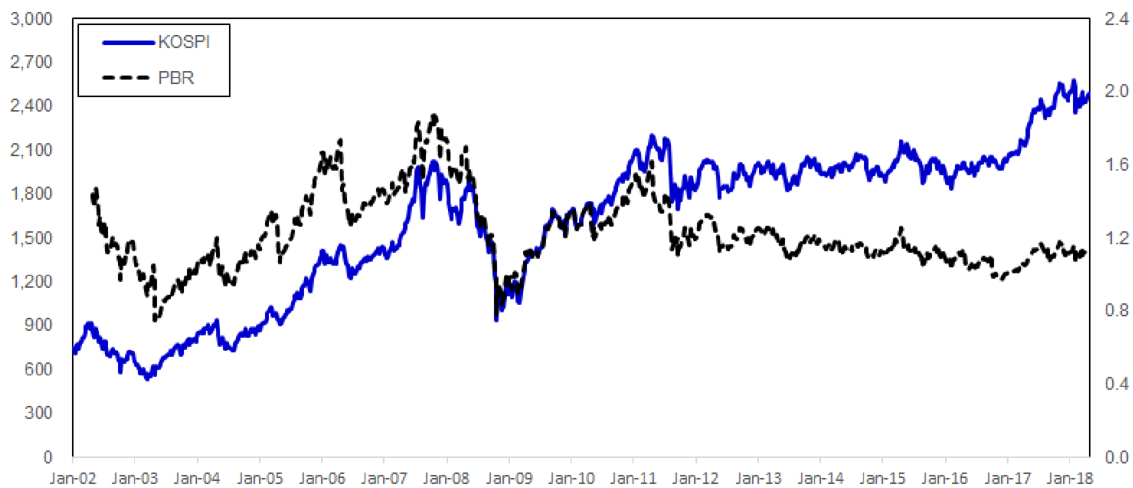
We empirically find that sector rotations have been occuring in the Korean stock market according to the stages of economic scenarios. During the BOXPI period, repeated sector rotations from CYC to DEF have prevented the KOSPI from increasing. The Bayesian variable selection analysis finds heterogeneities in the determinants of returns across sectors and sub-periods in terms of both their importance probabilities and the sensitivities of returns to them. Especially, low valuation, i.e., low PBR, has played an important role in preventing additional falls of the KOSPI. In conclusion, we can interpret the BOXPI as a consequence of the sector rotations from CYC to DEF sectors and the overall low valuation of Korean stock market.

We can consider several interesting further interesting research topics related to the

Figure 7: KOSPI and Its PBR.



(a) KOSPI and its recalculated values on the basis of PBR multiples



(b) KOSPI (left axis) and its PBR (right axis)

Note. *Figure 7–(a) presents the KOSPI and its recalculated values based on PBRs of 0.8×, 1.0×, and 1.2×. Figure 7–(b) shows the KOSPI and its trailing PBR. The data are obtained from the KRX.*

current study. First, we need to confirm the generality of the proposed model by applying it to other countries or country groups to explain sector rotation. Second, our inferences about the sector rotations and the upper bound of the market index movement rely on the asymmetric proportions of the sectors of the Korean stock market. Therefore, comparing sector rotations of countries with different industry structures will deepen the understanding of sector rotation. Lastly, the performance of the sector rotation strategy implied in our continuous-time model can be compared to the existing sector rotation strategies mentioned in this study.

References

Baker, S. R., Bloom, N., and Davis, S. J. (2016), “Measuring Economic Policy Uncertainty*,” *The Quarterly Journal of Economics*, 131, 1593–1636. 5

Chordia, T. and Shivakumar, L. (2002), “Momentum, Business Cycle, and Time-varying Expected Returns,” *The Journal of Finance*, 57, 985–1019. 1

Chui, A. C., Titman, S., and Wei, K. J. (2010), “Individualism and Momentum around the World,” *The Journal of Finance*, 65, 361–392. 7

Conover, C. M., Jensen, G. R., Johnson, R. R., and Mercer, J. M. (2008), “Sector Rotation and Monetary Conditions,” *The Journal of Investing*, 17, 34–46. 1

Du, D. and Denning, K. (2005), “Industry momentum and common factors,” *Finance Research Letters*, 2, 107–204. 1

George, E. I. and McCulloch, R. E. (1993), “Variable Selection Via Gibbs Sampling,” *Journal of the American Statistical Association*, 88(423), 881–889. 4.1

— (1997), “Approaches for Bayesian Variable Selection,” *Statistica Sinica*, 7, 339–373. 4.1

Gomes, J. F., Kogan, L., and Yogo, M. (2009), “Durability of Output and Expected Stock Returns,” *Journal of Political Economy*, 117, 941–986. 1, 3.3, 4.2

Greenberg, E. (2012), *Introduction to Bayesian Econometrics*, Cambridge University Press. 3.2

Hutson, E. and O’Driscoll, A. (2010), “Firm-level exchange rate exposure in the Eurozone,” *International Business Review*, 19, 468 – 478, integrating Contemporary Finance and International Business Research. 1

Jacobsen, B., Stangl, J., and Visaltanachoti, N. (2011), “Sector Rotation Across the Business Cycle,” Working Paper, Available at SSRN: http://ssrn.com/abstract=1714016. 1, 1

Jegadeesh, N. and Titman, S. (1993), "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *"The Journal of Finance"*, 48, 65–91. 1, 7

Kogan, L. and Papanikolaou, D. (2010), "Growth Opportunities and Technology Shocks," *American Economic Review*, 100, 532– 536. 3.1

Moskowitz, T. J. and Grinblatt, M. (1999), "Do Industries Explain Momentum?" *The Journal of Finance*, 54, 1249–1290. 1, 7

Muller, A. and Verschoor, W. F. (2009), "The effect of exchange rate variability on US shareholder wealth," *Journal of Banking & Finance*, 33, 1963 – 1972, financial Globalisation, Risk Analysis and Risk Management. 1

Papanikolaou, D. (2011), "Investment Shocks and Asset Prices," *Journal of Political Economy*, 119, 639–685. 5, 3.1, 6

Petersen, B. and Strongin, S. (1996), "Why are some industries more cyclical than others?" *Journal of Business & Economic Statistics*, 14. 1, 3.3

Rapach, D., Strauss, J., Tu, J., and Zhou, G. (2015), "Industry Interdependencies and Cross-Industry Return Predictability," *SSRN Electronic Journal*. 1

Sassetti, P. and Tani, M. (2006), "Dynamic Asset Allocation Using Systematic Sector Rotation," *The Journal of Wealth Management*, 8, 59–70. 3.1

Tiwari, A. and Vijh, A. M. (2005), "Sector Fund Performance: Analysis of Cash Flow Volatility and Returns," Working Paper, Available at https://www.biz.uiowa.edu/faculty/atiwari/sectorfunds.pdf. 3.1