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When does the Japan Empowering Women Index Outperform its Parent and the ESG Select Leaders Indexes?*

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Abstract

This paper examines and compares the performance of the Japan Empowering Women Index (WIN), Japan ESG Select Leaders Index (SLI), and their parent, the Japanese Investable Market Index (IMI). Without regime switching, our benchmark analysis suggests that none of the indexes outperforms the market on average. We also investigate the possible regime-dependent performance of each index to identify the periods when WIN outperforms the market, the IMI, and the SLI, if ever. Our results indicate regime-dependent performance of the WIN and IMI and regime-independent performance of the SLI. For example, when the market performance of the previous month is relatively poor, the WIN tends to outperform the market, while the IMI tends to underperform. Our results also show that, when the market volatility of the previous month is relatively small, the WIN outperforms the market. However, the WIN and IMI tend to underperform the market under the high market volatility regime.

Keywords: Gender diversity, ESG investment, Fama-French factor model, Smooth-transition model
JEL classification: G11, G12, M14, Q56

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1 Introduction

Environmental, social, and governance (ESG) investment has attracted great attention over the last decade or so. The principles of ESG investments were established when Mr. Kofi Annan, then-secretary general of the United Nations, proposed the principles for responsible investment (PRI). Since then, ESG investment has spread mainly among institutional investors in various countries who invest for the long term, because companies will ultimately be more stable in the long term if a firm is assessed not only by corporate performance and financial status, but also by considering efforts to address sustainable measures, such as ESG issues. Moreover, in 2015, sustainable development goals (SDGs) were adopted at the UN Summit, accelerating the further development of ESG investment. Furthermore, the variety of ESG-related mutual funds is also increasing, and ESG investment is becoming more prevalent even among individual investors. Consequently, more than 3,000 institutions have signed the PRI in 2020, and the total assets under management in ESG investing have reached more than 100 trillion US dollars.[1]

In Japan, ESG investment started to spread in earnest in 2015 when the Government Pension Investment Fund (GPIF), which manages and administers more than 170 trillion yen of pension assets, signed the PRI. This means that the history of ESG investment in Japan is still short compared to Europe and the United States. Accordingly, it has been pointed out that the development of investment policies and systems by Japanese institutional investors as well as the development of information that can be used by investors are one of the most important issues that need to be addressed for Japan (Arao et al. (2020)).

Notably, the environment surrounding ESG investment in Japan has been changing since Prime Minister Yoshihide Suga announced the objective of zero greenhouse gas emissions by 2050 in October 2020. In addition, the Ministry of Economy, Trade and Industry (METI) and the Ministry of the Environment (MOE) jointly released the Disclosure and Engagement Guidance to Accelerate Sustainable Finance for a Circular Economy in January 2021. Because of these initiatives, the number of investment management companies in Japan that handle ESG-related investment trusts has been increasing, and ESG investment is expected to become more widespread in the future.

Although ESG investment is desirable from an ethical perspective, such as contributing to the achievement of the SDGs, ESG investment may not be optimal from the perspective

[1] These numbers are obtained from the PRI's website: https://www.unpri.org/

of risk and return in traditional finance theory because the companies to be invested in are screened by non-financial information. For example, Benlemlih et al. (2018) report that an investment strategy based on the corporate social responsibility (CSR) rating, which is one of the ESG issues, does not necessarily result in a desirable portfolio concerning traditional finance theory. Therefore, it is meaningful to compare the investment performance based on ESG investing principles with the performance of conventional index funds. In addition, Lins et al. (2017) document that the performance of CSR investment outperforms during the financial crisis. This finding suggests that it is also instructive to investigate whether the performance of CSR and ESG investments may change depending on market conditions. Consequently, the contribution of this paper is to tackle these important issues using major ESG indexes in Japan.

More specifically, the first contribution of the paper is to examine the performance of the MSCI Japan Empowering Women Index (WIN), which focuses on gender diversity in Japan as an ESG investment. We also compare its performance with the MSCI Japan ESG Select Leaders Index (SLI), which is a more comprehensive ESG index, and the MSCI Japan Investable Market Index (IMI), a parent index of WIN and SLI.[2] To this end, we employ the Fama-French five- (FF5) factor model proposed by Fama and French (2015) and compare the alpha of each index. Peillex et al. (2019) also investigate the performance of WIN and compare it with the IMI based on the major asset pricing models, including FF5 model, the Capital Asset Pricing Model (CAPM) and Fama-French three- (FF3) factor model (Fama and French (1993)). One of our contributions over their study is to provide a more comprehensive comparison by examining the SLI in addition to the WIN and IMI. The second and more important contribution of the paper is to investigate the possible regime-dependent behavior of each index to identify the periods when WIN outperforms the IMI and SLI, if any. This is a meaningful exercise, because some of the previous studies, such as Lins et al. (2017), suggest that the performance of CSR and ESG indexes could depend on market conditions. To do so, we extend the benchmark FF5 model to the smooth-transition FF5 (STFF5) model to accommodate the regime-dependent performance. For this analysis, we consider two types of regimes, depending on the market performance or market volatility of the previous month. This provides clear and important differences from previous studies, such as Peillex et al. (2019).

[2]Precisely speaking, we use the IMI Top 500 index until November 2018 and the IMI Top 700 index after that, following the change of the parent index for the WIN and SLI.

This study offers several interesting findings. First, we confirm that none of the index has a significant alpha based on the FF5 model. In other words, the FF5 model can describe the excess returns of each index reasonably well on average. However, this does not necessarily mean that each index always performs similarly and makes no significant alpha. Indeed, our results based on the STFF5 model indicate a regime-dependent performance of the WIN and IMI and regime-independent performance of the SLI. For example, when the market performance of the previous month is relatively poor, the WIN tends to outperform the market, while the IMI tends to underperform the market and the SLI tends to have fair performance. This indicates that the WIN has better performance than the IMI and SLI in this period. We also find that, when the market volatility of the previous month is relatively small, the WIN outperforms the market, and the other two indexes do not outperform the markets. Conversely, when the market-realized volatility of the previous month is relatively large, the WIN and IMI tend to underperform the market. Therefore, our analyses can successfully identify some episodes when the WIN outperforms the IMI and SLI, which could have significant implications for policy issues and investment strategies.

This paper is organized as follows. Section 2 summarizes the literature on CSR and ESG investments. Section 3 describes the methodology, while Section 4 summarizes the results of the empirical analysis. Section 5 provides the conclusions of this paper.

2 Related Literature

Broadly speaking, this study is related to the literature examining a relationship between the firm's ESG performance and firm value and performance, including stock market performance. More specifically, this study investigates the performance of ESG investments, focusing on the gender-diversified portfolio represented by the WIN in Japan. Therefore, this paper is also related to literature on the performance of gender-diversified firms and investment. In this section, we briefly review these two strands of literature.

There are increasing studies analyzing the relationship between the firms' ESG performance and firm value. For example, Friede et al. (2015) conduct a meta-analysis on the impact of ESG performance on corporate performance and find that ESG performance has a positive or uncorrelated impact on corporate performance and no negative impact. Benlemlih et al. (2018) report that a higher CSR rating decreases a systematic risk and increases firm value. Similarly, Zhang and Zi (2021) report that the CSR has a positive impact on corporate value based on an analysis of 17 countries. Moreover, Yu et al. (2018) argue the disclosure of the ESG activities is associated with higher firm value through reducing information asymmetry and agency costs, while Alareeni and Hamdan (2020) suggest that there is a positive relationship between the disclosure of ESG activities and firm value, as measured by Tobin's Q.

There are also studies on the relationship between ESG performance and indicators used for stock investment, such as ROA and ROE, and risk.Clarkson et al. (2013) analyze five industries in the U.S. (pulp and paper, chemicals, oil and gas, steel, and utilities) and report a positive relationship between the ESG and ROA. Suto and Takehara (2019) report that CSR activities are positively related to financial indicators such as ROA and ROE by analyzing Japanese companies. Alareeni and Hamdan (2020) document that the disclosure of environmental and CSR factors, which are part of the ESG factors, has a negative relationship with ROA and ROE. Suto and Takehara (2020) suggest that the CSR intensity stabilizes stock returns for high-CSR firms in the long run and moderates management disclosure bias in the short run based on the Japanese stock market. Similarly, Fan and Michalski (2020) conduct an analysis on the Australian stock market and find that portfolios with reduced risk can be made by considering ESG scores. Finally, Gillan et al. (2021) argue that the ESG and CSR performance is often relevant to risk and corporate values, but that more detailed analysis is needed to reach a consensus.

As can be seen above, many studies examining ESG performance and firm value have reported a positive relationship between them. However, there are still limited number of studies showing clear evidence about the performance of the ESG investment. Many early studies analyze the relationship between the CSR and stock performance or performance of a socially responsible investment (SRI). For example, Derwall et al. (2005) find that the stock performance of companies with higher CSR standards tends to be higher. Moreover, Statman (2006) document that the SRI index basically performs better than the S&P500 index, but that the S&P500 index performs better during the economic boom in the early 2000s. Orlitzky et al. (2003) and Margolis et al. (2014) report that there is a positive correlation between CSR and corporate financial performance by meta-analyzing the results of previous studies. Edmans (2011) focuses on employee satisfaction in CSR and confirms a positive correlation between employee satisfaction and stock return. Eccles and Serafeim (2014) show that stocks of higher-CSR firms tend to perform better than their peers. However, Humphrey and Lee (2011) find no significant difference in the performance between SRI funds and conventional funds in Australia. Similarly, Managi et al. (2012) demonstrate that the performance of the SRI and conventional indexes are very similar, even if bear and bull markets are distinguished for the US, UK, and Japan. Finally, Renneboog et al. (2008) point out that investors who invest based on CSR regardless of financial performance appear to be willing to accept suboptimal financial performance to pursue social or ethical objectives.

There are also several studies on CSR activities and the performance of corporate stock returns in crisis periods. Lins et al. (2017) report that firms with higher CSR have higher stock returns during financial crises. Following their study, Rjiba et al. (2020) show that social capital from CSR activities is effective in mitigating negative financial shocks in times of economic uncertainty and that CSR activities are more valued in times of high uncertainty. Zhang et al. (2021) also document that CSR activities play an insurance role in crisis periods, enhancing the stock performance of those firms with higher CSR scores during the crisis. Similarly, Ellouze (2020) analyzes the effect of CSR activities during the crisis period for European firms and confirms CSR activities have an insurance role as in the U.S.

In this paper, we contribute to existing studies by providing new empirical evidence about the performance of ESG investment in Japan. Moreover, we investigate the regime-dependent performance of ESG indexes and identify those periods when ESG indexes outperform conventional indexes, if any. To this end, one of our focused ESG indexes is the WIN, which can be used to measure the portfolio performance consisting of gender-diversified firms in Japan. Therefore, we next summarize the literature on the relationship between the gender diversity of firms and their corporate and stock performance.

Many studies on gender diversity focus on the diversity of board members. For instance, Campbell and Minguez-Vera (2008) find that, in Spain, an early adopter of legal gender diversity, female representation on the board of directors has a positive impact on corporate financial performance. However, Adams and Ferreira (2009) demonstrate that the presence of female directors strengthens the control mechanism over management, but the average relationship with firm performance is negative. Moreover, Carter et al. (2010) and Chapple and Humphrey (2014) document no clear relationship between board gender diversity and corporate performance. Similarly, Chapple and Humphrey (2014) compare the portfolios of firms with and without women board members and find no clear difference in performance. Post and Byron (2015) and Byron and Post (2016) provide a meta-analysis of the relationship between female directors and corporate performance. They confirm that the impact of female directors on corporate social reputation and accounting performance depends on the degree of gender parity. Furthermore, Shaukat et al. (2016) report that companies with a higher CSR orientation of their board of directors, including gender diversity, have higher environmental and social performance. Ruiz-Jimenez et al. (2016) also document that higher gender diversity on the board of directors is associated with higher innovation performance. Bernile et al. (2018) find that higher board diversity is associated with lower risk levels, while Pucheta-Martinez et al. (2018) report that, up to a certain percentage, female directors improve corporate performance. Finally, Peillex et al. (2019) focus on the WIN in Japan and find that its rate of return does not deteriorate compared with its parent index.

This paper, like Peillex et al. (2019), investigates the performance of the WIN and compares it with not only the parent IMI but also a more general ESG SLI. In addition, we examine whether their performance depends on economic conditions and identify when and which ESG indexes outperform the conventional index, if any. This distinguishes our study from others, making a clear contribution to the existing literature.

3 Methodology

3.1 Benchmark Model

The main purpose of this paper is to examine the performance of the WIN and compare it to the IMI and SLI. To this end, our benchmark model is the FF5 model (Fama and French (2015)). This is arguably the most updated version of one of the most widely used models, the FF3 model (Fama and French (1993)). Fama and French (2017) employ the FF5 model to analyze international stock returns, including Japan. In addition, Peillex et al. (2019) apply the FF5 model to compare the performance of the WIN and IMI. The FF5 factor model is given by the following equation:

$$\begin{aligned} R_{i,t} - R_{f,t} &= \alpha + \beta_i^{MKT}(R_{m,t} - R_{f,t}) + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t \\ &\quad + \beta_i^{RMW} RMW_t + \beta_i^{CMA} CMA_t + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where t indicates the month. $R_{i,t}$ denotes the return on the index i, calculated by taking the log difference of each index and multiplying it by 100 to express it as a percentage. $R_{f,t}$ is a risk-free rate, and $R_{m,t}$ is the return on the market portfolio. Thus, $R_{m,t} - R_{f,t}$ is the market (MKT) factor, which is the basis for CAPM. Subsequently, two factors, SMB_t and HML_t, are two additional factors for the FF3 model. The SMB factor is computed by the difference in returns between diversified portfolios consisting of small and large firms' stocks in Japan, while HML_t is the difference in returns between diversified portfolios of value and growth Japanese stocks, defined as those stocks with a high and low book-to-market ratio, respectively. The last two factors, RMW_t and CMA_t, are proposed by Fama and French (2015), completing the FF5 model. Specifically, RMW_t is the difference between the returns on diversified portfolios of Japanese stocks with robust and weak profitability, and CMA_t is the difference between the returns on diversified portfolios of the Japanese stocks of low and high investment firms. Finally, $\varepsilon_{i,t}$ is the error term.

The significant positive α in Equation (1) indicates that the portfolio makes higher returns than expected by the FF5 model. In other words, α can be interpreted as the excess returns of the portfolio, given by its risk exposure to each risk factor described above based on the FF5 model. In this sense, in the FF5 model, the portfolio performance can be assessed and compared by α. We estimate Equation (1) using ordinary least squares (OLS) and calculate the heteroskedasticity and autocorrelation consistent (HAC) standard errors based on Newey and West (1987) for statistical inferences.

3.2 Smooth-Transition FF5 Model

If the market is efficient and the FF5 model is the true asset pricing model, each index should have an insignificant α when the FF5 model is estimated. This simply means that each index is fairly priced on average based on the FF5 model. However, this does not necessarily mean that the performance of each index is always similar. In other words, even if all indexes are fairly priced on average, there might be some periods when one index performs better than others and vice versa. Another objective of the paper is to empirically identify the periods, if any, when the WIN outperforms the IMI and SLI. To this end, we extend the benchmark FF5 model to accommodate regime switching using a smooth-transition framework.

The smooth-transition model is developed within the autoregressive model by, among others, Chan and Tong (1986) and Granger and Teräsvirta (1993); its statistical inference is established by Teräsvirta (1994). Since then, the smooth-transition model has been applied to many types of models.

In this study, we apply the smooth transition model to α in the FF5 model (1) to capture the possible regime-dependent α depending on the market conditions.[3] We call this model

[3]Theoretically speaking, we could make all coefficients in the FF5 model (1) regime dependent. However, given the small sample size, it is not practical to do so, making the estimation imprecise, if not impossible. Moreover, regime-dependent α is sufficient for the purpose of our analysis.

a smooth-transition FF5 (STFF5) model. Specifically, α in the STFF5 model is given as follows:

$$\alpha_t = \alpha_1(1 - G(s_{t-1}; c, \gamma)) + \alpha_2 G(s_{t-1}; c, \gamma)$$

where $G(\cdot\,; c, \gamma)$ is a transition function taking values between zero and one with a transition variable s_{t-1}. The transition function has two parameters c and γ, which determine the threshold between the two regimes and the speed of the regime transition, respectively. When $G(s_{t-1}) = 0$, α_t becomes equal to α_1. We call this regime "regime 1." Similarly, the other regime, called "regime 2," is characterized by $G(s_{t-1}) = 1$ and $\alpha_t = \alpha_2$.

The transition function and the transition variable are determined according to the purpose of the analysis. In this study, we try to identify the monotonic regime transition, depending on market conditions, such as market performance and volatility. If one is interested in analyzing a monotonic regime transition with a transition variable, a logistic transition function is commonly used. Following this convention, we use the following logistic transition function:

$$G(s_{t-1}; c, \gamma) = \frac{1}{1 + \exp\bigl(-\gamma(s_{t-1} - c)\bigr)}, \quad \gamma > 0. \tag{2}$$

In general, the behavior of stock markets tends to change with market conditions. Hence, it is quite reasonable and meaningful to examine whether the α of each index depends on market conditions. Therefore, we consider two transition variables: the general market performance, $s_{1,t}$, captured by the past five-week return of IMI, as well as market volatility, $s_{2,t}$, measured by the past five-week realized volatility of IMI based on the daily returns.[4] As is conventional, we date the variable s at time $t-1$ to avoid contemporaneous feedback. With the logistic transition function (2) and transition variable $s_{1,t}$, we can interpret α_1 as the alpha when the market performance of last month was poor and α_2 as the alpha when the market performance of last month was good. This is because if the last month's market performance is poor, $s_{1,t-1}$ takes smaller values, and, hence, $G(s_{1,t-1})$ is close to zero. Conversely, if last month's market performance is relatively good, $s_{1,t-1}$ becomes large, and $G(s_{1,t-1})$ nears one. Similarly, if we use $s_{2,t}$ as a transition variable, α_1 (α_2) can be regarded as the alpha when the market volatility of last month is low (high).

[4] We chose five weeks instead of one month to make the number of business days equal regardless of the months, though we did not adjust for holidays. Nota that we confirmed all results were qualitatively similar even if we used four weeks. In addition, we standardized each transition variable so it has a mean of zero and standard deviation of one.

One advantage of the logistic transition function (2) is that it can express various forms of the transition between regime 1 (α_1) and regime 2 (α_2) depending on the values of c and γ. The location parameter c determines the threshold between two regimes. More specifically, if s_{t-1} is less (greater) than c, the weight on α_1 is greater than 1/2, implying α_t is nearer α_1 at time t. The smoothness parameter γ determines the speed of the transition from α_1 to α_2 as the market performance over the past five weeks improves. More specifically, the transition is smoother (faster) as γ takes a smaller (larger) value. Once γ exceeds a certain value, the transition function behaves like a step function with a very rapid transition. Accordingly, we set an upper bound of 300 for γ.

Following the suggestion of Granger and Teräsvirta (1993), we estimate c and γ using a grid search.[5] Given the fixed values of c and γ, the STFF5 model becomes a standard linear regression model, and we can estimate the remaining parameters using OLS with HAC standard errors.

4 Empirical Results

In this section, we summarize our empirical results. First, we report the results of the benchmark FF5 model to examine the performance of the WIN on average and compare it with that of the IMI and SLI. Then, we show the results of STFF5 to see whether we can observe differences in the performance of each index, depending on the market conditions.

Our empirical analysis is based on the monthly data of the WIN, IMI, and SLI provided by the MSCI. The sample period of our analysis is from April 2013 to October 2020. The Japanese stock market seems to be affected considerably by the monetary policy of the Bank of Japan (BoJ), particularly after the BoJ introduced the aggressive monetary easing called quantitative and qualitative easing (QQE) in April 2013. Indeed, the behavior of Japanese stock prices appear to be very different since the beginning of 2013. To deal with this possible structural change due to the introduction of QQE, our beginning of the sample period coincides with the start of QQE.

For the IMI, we use the MSCI Japan IMI Top 500 index until November 2018 and IMI Top 700 index afterward, following the change of parent index for the WIN and SLI. We also obtained risk-free rates and all risk factors for the FF5 model (1) from the Kenneth R.

[5]One cost of estimating c and γ with a grid search is that the standard errors of c and γ cannot be evaluated. Thus, the standard errors in the regression results in the next section do not consider the effects of estimating c and γ.

French data library.[6] Following Fama and French (2017) and Peillex et al. (2019), all data are denominated in US dollars to make our results comparable with their results.

4.1 Results of the FF5 model

We start by estimating the benchmark FF5 model (1). Table 1 reports the estimated coefficients of the FF5 model and their p-values based on the HAC standard errors to correct for heteroskedasticity and autocorrelation. As seen in the second and third rows, the MKT, SMB, and CMA factors are significant for at least a 10% significance level, and those factors seem to capture the behavior of monthly WIN excess returns with nearly 0.97 adjusted R^2. More importantly, the α of WIN is estimated insignificantly with a relatively small estimate of 0.05% or 0.60% annually. This implies the WIN makes fair excess returns given the exposures to risk factors considered in the FF5 model (1) on average. That is, there is no evidence the WIN can earn extra excess returns more than expected from the FF5 model.

[Table 1 around here]

The next two rows of Table 1 document the results for the IMI. Similar to WIN, the MKT, SMB, and CMA factors are significant for explaining the behavior of monthly IMI excess returns with 0.99 adjusted R^2. Its α is significant only at the 10% significance level and estimated as -0.10% or -1.14 annually. Although our empirical evidence shows some evidence of the IMI's underperformance during this period, the evidence is rather weak and insignificant at the 5% significance level. Therefore, it is reasonable to say that IMI is also fairly priced based on the FF5 model (1) on average. More importantly, the results show that we cannot find any evidence the IMI outperforms the WIN based on the FF5 model, which is in line with Peillex et al. (2019).

The last two rows of Table 1 report the SLI results. In the case of the SLI, only MKT and SMB factors are significant at the 5% significance level, but the FF5 model still has good explanatory power on the monthly SLI excess returns with 0.98 adjusted R^2. More notably, its α is estimated as insignificant, with a very small estimate of 0.03% or 0.34% annually. Clearly, the SLI performs ordinarily, following the FF5 model (1).

In summary, our results suggest that the behavior of excess returns on all three indexes are well captured by the FF5 model. We also find no statistical evidence of outperformance with the positive α of each index, compared with the benchmark FF5 model. Moreover, our

[6] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

results demonstrate that there is no clear evidence that the performance of the WIN and SLI is worse than IMI, though these two indexes restrict the investment universe with sustainable criteria from the parent IMI. In other words, investing in the WIN and SLI does not come at a cost compared to investing in its parent IMI. The results of WIN are consistent with those of Peillex et al. (2019); however, we provide additional similar results for the SLI.

4.2 Results of the STFF5 model based on the previous month's market performance

The results of the previous subsection indicate that each index is fairly priced on average based on the FF5 model without a significant α at the 5% significance level. However, this does not necessarily mean that each index always performs similarly and makes no significant α. Put differently, even if all indexes are fairly priced on average based on the FF5 model, it would be possible for one index to perform better than others and vice versa under some market conditions. To explore this possibility, we extend the FF5 model to the STFF5 model expressed by equations (1)-(2) with regime-dependent α. Regarding the transition variables, we consider two variables to capture two different market conditions. The first variable is the general market performance, $s_{1,t}$, captured by the past five-week return of IMI, and the market volatility, $s_{2,t}$, measured by the past five-week realized volatility of IMI. Each result will be presented in this subsection and the following subsection.

First, we apply the STFF5 model with the market performance $s_{1,t}$ as a transition variable to the WIN. The estimated parameters of the transition function (2) are summarized in Table 2. As can be seen, c is estimated as 0.05, and γ is estimated as 300. Note that each transition variable is standardized, and the mean and SD of s_1 before standardization are 0.02 and 0.17, respectively. Thus, $c = 0.05$ suggests the center of transition would be $0.02 + 0.05 \times 0.17$, which is roughly 0.03%. Moreover, a large estimate of γ indicates that this transition occurs quickly. In other words, although our STFF5 model allows a smooth transition between two regimes, the data prefers quick transition. In summary, the estimation results of the transition function imply that if the IMI return over the last five weeks is less than 0.03%, α tends to be α_1. If it is larger than 0.03%, α takes the value of α_2. This result can be also confirmed graphically by the top-left panel of Figure 1. It plots the estimated time series of the transition function (2), which can be considered as the weight of the regime 2 or α_2. Clearly, the transition function fluctuates quite often, reflecting the market performance over the past five weeks. According to the estimation results, 47 out of

91 months are classified as regime 1, while the rest of 44 months are sorted to regime 2.[7]

[Figure 1 around here]

Although the estimated transition function suggests that the two regimes are quite well identified, this does not necessarily mean that two regimes are meaningfully different. To check this, Table 3 reports the estimation results of the rest of the parameters of the STFF5 model. As can be seen, the estimate and significance of coefficients on each risk factor is reasonably close to those of the FF5 model, although the CMA factor becomes insignificant. Nonetheless, a noticeable difference can be observed between α_1 and α_2. α_1 is significantly positive, with a relatively large estimate of 0.21% or 2.45% annually. In contrast, α_2 is insignificant with a negative sign. These results imply that if the market condition measured by the performance of the conventional index over the last month is not good with less than 0.03% return, the WIN tends to outperform the market that month by more than 0.2% on average. Conversely, if the market condition of the last month is relatively good with more than 0.03% return, the WIN behaves ordinarily, following the FF5 model. These results clearly demonstrate the regime-dependent behavior of the WIN with remarkable performance in regime 1.

[Table 3 around here]

Next, we conduct the same analysis using the IMI. As can be seen from Table 2, the parameters of the transition function (2), c and γ, are -0.46 and 300, respectively. This implies that if the IMI return over the last five weeks is less than $0.02-0.46\times0.17=-0.05\%$, the regime would be regime 1. Otherwise, the regime would be regime 2. This result can be graphically seen from the second-left panel of Figure 1, plotting the estimated time series of the transition function (2). As discussed, the values of the transition function can be considered as the weight of regime 2 or α_2. The results indicate that 27 out of 91 months are classified as regime 1. The difference between the two regimes can be observed from Table 3, showing the estimation results of the rest of the parameters of the STFF5 model with s_1 transition variable. Like the WIN, the estimates and significance of all risk factors are reasonably close to those of the FF5 model, although the CMA factor becomes significant. However, the estimates of α_1 and α_2 indicate remarkable distinctions from the FF5 model and

[7]For this calculation and similar calculations below, we use 0.5 as the threshold for the transition function to distinguish two regimes. In other words, if the value of the transition function at month t is smaller (larger) than 1/2, we classified month t as in regime 1 (regime 2).

the results of the WIN. Specifically, for the IMI, α_1 is significantly negative with estimates of -0.20%, showing a great contrast to the significant positive estimate of the WIN. Contrarily, α_2 is insignificantly estimated as -0.05%, suggesting that IMI is fairly priced by the FF5 model on average in regime 2. These results provide very interesting similarity and difference between the WIN and IMI. Although both indexes follow the FF5 model on average when the market performance of the previous month was relatively good, the WIN tends to outperform the market, while the IMI underperforms the market, when the market performance of the previous month is relatively poor.

Finally, we apply the same STFF5 model consisting of equations (1)-(2) with s_1 transition variable to the SLI. The results shown in Table 2 indicate that the estimates of c and γ are given by 0.56 and 300, respectively. This implies the regime will shift from 1 to 2 quickly, depending whether the IMI return over the last five weeks is less than $0.02 + 0.56 \times 0.17 = 0.12\%$. The time series plot of the estimated transition function shown in the bottom-left panel illustrates the actual dynamics of regimes based on estimation results. For the SLI, the regime is classified as regime 1 more often than the other two indexes with 67 out of 91 months. To see the disparities between two regimes, we can refer the estimation results of the rest of the parameters of the STFF5 model, reported in Table 3. The estimation results for the coefficients on the risk factors are essentially the same as the FF5 model's, shown in Table 1. Moreover, insignificant estimates of α_1 and α_2 suggest the SLI appears fairly priced by the FF5 model on average in both regimes. This contrasts greatly with the other two indexes, as both show some discrepancy from the FF5 model under the relatively poor market condition in regime 1.

In sum, our results demonstrate the compelling similarities and differences in regime-dependent behaviors across three indexes. When the market performance of the previous month is relatively good, all indexes appear to follow the FF5 model on average. However, when the market performance of the previous month is relatively poor, the performance of each index differs considerably. Specifically, the WIN tends to outperform the market, while the IMI tends to underperform. In contrast, the SLI does not have any tendency to deviate from the FF5 model. Therefore, the STFF5 model can successfully identify episodes when the WIN outperforms the parent and leaders index, which could have significant implications for policy issues as well as investment strategies.

4.3 Results of the STFF5 model based on the previous month's market volatility

In this subsection, we conduct the same analysis with the previous subsection but using the market volatility, $s_{2,t}$, measured by the realized volatility of the IMI over the past five weeks as a transition variable. We start by applying the STFF5 model to the WIN. The estimated parameters of the transition function (2) can be found in Table 2. The results show that c is estimated as 0.09 and γ is estimated as 300. This implies that the center of transition would be slightly less than the mean and the transition occurs quickly. In other words, although our STFF5 model allows a smooth transition between two regimes, the data prefers a quick transition. Note that s_2 is standardized, and the mean and SD of s_2 before standardization are 16.5 and 7.2, respectively. Thus, our estimation results of the transition function imply that, if the IMI-realized volatility over the last five weeks is less than $16.5+0.09\times 7.2 = 17.2\%$, the regime tends to be regime 1 characterized by α_1. If it is larger than 17.2%, α takes the value of α_2. The actual regime transition can be confirmed graphically by the top-right panel of Figure 1, plotting the estimated time series of the transition function (2) or the weight on regime 2. The transition function fluctuates less often compared with the results using s_1, reflecting the persistence of realized volatility. According to the estimation results, 60 out of 91 months are classified as regime 1, while the rest of 31 months are sorted to regime 2.

To see the difference in α between two regimes, Table 4 reports the estimation results of the rest of the parameters of the STFF5 model. Even if we use s_2 as the transition variable, the estimate and significance of the coefficient on each risk factor is reasonably close to those of the FF5 model, although we can see a clear difference between α_1 and α_2. Specifically, α_1 is significantly positive, with a relatively large estimate of 0.17% or 1.99% annually. In contrast, α_2 is significantly and negatively estimated as -0.19% or -2.24% annually. These results imply that if the market volatility over the last month is small, the WIN tends to outperform the market this month by 0.17% on average. On the contrary, if the market volatility of the last month is relatively large, the WIN underperforms the market by more than 2%.

[Table 4 around here]

Next, we estimate the STFF5 model with s_2 as a transition variable using the IMI. The parameters of the transition function, c and γ, reported in Table 2 suggest that if the IMI-realized volatility over the last five weeks is less than $16.5 - 0.01 \times 7.2 = 16.4\%$, the regime tends to be regime 1. Otherwise, the regime tends to be regime 2. The estimated dynamics of the regime can be seen from the time series plot of the estimated transition function shown in the second-right panel of Figure 1, indicating that 54 out of 91 months are classified as regime 1. The rest of the parameter estimates are reported in Table 4. Similar to the WIN, the estimates and significance of all risk factors are very close to those of the FF5 model. However, the estimates of α_1 and α_2 indicate a clear distinction from the results of the WIN. Specifically, for the IMI, α_1 is insignificant with estimates of 0.01%, showing a great contrast to the significant positive estimate for the WIN. However, α_2 is significantly and negatively estimated as -0.27%, suggesting the IMI underperforms the market considerably in regime 2. These results provide a similarity and difference between the WIN and IMI. Although both indexes underperform the market when the market volatility of the previous month is relatively high, the WIN only tends to outperform the market when the market volatility of the previous month is relatively low.

Finally, we apply the same STFF5 model consisting of equations (1)-(2) with a s_2 transition variable to the SLI. The estimates of c and γ are reported in Table 2 and given by -0.02 and 300, respectively. This implies that the regime will shift from 1 to 2 quickly, depending whether the IMI-realized volatility over the last five weeks is less than $16.5 + 0.18 \times 7.2 = 17.8\%$. The time series plot of the estimated transition function shown in the bottom-right panel illustrates the actual dynamics of regimes based on the estimation results, suggesting that the regime is classified as regime 1 for 62 out of 91 months. Nonetheless, the estimation results of the rest of the parameters of the STFF5 model, reported in Table 4, demonstrate the regime-independent feature of the SLI. Specifically, the estimation results for the coefficients on the risk factors are essentially the same as those of the FF5 model shown in Table 1. Moreover, both α_1 and α_2 are insignificant, suggesting the SLI appears fairly priced by the FF5 model on average in both regimes. This is a great contrast to the other two indexes, both of which show the regime-dependent performance.

In summary, our results demonstrate the various regime-dependent behavior of each index. When the market volatility of the previous month is relatively small, only the WIN outperforms the market, while the IMI and SLI appear to follow the FF5 model on average. However, the market-realized volatility of the previous month is relatively large, the WIN and IMI tend to underperform the market, although the SLI still follows the FF5 model. Therefore, the STFF5 model with a s_2 transition variable can successfully identify a regime characterized by low market volatility, when the WIN outperforms the parent and leaders indexes.

4.4 Results of the STFF5 model under the common regime assumption

The results in the previous subsections show the clear difference in regime-dependent behavior across returns of the WIN, IMI, and SLI. Both WIN and IMI show some regime-dependent performance with remarkable difference during the poor-performance and low-volatility regimes. In contrast, the SLI demonstrates the regime-independent performance regardless of the performance and volatility regimes. Note that, in previous subsections, we allow each index return to have its own regime classifications. In other words, regimes of each index return are different, as we saw in Figure 1. One might think this could be why each index return shows different regime-dependent performance. To address this issue, we re-estimate the STFF5 model for the IMI and SLI using the estimated transition function from the WIN in this subsection.

Tables 5 and 6 report the estimation results of the STFF5 model using WIN regimes based on the previous month's stock market performance and volatility transition variable, respectively. In these tables, the results for the WIN are the same as those in the previous subsections, but shown for reference. As can be seen, if we use the WIN regimes for other two indexes, the estimation results of the FF5 model would be different but our main conclusion remains the same. For example, the IMI still indicates regime-dependent performance with a significantly negative α in regime 2 at least for the 10% significance level, regardless of transition variables. In contrast, the SLI does not have statistical evidence of regime-dependent behavior, and its α is not significantly different from 0, regardless of regimes and transition variables.

The analysis of this subsection further confirms the difference in the regime-dependent behavior between the WIN and two other indexes. Although both WIN and IMI show regime-dependent performance, only the WIN has a significantly positive α in regime 1 for both transition variables. Moreover, the SLI seems to be fairly priced based on the FF5 model, no matter which transition variable we use and regime we consider. In summary, when the performance of the stock market in the previous month is poor or the volatility of the stock market in the previous month is low, only the WIN tends to outperform the market, and hence the other two indexes, demonstrating some attractiveness to investing the WIN over the other two indexes.

5 Conclusion

In this paper, we examine and compare the performance of the WIN and SLI, and their parent index, IMI. While the WIN and SLI constitute a desirable portfolio from an ethical perspective because it uses non-financial information such as women's activities for screening, it may perform worse than a portfolio based on standard finance theory (market funds). Therefore, it is an important issue to consider the performance of the WIN and SLI. It is also meaningful to investigate whether the performance of those indexes may change depending on market conditions. The objective of this paper is to provide new empirical evidence and implications for these issues.

Our benchmark FF5 model suggests that none of the index has a significant alpha, meaning that the FF5 model can describe the excess returns of each index reasonably on average. However, this does not necessarily mean that each index always performs similarly and makes no significant alpha. Indeed, our results based on the STFF5 model indicate a regime-dependent performance of the WIN and IMI and regime-independent performance of the SLI. More specifically, when the market performance of the previous month is relatively good, all indexes appear to follow the FF5 model on average. However, when the market performance of the previous month is relatively poor, the WIN tends to outperform the market, while the IMI tends to underperform. In addition, when the market volatility of the previous month is relatively small, the only WIN outperforms the market, while the IMI and SLI appear to follow the FF5 model on average. This demonstrates the WIN has better performance than the IMI and SLI in these regimes. Conversely, when the market-realized volatility of the previous month is relatively large, the WIN and IMI tend to underperform the market, although the SLI still follows the FF5 model. Therefore, our analyses can successfully identify some episodes when the WIN outperforms the parent and leaders' indexes, which have significant implications for policy issues and investment strategies.

Over the last decade, one of the highest-priority policies for the Japanese government was to promote female participation and career advancement in the workplace. Nonetheless, the promotion of gender diversity is still very behind other advanced countries. Indeed, according to the recent report by World Economic Forum (2021), Japan ranked 120th among 156 countries in the gender gap rankings in 2021, indicating Japan is one of the worst countries among advanced countries concerning gender diversity. Consequently, executing policies to enhance gender diversity will likely remain the important policy issue in Japan over the next decade. Our results demonstrate the potential of the WIN to achieve both ethical and financial performance, showing better performance than the conventional index and other ESG indexes in some regimes. In other words, we could construct a trading strategy by utilizing our results, which is financially beneficial in addition to ethically preferable. If this is the case, the WIN could attract more investment from ethical investors, which helps further enhance the gender diversity of those firms included in the WIN. This could improve the effectiveness of policies to enhance the gender diversity in Japan.

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Table 1: Estimation results of the FF5 model

Index		α	MKT	SMB	HML	RMW	CMA	Adj. R^2
WIN	Est	0.051	0.973	-0.131	-0.052	0.046	0.090	0.968
	P-val	0.397	0.000	0.000	0.171	0.440	0.072	
IMI	Est	-0.095	1.003	-0.118	0.043	0.031	-0.075	0.988
	P-val	0.055	0.000	0.000	0.283	0.691	0.019	
SLI	Est	0.028	0.956	-0.162	-0.049	-0.045	-0.019	0.975
	P-val	0.592	0.000	0.000	0.205	0.417	0.753	

Table 2: Estimated parameters of the transition function for the STFF5 model

	s_1		s_2	
Index	c	γ	c	γ
WIN	0.0520	300	0.0909	300
IMI	-0.4626	300	-0.0105	300
SLI	0.5632	300	0.1763	300

Table 3: Estimation results of the STFF5 model with the market-performance transition variable

Index		α_1	α_2	MKT	SMB	HML	RMW	CMA	Adj. R^2
WIN	Est	0.207	-0.121	0.974	-0.124	-0.056	0.034	0.078	0.970
	P-val	0.001	0.177	0.000	0.000	0.124	0.527	0.111	
IMI	Est	-0.201	-0.049	1.004	-0.126	0.040	0.031	-0.073	0.988
	P-val	0.027	0.237	0.000	0.000	0.279	0.673	0.015	
SLI	Est	0.061	-0.068	0.956	-0.156	-0.049	-0.049	-0.025	0.975
	P-val	0.268	0.637	0.000	0.000	0.182	0.379	0.687	

Table 4: Estimation results of the STFF5 model with the market-volatility transition variable

Index		α_1	α_2	MKT	SMB	HML	RMW	CMA	Adj. R^2
WIN	Est	0.166	-0.186	0.978	-0.132	-0.051	0.031	0.047	0.969
	P-val	0.022	0.038	0.000	0.000	0.123	0.588	0.329	
IMI	Est	0.014	-0.266	1.004	-0.117	0.041	0.015	-0.109	0.989
	P-val	0.745	0.000	0.000	0.000	0.236	0.823	0.001	
SLI	Est	0.084	-0.102	0.959	-0.163	-0.051	-0.055	-0.042	0.975
	P-val	0.146	0.253	0.000	0.000	0.168	0.342	0.462	

Table 5: Estimation results of the STFF5 model using the WIN regimes based on the market-performance transition variable

Index		α_1	α_2	MKT	SMB	HML	RMW	CMA	Adj. R^2
WIN	Est	0.207	-0.121	0.974	-0.124	-0.056	0.034	0.078	0.970
	P-val	0.001	0.177	0.000	0.000	0.124	0.527	0.111	
IMI	Est	-0.110	-0.079	1.003	-0.119	0.043	0.032	-0.073	0.988
	P-val	0.137	0.075	0.000	0.000	0.271	0.682	0.013	
SLI	Est	0.016	0.042	0.956	-0.162	-0.049	-0.044	-0.018	0.975
	P-val	0.761	0.662	0.000	0.000	0.197	0.429	0.767	

Table 6: Estimation results of the STFF5 model using the WIN regimes based on the market-volatility transition variable

Index		α_1	α_2	MKT	SMB	HML	RMW	CMA	Adj. R^2
WIN	Est	0.166	-0.186	0.978	-0.132	-0.051	0.031	0.047	0.969
	P-val	0.022	0.038	0.000	0.000	0.123	0.588	0.329	
IMI	Est	-0.046	-0.196	1.005	-0.118	0.043	0.025	-0.093	0.988
	P-val	0.425	0.000	0.000	0.000	0.266	0.754	0.001	
SLI	Est	0.075	-0.068	0.958	-0.162	-0.048	-0.051	-0.037	0.975
	P-val	0.236	0.436	0.000	0.000	0.184	0.368	0.532	

Figure 1: Time series plots of estimated transition function